Measuring Stock Market Volatility: An Experience from Chittagong Stock Exchange

Md. Abdur Rahman Forhad*
Amirul Islam

Abstracts

Measuring Volatility is an important area of research in financial markets and a lot of efforts have been expended in improving volatility models to make a better pricing of stocks and better risk management. This study uses the Autoregressive Conditional Heteroscedasticity (ARCH) models and its extension, the Generalized ARCH (GARCH) model to find out the presence of the stock market volatility on Chittagong Stock Exchange (CSE). The analysis was done using a time series data for the period, January 2005- May 2008 on all of the indices like All Share Price Index (ASPI), CSE Selective Index (CSE 30), CSE Selective Categories Index (CSCX) calculated by CSE. There is a strong evidence of volatility on the daily returns of all the indices of CSE characterized by the above models. The most volatile series is ASPI of CSE, because of the uncertainty in prices of all the stocks enlisted in CSE over the examined period. The degree of market volatility of CSE can help forecasters to predict the path the market as well as the economy's growth and the structure of volatility can help the investors to make their portfolio decisions.

1. Introduction

Financial markets play an important role in the process of economic growth and development by facilitating savings and channeling funds from depositors to investors. While there have been numerous attempts to develop the financial sector, small island economies are also facing the problem of high volatility in numerous fronts including volatility of its financial sector. Volatility forecasting is an important task in financial markets. Volatility is not the same as risk. When it is interpreted as uncertainty, it becomes a key input to many investment decisions

* Lecturer in Economics Department of Humanities Dhaka University

** Associate Professor Department of Economics University of Chittagong

and portfolio creations. Investors and portfolio managers have certain levels of risk which they can bear. A good forecast of the volatility of asset prices over the investment holding period is a good starting point for assessing investment risk. Volatility may impair the smooth functioning of the financial system and adversely affect economic performance. Similarly, stock market volatility also has a number of negative implications. One of the ways in which it affects the economy is through its effect on consumer spending (Campbell, 1996; Starr-McCluer, 1998; Ludvigson and Steindel 1999 and Poterba 2000). The impact of stock market volatility on consumer spending is related via the wealth effect. Increased wealth will drive up consumer spending. However, a fall in stock market will weaken consumer confidence and thus drive down consumer spending. Stock market volatility may also affect business investment (Zuliu, 1995) and economic growth directly (Levine and Zervos, 1996 and Arestis et al 2001). A rise in stock market volatility can be interpreted as a rise in risk of equity investment and thus a shift of funds to less risky assets. This move could lead to a rise in cost of funds to firms and thus new firms might bear this effect as investors will turn to purchase of stock in larger, well known firms. Volatility is the most important variable in the pricing of derivative securities, whose trading volume has increased in recent years. To price a stock, we need to know the volatility of the underlying asset from now until the stock matures. Most investors and financial analysts are concerned about the uncertainty of the returns on their investment assets, caused by the variability in speculative market prices (and market risk) and the instability of business performance (Alexander, 1999). Recent developments in financial econometrics require the use of quantitative models that are able to explain the attitude of investors not only towards expected returns and risks, but towards volatility as well. Hence, market participants should be aware of the need to manage risks associated with volatility.

The degree of stock market volatility can help forecasters predict the path of an economy's growth and the structure of volatility can imply that investors now need to hold more stocks in their portfolio to achieve diversification (Krainer, J, 2002:1). This article benefits from developments in the measurement of volatility through econometric techniques. Here, the Autoregressive Conditional Heteroscedasticity (ARCH) model introduced by Engle (1982) and its extension, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH)model, (Bollerslev, 1986) is used to estimate the conditional variance on the stock market of Bangladesh. This method allows for an objective determination of the presence of volatility.

This paper can be divided into 8 sections. Following the introduction in sectic section 2 provides a short overview of the stock market of Bangladesh, secti reviews the literature of GARCH methodology, section 4 discusses the data methodology, section 5 assumes the research hypothesis, section 6 explain: empirical analysis of volatility scenario on stock market of Bangladesh, secti suggests proposals to reduce the volatility and section 8 concludes this analy

2. Stock market in Bangladesh- A brief discussion

Stock Exchange organized market for trading of stocks and bonds. In early 1 five years after the independence of Pakistan, the Calcutta Stock Exch prohibited the transactions of Pakistani stocks. This necessitated the formatic a stock exchange in East Pakistan and the East Pakistan Stock Exch Association Ltd. was incorporated on 28 April 1954. It was the changed by name to East Pakistan Stock Exchange Ltd. on 23 June 1962 and finally to D Stock Exchange (DSE) on 14 May 1964. Although the DSE was incorporat 1954, formal trading started in 1956 in Narayanganj.

Any individual of sound mind and over 21 years of age can apply to beco member of the stock exchange by purchasing a share of DSE and after obta dealer/broker license from the Securities and Exchange Commission (SEC) Securities and Exchange Commission (SEC) was established on June 8, under the Securities and Exchange Commission Act 1993 (Act

15 of 1993) as a capital market regulator with a view to ensuring proper issu of securities, protection of the interest of investors in securities, developme the capital and securities markets, and regulation of the capital and secu markets in Bangladesh.

DSE is a self-regulated not-for-profit organization. DSE Council is the hi policy making body of the stock exchange. DSE Council was constituted l members only earlier prior to issuance Dhaka Stock Exchange Council Administration Regulation, 2000.

