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Modeling Stock Market Volatility Using Univariate GARCH Models: Evidence from Bangladesh

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Abstract

This paper investigates the nature of volatility characteristics of stock returns in the Bangladesh stock markets employing daily all share price index return data of Dhaka Stock Exchange (DSE) and Chittagong Stock Exchange (CSE) from 02 January 1993 to 27 January 2013 and 01 January 2004 to 20 August 2015 respectively. Furthermore, the study explores the adequate volatility model for the stock markets in Bangladesh. Results of the estimated MA(1)-GARCH(1,1) model for DSE and GARCH(1,1) model for CSE reveal that the stock markets of Bangladesh capture volatility clustering, while volatility is moderately persistent in DSE and highly persistent in CSE. Estimated MA(1)-EGARCH(1,1) model shows that effect of bad news on stock market volatility is greater than effect induced by good news in DSE, while EGARCH(1,1) model displays that volatility spill over mechanism is not asymmetric in CSE. Therefore, it is concluded that return series of DSE show evidence of three common events, namely volatility clustering, leptokurtosis and the leverage effect, while return series of CSE contains leptokurtosis, volatility clustering and long memory. Finally, this study explores that MA(1)-GARCH(1,1) is the best model for modeling volatility of Dhaka stock market returns, while GARCH models are inadequate for volatility modeling of CSE returns.

Keywords: Heteroskedasticity, Volatility Clustering, GARCH, Asymmetric Volatility

JEL Classification Code: C32, C58, G10, G12

1. Introduction

Volatility is the most influential element in asset pricing and portfolio management. Univariate volatility modeling has been one of the most active areas of research in empirical finance and time series econometrics from the inventions of Engel's (1982) autoregressive conditional

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heteroskedasticity (ARCH) model and Bollerslev's (1986) GARCH model.

Financial time series data exhibit common characteristics which are frequently mentioned as the 'stylized facts'. The common empirical statement is that financial market volatility is time varying and persistent, shows clustering, responds asymmetrically to shocks, and is different across assets, asset classes and countries (Bollerslev et al., 1986). More specifically, financial time series data show evidence of three common events, namely volatility clustering, leptokurtosis and the leverage effect.

Volatility clustering implies that a period of low volatility run after periods of low volatility. In financial time series, one often observes that big shocks tend to be followed by big shocks in either direction, and small shocks tend to follow small shocks. Leptokurtosis means that the distributions of financial data follow non-normal distribution. Leverage effect or asymmetric volatility implies that volatility rises when stock prices go down and decreases when stock prices go up, i.e., the consequence of bad news on stock market volatility is greater than the consequence tempted by good news (Alshogeathri, 2011). There have been a large number of empirical applications of modeling volatility found on both developed and developing stock markets, see for example Mougoué and Whyte (1996), Engle and Patton (2001), Ogum et al. (2005), Charles and Darné (2014). Besides, Mecagni and Sourial (1999) explore that the stock returns of the Egyptian stock market exhibit volatility clustering.

Employing GARCH models on the Athens Stock Exchange, Siourounis (2002) and Athanassiou, Kollias and Syriopoulos (2006) show that asymmetric leverage effect is statistically acceptable for Athens Stock Exchange. Employing GARCH methodologies, Kumar and Dhankar (2010) find the presence of conditional heteroskedasticity and asymmetric effect in US stock market returns. Goudarzi and Ramanarayanan (2011) reveal that BSE500 (India) returns series reacts to the good and bad news asymmetrically. Rayhan, Sarkar and Sayem (2012) reveal that monthly DSE returns follow GARCH properties. They also find that DSE return volatility follows leverage effect or asymmetric volatility.

The stock markets of Bangladesh have progressed accompanied by the overall economy after the process of liberalization in early 1990s. Besides, the stock market crashes in 1996 and 2010-11 have enlightened that it is important to protect the stock market from drastic fluctuations. This scenario has generated a question-what kinds of volatility characteristics of stock returns prevail in the Bangladesh stock markets? Thus, assessing the volatility of stock returns in Bangladesh would be an informative examination as there are several indications for investors and policymakers. To date, at least to our knowledge, no comprehensive investigations have done on modeling volatility of both the stock markets in Bangladesh. The aim of this paper is to fill this void by comprehensively investigating the extent to which the DSE and CSE exhibit the stylized facts. It is also very significant to detect which model is a better fit for the DSE and CSE as different models fit well for different stock market return series. The study is organized in four sections as follows: Section 2 presents the data and methodology; and Section 3 reports the findings; and Section 4 concludes the study.