The Chittagong Stock Exchange Ltd (CSE) was set up in 1995. It is also a regulated non-profitable organization like DSE and formation of the Co numbers of council members and the mechanism of appointment of councilo similar to DSE. CSE is administered under the Chittagong Stock Exch (Board and Administration) Regulations, 2000.

3. Selected Literature Review

In the last few decades a growing number of scholars have focused the attention of the analysis and forecasting of volatility, due to its crucial role in financial markets. So far in the literature, many models have been put forward, but those that to be the most successful and the popular are the GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models by Bollerslev(1986) who generalizes the seminal idea on ARCH (Autoregressive Conditional Heteroscedasticity) by Engel(1982).Their incredible popularity stems from their ability to capture, with a flexible structure, some of typical stylized facts in financial time series, such as volatility clustering, that is the tendency for volatility periods of similar magnitude to cluster. Usually GARCH model can take into account the time-varying volatility phenomenon over a long period (French et al., 1987, Franses and Van Dijk, 1996) and provide very good in-sample estimates. The empirical evidence is rather mixed as to which volatility forecast model performs best. Akgiray (1989) researched US stock markets and found that a GARCH (1, 1) model outperformed more traditional technical analysis. Brailsford and Faff (1996) (hereafter BF) employed Australian data to compare the predictive performance of several statistical methods with GARCH and TGARCH models. The results suggested that the ARCH class of models and a simple regression model provide superior forecasts of volatility. However, the various model

rankings were shown to be sensitive to the error statistic used to assess the accuracy of the forecasts. Mcmillan et al. (2000) evaluated the performance of ten alternative models for predicting the UK FTA all share and FTSE100 stock index volatility at monthly, weekly and daily frequencies. Like BF (1996), they found that the ranking of different forecasting models is dependent on the series, frequency and evaluation criteria.

Instead of statistical evaluation criteria, model performance could be judged by some measures of economic significance. Karolyi (1993) tested forecast accuracy by measuring the impact on option pricing errors. Brooks and Persand (2003) evaluated how adequately the forecasting models perform in modern risk management setting.

Hassan et.al (2000) empirically examines the issue of market efficiency and time-varying risk return relationship for Bangladesh. The results show a significant relationship between conditional volatility and the stock returns, but the risk-return parameter is negative and statistically significant.

Chowdhury and Rahman (2004) have studied the relationship betwee predicted volatility of Dhaka Stock Exchange returns and that of sel macroeconomic variables of Bangladesh economy. They have followe methodology of Schwert (1989; 1990) to calculate the predicted volatility variables used in the study. They have calculated volatility from errors after an autoregressive and seasonality adjusted forecasting model

Chowdhury and Iqbal (2005) show that DSE returns have high vol persistence and tend to go away from mean infinitely. However, when data c months before and after the crash of 1996 are omitted, volatility persistenc reduced and has the tendency to go back to mean volatility after its departure mean. Investors do not differentiate between positive and negative sho volatility.

4. Data and methodology

All relevant data are collected from CSE publications. There are three ty indices in the Chittagong Stock Exchange. These are the all share price (ASPI), CSE 30 and the CSCX. The daily all share price indices (ASPI) in all the listed companies in the Chittagong stock Exchange (CSE). The CSE calculated by CSE and its original is CSE Selective Index where no Z cat share is enlisted. There is another index calculated by CSE is CSE Sel Categories Index (CSCX) which is calculated from the enlisted compani CSE. The daily share price indices (ASPI, CSE 30, CSCX) on CSE are coll from the Data Stream and the observation period ranges from 1st January 2(31st May, 2008. The empirical analysis of this study uses daily data of cl prices for the all share price index (ASPI) on indicated sample period.

This paper wants to explain the volatility scenario by a comparison amon three daily all share price indices of CSE. The study examined the distributi stock returns, where the stock return is calculated as the log difference of stock price index: $R_t = \ln(P_t) - \ln(P_{t-1})$. To explain the volatility of the CSE study uses the Generalized Autoregressive Conditional Heteroscedas (GARCH) as a methodology.

The Autoregressive Integrated Moving Average (ARIMA) model, as deve by Box and Jenkins (1976), has been used in earlier studies in forec movements of stock prices. However, one of the assumptions in the AR model is that the disturbance terms in the model have a constant condi variance through time. This assumption constrains ARIMA model's abil capturing the volatility of stock returns because prior research has shown that the stock returns usually exhibit a characteristic known as volatility clustering, in which changes from this period to next period is far from constant and of unpredictable sign.

The ARCH model was developed to explain heteroscedasticity in a study on the UK inflation rate (Engle 1982). Engle suggested that the variance of the inflation rate should be modeled separately, and directly, in terms of past disturbances. This modeling technique explicitly recognizes the temporal dependence suggested by the phenomenon of volatility clustering. According to the ARCH model the conditional error distribution is normal, but with conditional variance equal to a linear function of past squared observations[1]. Thus, there is a tendency for extreme values to be followed by other extreme values of unpredictable sign. Engel postulated the form of an ARCH (p) model as;

$$\sigma^2{}_t = \gamma_0 + \sum_{i=1}^{p} \alpha_i\, \varepsilon_{t-p}{}^2 \quad \ldots\ldots (1)$$

Where $\varepsilon_t \sim N(0, 1)$, $\gamma_0, \alpha_i > 0$

Engle's original **ARCH** model was extended to a Generalized ARCH or **GARCH** model (Bollerslev 1986) which was designed to be more parsimonious and computationally less intensive. In addition to modeling the variance on past observations, the GARCH (p,q) model also incorporates past variances.

$$\sigma^2{}_t = \gamma_0 + \sum_{i=1}^{p} \alpha_i\, \varepsilon_{t-p}{}^2 + \sum_{i=1}^{q} \beta_i\, \sigma_{t-q}{}^2 \quad \ldots\ldots (2)$$

Where $\varepsilon_t \sim N(01)$, $\gamma_0, \alpha_i, \beta_i > 0$

The most commonly used specification in applied financial research is the GARCH (1, 1), model which is given by:

$$\sigma_t{}^2 = \gamma_0 + \alpha_1 \varepsilon^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1} \quad \ldots\ldots (3)$$

Where $\gamma_0, \alpha_1, \beta_1 > 0$

The size and significance of a_i indicates the magnitude of the effect imposed by the lagged error term ? $_{t-1}$ on the conditional variance ($s^2{}_t$). In other words, the size and significance of a_i implies the existence of the ARCH process in the error term (volatility clustering). The economic interpretation of the ARCH effect in stock markets has been provided within both micro and macro area. According to Bollerslev *et al.* (1992, p.32) and other studies, the ARCH effect in stock returns could be due to clustering of trade volumes, nominal interest rates, volatility on stock returns is captured by the coefficient of $s^2{}_t$. In other words, the coefficient b represents the index of relative risk aversion (time-varying risk premium). A significant and positive coefficient implies that investors trading stocks were compensated with higher returns for bearing higher levels of risk. A significant negative coefficient indicates that investors were penalized for bearing risk. Engle and Bollerslev (1986), Chou (1988), Bollerslev, Chow and Kroner (1992) showed that the persistence of shocks to volatility depends on the sum of the parameters. Values of the sum lower than unity imply a tendency for the volatility response to decay over time. In contrast, values of the sum equal (or greater) than unity imply indefinite (or increasing) volatility persistence to shocks over time. However, a significant impact of volatility on the stock prices can only take place if shocks to volatility persist over a long time (Poterba and Summers, 1986).

A lot of works have been carried out in recent years on the GARCH family of models and their application to financial time series.

5. Research Hypotheses:

This paper examines whether the volatility of stock market in Bangladesh is present or not, i.e. is there any GARCH effect in the stock return. The null hypothesis can be written as

: There is no GARCH effect (no volatility) in the stock return in CSE

: There is GARCH effect (volatility) in the stock return in CSE

6. Empirical Analysis

6.1 Variables

The daily stock returns are used as an individual time –series variable. Market returns are calculated from the daily price indices without adjustment of dividend, bonus and right issues. The daily all share price indices include all the listed companies in the Chittagong stock Exchange (CSE). The CSE 30 is calculated by CSE and its original is CSE Selective Index where no Z category share is enlisted.

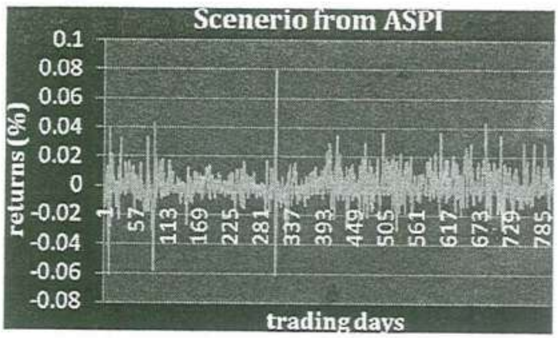
Table-1: Descriptive Statistics of the Variables:

variable	Number of obs.	Mean		Std. Deviation	Skewness		Kurtosis	
		Statistic	S.E		Statistic	S.E	Statistic	S.E
R_1	832	0.001069	.000403649	0.011650	0.040978	0.085	8.590702	0.169
R_2	832	0.000970	.00099628	0.014624	0.74085	0.085	45.21726	0.169
R_3	832	0.000957	.000398251	0.011472	0.2074	0.085	9.845844	0.169

There is another index calculated by CSE is CSE Selective Categories Index (CSCX) which is calculated from the enlisted companies of CSE Many researchers confirm that their conclusions remain unchanged whether they adjusted their data for dividend or not (for example, Lakonishok and Smidt, 1988; Fishe, Gosnell and Lasser, 1993). The descriptive statistics of daily, monthly returns of the DSE and CSE can be explained by:

The mean continuously compounded of all returns for ASPI, CSE 30 and CSCX range are close to zero. A visual analysis of the volatility of returns (daily) can be gained from the both market can plot as:

(a)



(b)

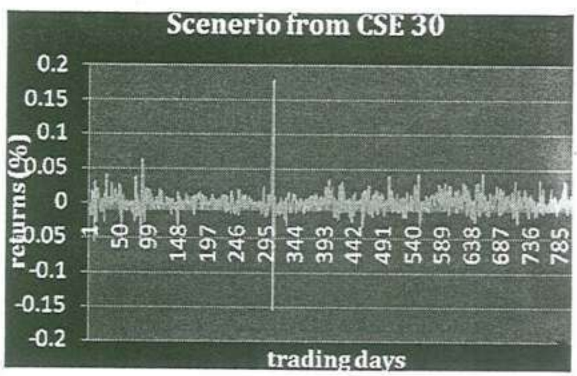
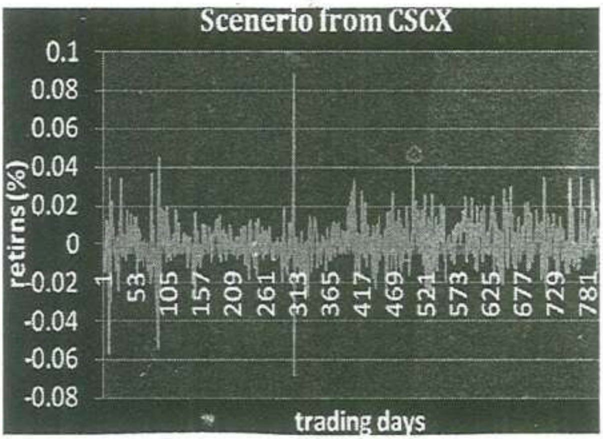