2. Methodology

2.1 Data and Data Sources

Bangladesh has two stock exchanges: Dhaka Stock Exchange (DSE) and Chittagong Stock Exchange (CSE). In this study, we use daily returns data of all share price index (DSI) from DSE for the period of 02 January 1993 to 27 January 2013 with a total of 4823 observations. The daily returns data of all share price index (CASPI) from CSE are also used from 01 January 2004 to 20 August 2015 with a total of 2832 observations. DSI data are provided in CD-ROM by the central library of the Dhaka Stock Exchange, while CASPI data are collected from the official website of CSE. The analysis is done using the EViews 8.1 econometric software packages. The daily data of two indices of different periods obtained from DSE and CSE are used to calculate returns as follows:

$$R = Ln\left(\frac{P_t}{P_{t-1}}\right) \times 100(1) \qquad (1)$$

where, R = Daily return, Ln = Natural Log, P_t= Price Index at time t, and P_{t-1}= Price Index at time t-1.

2.2 Research Methods

The modeling process consists of four stages: identification, specification, estimation and diagnostic checking (Cromwell, Labys and Terraza, 1994). Identification stage of volatility modeling in this study covers descriptive statistics, unit root tests and autocorrelation test. We specify and estimate GARCH model to assess the symmetric volatility of stock returns and EGARCH model to explore the asymmetric volatility of stock returns prevailing in the Bangladesh stock markets. The diagnostic checking of the estimated GARCH models is performed by using Ljung-Box test statistics and ARCH LM test up to a specific order.

2.2.1 Descriptive Statistics

Descriptive statistics, such as, mean, median, standard deviation, skewness, kurtosis and Jarque-Bera are estimated in this study. The normal distribution is found to have a kurtosis of three. A distribution with kurtosis greater than three is leptokurtic that is a well-known stylized fact in the finance literature. Krichgassner and Wolters (2007) state that the rejection of the normality test based on Jaque-Bera test gives evidence for the existence of GARCH effects.

2.2.2 Unit Root Test

Since, ARMA-GARCH processes are stationary processes, we have to make sure that both the return series are stationary. Thus, we have applied two extensively used unit root test, namely Augmented Dickey Fuller (ADF) and Phillips-Peron (PP) test. The ADF test is performed using the following three equations:

$$\Delta Y_t = \alpha + \beta T + \gamma \Delta Y_{t-١} + \delta_i \sum_{i=١}^{m} \Delta Y_{t-i} + \varepsilon_t \text{ (trend and intercept)} \qquad (٢)$$

$$\Delta Y_t = \alpha + \gamma \Delta Y_{t-١} + \delta_i \sum_{i=١}^{m} \Delta Y_{t-i} + \varepsilon_t \text{ (intercept only)} \qquad (٣)$$

$$\Delta Y_t = \gamma \Delta Y_{t-١} + \delta_i \sum_{i=١}^{m} \Delta Y_{t-i} + \varepsilon_t \text{ (no trend, no intercept)} \qquad (٤)$$

where α is an interecpt (constant), β is the coefficient of time trend T, γ and δ are the parameters where, $\gamma = \rho$-1, ΔY is the first difference of Y series, m is the number of lagged first differenced term, and ε is the error term. The test for a unit root is conducted on the coefficient of Y_{t-1} in the regression.

Phillips and Perron (1988) have developed a non-parametric unit root conception. The PP test test is performed using the following equation

$$\Delta Y_t = \alpha + \beta T + \gamma \Delta Y_{t-١} + \varepsilon_t \qquad (٥)$$

where α is a constant, β is the coefficient of time trend T, γ is the parameter and ε is the error term.

2.2.3 Autocorrelation Test

Another well-known stylized fact in finance literature related to stock market return is volatility clustering. Volatility clustering means the data is auto-correlated. The nonzero auto-correlation of stock return series associated with Ljung -Box Q statistics suggest for the presence of ARCH effect or volatility clustering in the returns series. This volatility clustering nature of DSI and CASPI returns is checked applying autocorrelation test.

The volatility clustering nature is also checked using serial autocorrelation test of squared returns. If the returns and squared returns of DSI and CASPI are correlated, we should follow a GARCH process to model our time series.

2.2.4 GARCH(1,1) Model

This study employs an extended version of Autoregressive Conditional Heteroskedasticity (ARCH) model named, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in view of the fact that GARCH is a parsimonious representation of higher order ARCH model.