Figure 1: Time Series Plots of Daily Returns obtained from the indices of Chittagong Stock Exchange



The graph shows the plots of continuously compounded return series of the ASPI, CSE 30 and CSCX of Chittagong Stock Exchange for the full sample period January 2005 to May 2008.From the figure 1 , the daily returns of these three indices seem fluctuate around zero around periods where returns seem to tranquil alongside periods with large increases and decreases. Returns of CSE 30 have higher variation moving between a ranges of and+18% to -16% where the range of the ASPI is 8% to -6% and for the CSCX is +9% to- 7%.

From the table 1, it can be seen that the frequency distribution of the return series is not normal. The skewness coefficient in less of unity, generally taken to be

Table-2: The GARCH effect and volatility asymmetry test

Name of the statistics	GARCH(1,1)					
	For the returns of ASPI		For the returns of CSE 30		For the returns of CSCX	
	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
g_0	1.68E-05	4.34E-06	9.53E-05	7.33E-06	2.77E-05	5.77E-06
a	0.234329	0.034656	0.753248	0.050075	0.239272	0.036115
b	0.665647	0.052234	0.026873	0.025489	0.567640	0.066265
a+b	0.899976		0.780121		0.806912	
N	832		832		832	
	0.839644		0.794477		0.842885	

**Kendall (1943) calculated the expected normal kurtosis equal to 3(n-1)/ (n+1), where, n= sample size* fairly extreme (Chou, 1969, p.109). In a Guassian distribution, one would expect these data to have a kurtosis coefficient of 2.99639 for both the returns of the DSE and CSE *. Kurtosis generally either much higher or lower indicates extreme leptokurtic or extreme platykurtic (Parkinson, 1987). The evidence for the value of all of these returns are leptokurtic. Generally, values for skewness zero and kurtosis value 3 represents that the observed distribution is perfectly normally distributed. So skewness and leptokurtic frequency distribution of stock return series of all indices of CSE indicates that the distribution is not normal. The Jarque-Bera (JB) statistic shows that we have to reject normality with a p-value of one (Appendix-1). In other words, the non-normal frequency distributions of the stock return series deviate from the prior condition of random walk model.

6.2 Results analysis

Firstly this paper checks whether the returns series is stationary. By considering the autocorrelation function (ACF), the partial autocorrelation function (PACF) and their respective confidence intervals of the returns series with the help of SPSS (version 13.0), it can be said that these returns series of CSE 30 and CSCX are stationary. The return series of ASPI are not stationary. By taking lag difference of 1 it can be made stationary.

By using the EVIEWS (version: 5), an econometric software the estimated GARCH (1, 1) can be written by:

According to Bollerslev (1986), by the help LM test statistic, the parameters of the GARCH (1, 1) model on the daily or monthly returns of Bangladesh stock market (CSE or DSE) are statistically significant.

The sum of the ARCH ($?_1$) and the GARCH ($?_1$) estimates are quite close to unity, which is an indication of a covariance stationary model with a high degree of persistence; and long memory in the conditional variance. The coefficient of the lagged squared returns is positive and statistically significant for most specifications. By the help of the three kinds of share price indices, it can be concluded that strong GARCH effects are apparent in the CSE. Also, the coefficient of lagged conditional variance is significantly positive and less than one, indicating that the impact of 'old' news on volatility is significant. The magnitude of the coefficientb is especially high for ASPI and CSCX indices, indicating a long memory in the variance compared with the other index CSE 30. From the table 2, the sum of a+b for the ASPI and CSCX are 0.899976, 0.806912 respectively and these are the rate at which the response function decays on daily basis. Since these rates are high than CSE 30, the response function to shocks is likely to die slowly. In other words, if there is a new shock it will have implication on returns for a longer period. In such markets old information is more important than recent information and that the information decays very slowly

The sizes of the parameters $?_1$ and $?_1$ determine the short-run dynamics of the resulting volatility time series. Large GARCH error coefficients, ? mean that volatility reacts intensely to market movements. Large GARCH lag coefficients, ?, indicate that shocks to conditional variance take a long time to die out, so volatility is 'persistent'. If ? is relatively high and ? is relatively low then volatilities tend to be more 'spiky' (Alexander, 2001). From the experiences of CSE the coefficients ? of ASPI and CSCX are lower than CSE 30.this implies that the volatility reacts intensely to stocks (companies) enlisted into these two indices. On the other hand, by comparing the GRACH coefficients ?, the stocks enlisted in the CSE 30 are less volatile than the stocks listed in ASPI and CSCX. Again the vitality of ASPI is higher than the volatility of CSCX. Perhaps the reason is that the ASPI is calculated by considering almost the stocks enlisted in CSE (category A,B,G,Z) and the CSCX is calculated by considering the A, B, G categories shares where the Z category is not considered (Share Bazar Shuchok,2005). Thus the investors might start losing confidence in the stocks of CSE other than the stocks enlisted in CSE 30.

This is way by which one can elucidate that the CSE (one of the important stock exchanges of Bangladesh) exhibit the clustering of volatilities. As it has been seen, GARCH models describe the time evolution of the average size of squared errors, that is, the evolution of the magnitude of uncertainty. The real economic challenge, however, is to explain GARCH behavior in terms of features of agents behavior and/or economic variables that could be empirically ascertained.

The existence of volatility may help some of the speculators to earn huge abnormal profits. The speculators may play a gamble on the stock market when volatility exists in the market. On the other hand the existence of volatility is accused for the losses of the small/risk adverse investors. When the stock prices are decreasing, the small/risk adverse investors seem this situation will be continued. To minimize the losses they sell their shares at the prices which are lower than the prices they have bought.

GARCH models can be interpreted as measuring the intensity of the flow of information (often called as massages). Volatility clustering is most easily understood as information clustering. Of course, many things influence the arrival process of information and its impact on prices. Trades convey the information to small investors of the stock market and the speculators can moderate the importance of the information. These can all be thought of as important determinants of the volatility that is picked up by GARCH.

Conclusion

Understanding stock market risk and return behavior is important for all countries but it is of more importance to developing countries like Bangladesh especially where the market consist of risk –averse investors as the opportunities to invest and diversify the investment is not much. The degree of volatility presence in the stock market would lead investors to demand a higher risk premium, creating higher cost of capital, which can impede investment and slows economic development.

This study shows the level of volatility (risk) presence in Chittagong Stock Exchanges, which is still in the emerging phase. It characterizes the risk and return behavior of the listed firms on the CSE but makes a comparison among the enlisted stocks into the three indices calculated by the authorities. Though the prediction on the stock market is very tough one, from the above analysis it can be said that the investment on the stock enlisted in CSE 30 is less risky than the investment in the other shares enlisted in the Chittagong Stock Exchanges.

References

1. Akgiray V., 1989, Conditional heteroscedasticity in time series of stock returns, *Journal of Business*, 62, 55-80.
2. Alexander, C. (1999) "Risk Management and Analysis,Volume 1: Measuring and Modelling
3. Financial Risk", John Wiley and Sons, New York, NY.
4. Antoniou, A.P Holmes and R Priestley (1998): "The Effects of Stock Index Futures Trading on stock index volatility: An Analysis of the Asymmetric Response of Volatility to News?" The *Journal of Futures Markets*, 18 (2), 151-166.
5. Arestis, P., P.O. Demetriades and K.B. Luintel (2001)"Financial Development and Economic
6. Growth: The Role of Stock Markets", *Journal of Money, Credit and Banking*, 33(2):16-41
7. Bollerslev T. (1986): "Generalised Autoregressive Conditional Heteroscedasticity" *Journal of Econometrics*, 31, 307-327.
8. Bollerslev, T. – Chou, R.Y. – Kroner, K. F. (1992): ARCH Modelling in Finance. *Journal of Econometrics 52, 5 – 59, 1992.*
9. Brailsford, T.J. & Faff, R.W. 1996, 'An evaluation of volatility forecasting techniques', *Journal of Banking and Finance*, vol. 20, pp. 419–38.
10. Brooks, C. and G. Persand. (2001) "The Trading Profitability of Forecasts of the Gilt-Equity Yield Ratio." Journal of International Forecasting 17, 11-29.
11. Campbell, J (1996) Consumption and the Stock Market: Interpreting International Experience", *NBER Working Paper*, 5610.
12. Chittagong Stock Exchange, www.csebd.com Chou, R. (1988). 'Volatility Persistence and Stock Valuations; Some Empirical Evidence
13. Using Chou, Y. L., (1969), *Statistical Analysts*. London: Holt Rinehart and Winston GARCH', *Journal of Applied Econometrics*, 3, 279-294.
14. Chowdhury, A. R. (1994), "Statistical Properties of Daily Returns from the Dhaka Stock
15. Exchange", *The Bangladesh Development Studies*, Vol. XXII, No. 4, pp. 61-76.
16. Chowdhury, S. S. H. and M. A. Rahman (2004), "On the Empirical Relation between
17. Macroeconomic Volatility and Stock Market Volatility of Bangladesh", *The Global Journal of Finance and Economics*, Vol. 1, No. 2, pp.209-225.
18. Cox, C C (1976): "Futures Trading and Market Information" *Journal of Political Economy*, 84, 1215-37.
19. Dacco, R., and S. Satchell. (1999) "Why do Regime Switching Models forecast so badly?" Journal of Forecasting 18, 1-16.

20. Engle, Robert F., and Tim Bollerselv, 1986, "Modeling the Persistence of Conditional Variances", Econometric Reviews, 5, pp1-50, 81-87.

21. Dhaka Stock Exchange, www.dsebd.com Engle, R. (1982), "Autorregressive Conditional Heteroskedasticity with Estimates of United Kingdom Inflation", *Econometrica,* 50, 987-1008.

22. Engle, R. F. (1982): Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U. K. Inflation. *Econometrica* 50, 987 – 1008.

23. Engle, R. F. – Rosenberg, J. (1995): GARCH Gamma. National Bureau of Economic Research Working Paper Series, *Cambridge. Working Paper* No, 5128, 1995.

24. Evewis ,version:5 Figlewski, Stephen(1981): "Futures Trading and Volatility in the GNMA Market" *Journal of Finance,* 36, 445-84.

25. Fishe, R., Gosnell, T., and Lasser, D. (1993). Good news, bad news, volume and the Monday effect. *Journal of Business Finance & Accounting*, Vol. 20, 881-892.

26. Franses P.H.and Van Dijk R.(1996), Forecasting Stock Market Volatility using the (non-linear) GARCH Models, *Journal of Forecasting,*15(3),229-35.

27. French K. R., G. W. Schwert, and R. Stambaugh (1987) "Expected Stock Returns and Volatility," *Journal of Financial Economics*, Vol. 19, pp. 3-29.

28. Frence K.R.(1987), Expected Stock Returns and Volatility, *Journal of Econometrics,*19.3-30.

29. Glosten, Jaganathan, Runkle (1991): Relationship between the Expected Value and the Volatility of the Nominal Excess Return on *Stocks. Northwestern University* 1991.

30. Heston, S. L. – Nandi Saikat: A Closed Form GARCH Option Pricing Model. Federal Reserve Bank of Atlanta, *Working Paper* 97 – 99, November 1997.

31. Islam M. S. and Rahman M. S. (2005), "Relation between Volatility and Retun in the Dhaka Stock Exchange (DSE): Evidence from Cross-sectional Approach", *Working Paper*, Department of Finance and Banking, University of Rajshahi, Bangladesh

32. Hassan M. K., A. M. Islam and S. A. Basher, (2000), "Market Efficiency, Time-varying Volatility and Equity Returns in Bangladesh Stock Market," *Working Paper*, Department of Finance and Economics, University of New Orleans

33. Johnstone,J.and DiNardo, J. (1997), "Econometric Methods, 4th Edition,*The McGraw-Hill Companies, Inc.*

34. Kendall, M. G., (1943), *The advanced Theory of Statistics*, Vol.1, London: Griffin.

35. Krainer, J (2002)"Stock Market Volatility", FRBSF Economic Letter, *Western Banking*, 2002- 32, pp1-4.

36. Krainer, J. and J.A. Lopez. 2001. Incorporating Equity Market Information into Supervisory Monitoring Models. FRBSF Working Paper 01-14.

37. Levine, R and S. Zervos (1996)"Stock Market Development and Long-Run Growth", *World Bank Economic Review*, 10(1):323-339.

38. Ludvigson, S and C. Steindel (1999)"How Important is the Stock Market Effect on Consumption"*Federal Reserve Bank of New York Economic Policy Review*, 5(1):29-51.

39. McMillan David G. and. Speight Alan E. H(2000), "Daily Volatility Forecasts: Reassessing the Performance of GARCH Models" *Journal of Forecasting* ,23, 449–460.

40. Pericli, A. and G. Koutmos (1997): "Index Futures and Options and Stock Market Volatility"*Journal of Futures Markets,* 17(8), 957-974.

41. Poterba, J. M (2000)"Stock Market Wealth and Consumption", *Journal of Economic Perspectives*, 14(2):99-118.

42. Powers M J (1970): "Does Futures Trading Reduce Price Fluctuations in the Cash Markets?" *American Economic Review,* 60, 460-4.

43. Parkinson, J, M. (1987) , "The EMH and the CAPM on the Nairobi Stock Exchange" , *East African Economic Review,* vol.3. no.2,pp- 105-110.

44. Raju M T and K Karande (2003): "Price Discovery and Voltatility on NSE Futures Market" *SEBI Bulletin,* 1(3), 5-15.

45. Schwert, W. (1989). "Why Does Stock Market Volatility Change Over Time?" *Journal of Finance* 44, pp. 1,115-1,153.

46. Schwarz T V and F Laatsch (1991): "Dynamic Efficiency and Price Leadership in Stock Index Cash and Futures Markets", *Journal of Futures Markets,* 11, 669-83.

47. Share Bazar Shocok: Babuhar O Ganona Padhoty,(2005), Chittagong Stock Exchange Ltd. Shazam, version: 8

48. Shenbagaraman P (2003): "Do Futures and Options Trading increase Stock Market Volatility?" *NSE Research Initiative,* Paper no. 20.

49. Stein J C (1987): "Information Externalities and Welfare Reducing Speculation" *Journal of Political Economy,* 95, 1123-45.

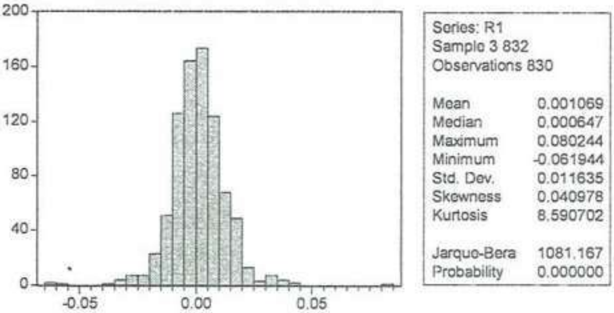
50. SPSS, version:12 Starr-McCluer, M (1998)"Stock Market Wealth and Consumer Spending", Board of Governors of the Federal Reserve System, *Finance and Economics Discussion Paper Series*, 98/20.

51. Thenmozhi M (2002): "Futures Trading, Information and Spot Price Volatility of NSE-50 Index Futures Contract" *NSE Research Initiative,* Paper no. 18.

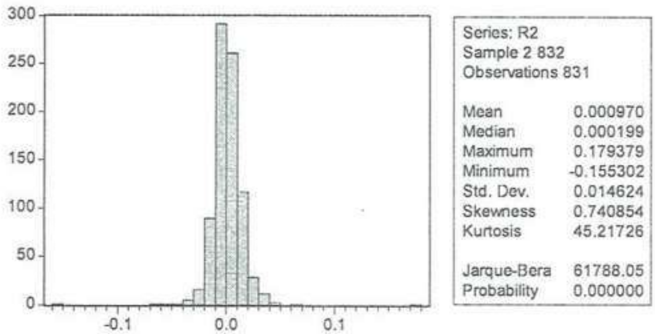
52. Zuliu, H (1995)"Stock market Volatility and Corporate Investment", *IMF Working Paper*, 95/102.

Appendix: 1

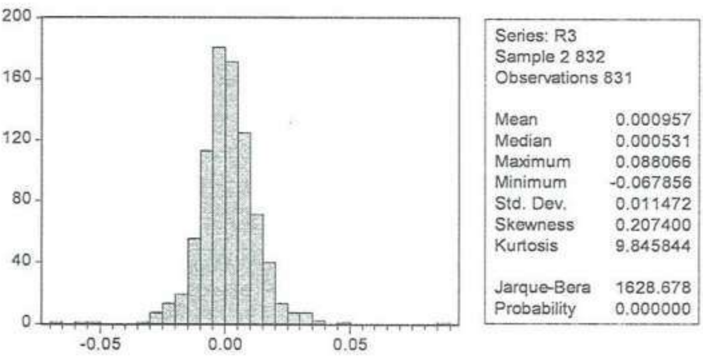
a)Descriptive Statistics of the returns of the ASPI :



b) Descriptive Statistics of the returns of the CSE 30:



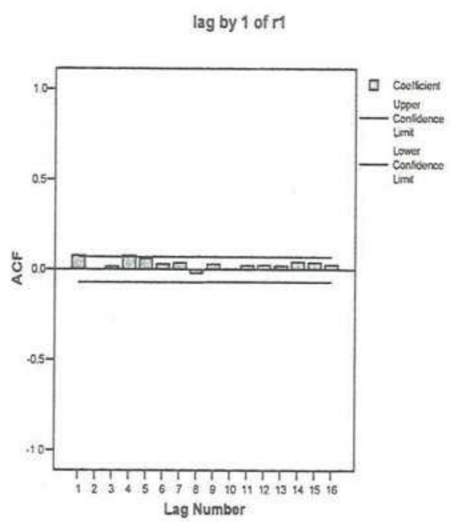
c) Descriptive Statistics of the returns of the CSCX:

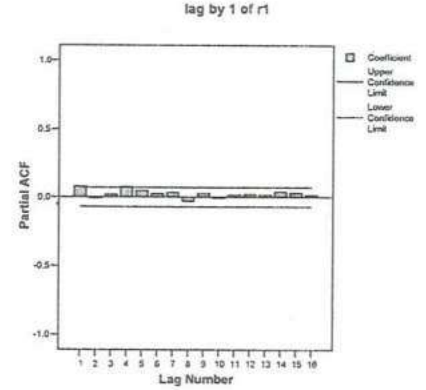


Appendix: 2

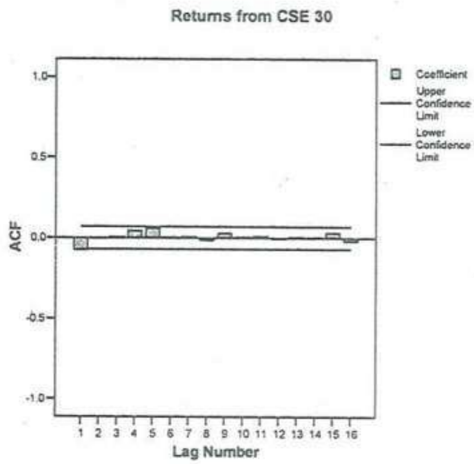
A visual plot of the return series can be introduced to check the series be stationary. The plot of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the series can be used to test whether the series is stationary or not. If the PACF and ACF lie between the lower and the upper confidence limit, then the series is stationary. (Ref: SPSS: Users manual guide; version 13).By introducing the SPSS, version: 12, this paper shows the correlogram of all three indices of CSE.

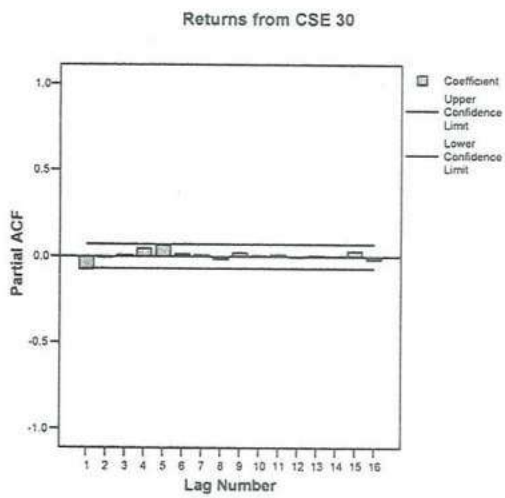
a) For daily returns of ASPI:



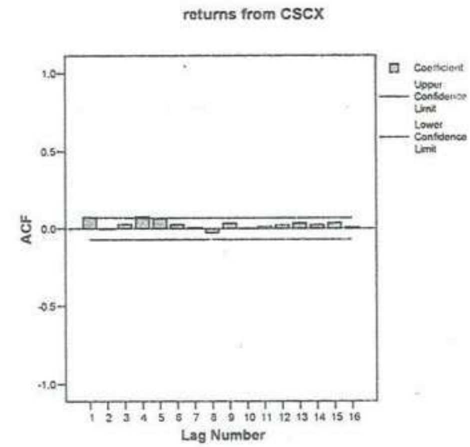


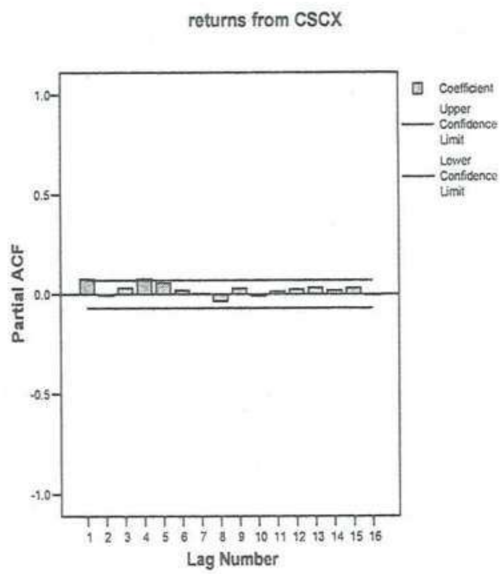
b) For daily returns of CSE 30:





c) For daily returns of CSCX:





Appendix: 3

a) GARCH model Estimation on returns of ASPI:

i) Model Estimation:

Dependent Variable: R1
Method: ML - ARCH (Marquardt)
Date: 09/09/08 Time: 00:10
Sample(adjusted): 3 832
Included observations: 830 after adjusting endpoints
Convergence achieved after 15 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	1.68E-05	4.34E-06	3.872740	0.0001
ARCH(1)	0.234329	0.034656	6.761537	0.0000
GARCH(1)	0.665647	0.052234	12.74354	0.0000
S.D. dependent var	0.011635	Mean dependent var		0.001069
S.E. of regression	0.011698	Akaike info criterion		-6.184784
Sum squared resid	0.113168	Schwarz criterion		-6.167718
Log likelihood	2569.685	Durbin-Watson stat		1.832047

ii) Diagnostic Checking :

ARCH Test:			
F-statistic	4340.732	Probability	0.000000
Obs*R-squared	697.7438	Probability	0.000000
R-squared	0.839644	Mean dependent var	0.939422
Adjusted R-squared	0.839450	S.D. dependent var	0.251379
S.E. of regression	0.100724	Akaike info criterion	-1.750453
Sum squared resid	8.410543	Schwarz criterion	-1.739087
Log likelihood	729.3133	F-statistic	4340.732
Durbin-Watson stat	3.768279	Prob(F-statistic)	0.000000

b) GARCH model Estimation on daily returns of CSE 30:

i) Model Estimation :

Dependent Variable: R2
Method: ML - ARCH (Marquardt)
Date: 09/09/08 Time: 00:15
Sample(adjusted): 2 832
Included observations: 831 after adjusting endpoints
Convergence achieved after 39 iterations
Variance backcast: ON

Coefficient	Std. Error	z-Statistic	Prob.	
	Variance Equation			
C	9.53E-05	7.33E-06	12.99162	0.0000
ARCH(1)	0.753248	0.050075	15.04230	0.0000
GARCH(1)	0.026873	0.025489	1.054318	0.2917
S.D. dependent var	0.014624	Mean dependent var		0.000970
S.E. of regression	0.014674	Akaike info criterion		5.8410080
Sum squared resid	-.178281	Schwarz criterion		-5.823959
Log likelihood	2429.939	Durbin-Watson stat		2.142375

ii) Diagnostic Checking :

ARCH Test:			
F-statistic	3204.607	Probability	0.000000
Obs*R-squared	660.2102	Probability	0.000000
R-squared	0.794477	Mean dependent var	0.946139
Adjusted R-squared	0.794229	S.D. dependent var	0.238688
S.E. of regression	0.108274	Akaike info criterion	-1.605903
Sum squared resid	9.718551	Schwarz criterion	-1.594537
Log likelihood	669.2526	F-statistic	3204.607
Durbin-Watson stat	3.713018	Prob(F-statistic)	0.000000

c) GARCH model Estimation on daily returns of CSCX:

i) Model Estimation:

Dependent Variable: R3
Method: ML - ARCH (Marquardt)
Date: 09/09/08 Time: 00:24
Sample(adjusted): 2 832
Included observations: 831 after adjusting endpoints
Convergence achieved after 17 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	2.77E-05	5.77E-06	4.804757	0.0000
ARCH(1)	0.239272	0.036115	6.625235	0.0000
GARCH(1)	0.567640	0.066265	8.566182	0.0000
S.D. dependent var	0.011472	Mean dependent var		0.000957
S.E. of regression	0.011526	Akaike info criterion		-6.204619
Sum squared resid	0.109999	Schwarz criterion		-6.187570
Log likelihood	2581.019	Durbin-Watson stat		1.839394

ii) Diagnostic Checking :

ARCH Test:			
F-statistic	4447.389	Probability	0.000000
Obs*R-squared	700.4374	Probability	0.000000
R-squared	0.842885	Mean dependent var	0.949809
Adjusted R-squared	0.842695	S.D. dependent var	0.228530
S.E. of regression	0.090639	Akaike info criterion	-1.961463
Sum squared resid	6.810571	Schwarz criterion	-1.950097
Log likelihood	816.9880	F-statistic	4447.389
Durbin-Watson stat	3.768760	Prob(F-statistic)	0.000000