Moreover, Alexander (2001) argues that ARCH models are not often used in financial markets because the simple GARCH models perform so much better. Since a large number of lags usually required by the ARCH (p) process, Bollerslev (1986) develops GARCH (p,q) model,where the variances of returns follow an ARMA process. We apply GARCH(1,1) model as Alexander (2001) argues that it is rarely necessary to use more than a GARCH(1,1) model. Additionally, Bollerslev (1986), Engle (1993) and Brook and Burke (1998) argue that standard GARCH (1,1) model is sufficient to capture all of the volatility clustering present in data. Both Auto Regressive (AR) and Moving Average (MA) components may be included in the variance equation of GARCH (1,1) model. The symmetric GARCH (1, 1) model jointly estimates two equations named the conditional mean equation and the conditional variance equation. The conditional mean equation can be written in the following form:

$$R_t = \mu + \sum_{i=1}^{p} \alpha_i R_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad (6)$$

where, R_t represents the monthly return. R_{t-i} and $\varepsilon_{t-j}$are the autoregressive and moving average components respectively. p and q are the orders of the process. Depending on the values of p and q, we can distinguish four different forms of the mean equation. i) When p=0 and q=0, the mean equation is a random walk model. ii) When p>0 and q>0, the mean equation is an ARMA(p,q) process. iii) When p>0 and q=0, the mean equation is an AR(p) process. iv) When p=0 and q>0, the mean equation is an MA(p) process. Using Box Jenkins methodology and Schwarz Information Criteria (SIC), an appropriate mean equation of GARCH (1,1) model is formulated for this study. The conditional variance equation is the fundamental contribution of the GARCH (p,q) model and can be written in the following form:

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t^2),$$

$$h_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2, \qquad (7)$$

$$\omega > 0, \alpha_i, \beta_j \geq 0 \rightarrow h_t^2 \geq 0, \qquad i = 1, \ldots p, \text{ and } j = 1, \ldots. q.$$

where, $\Omega_{t-1}$is the set of all information available at time t-1. Ω is the mean of yesterday's forecast. α_i is the coefficient of the ARCH term $\varepsilon_{t-1}^2$and β_j is the coefficient of the GARCH term h_{t-j}^2. A large positive value of α_i indicates strong volatility clustering is present in the time series, while a large value of β_j indicates that the impact of the shocks to the conditional variance lasts for a long time before dying out, i.e., volatility is persistent. α+β is less than one or very close to one is an indication of a covariance stationary model with a high degree of persistence and long memory in the conditional variance.

2.2.5 EGARCH (1,1) Model

It is usually observed in stock markets that volatility is higher in a falling market than in a rising market. The symmetric GARCH model cannot capture this leverage or asymmetric effect which has become quite visible in equity markets during the last two decades. In order to correct the weaknesses of GARCH model, particularly with regard to its failure to address the issue of asymmetric effect in the volatility, the asymmetric volatility model such as exponential GARCH (EGARCH) is proposed. The first asymmetric GARCH model named, EGARCH model developed by Nelson (1991) can explain the existence for asymmetry in volatility. The conditional variance equation of EGARCH (1, 1) model can be written in the following form:

$$\ln h_t^2 = \omega + \alpha |z_{t-1}| + \gamma z_{t-1} + \beta \ln h_{t-1}^2 \qquad (8)$$

where, z_{t-1} term shows the asymmetric impact of positive and negative Shocks. The asymmetry term $\gamma < 0$ implies that negative shocks has a greater impact on volatility rather than the positive shocks. The negative asymmetric term also suggests for leverage effect that negative shocks do obviously have a bigger impact on future volatility than positive shocks of the same magnitude.

2.2.6 Diagnostic Checking

The performance of the estimated GARCH models is evaluated by using Ljung-Box test statistics, for instance Q(p), and $Q^2(P)$. These tests examine the null hypothesis of no autocorrelation and homoscedasticity in the estimated residuals and squared standardized residuals up to a specific lag respectively. ARCH LM test is also used to test the null hypothesis of no remaining ARCH effects up to a specific order.

3. Empirical Results

3.1 Data Statistics

Descriptive statistics of the daily returns of RDSI and RCASPI are shown in Table 1. We observe that the kurtosis of 257.593 and 9.723853 of RDSI and RCASPI respectively mean that distributions are leptokurtic, i.e., both return series have fatter tails than a normal distribution where there are higher likelihood of large gains or large losses on an investment. This excess kurtosis also indicate that the volatility of the investment in DSE and CSE of Bangladesh is high. It suggests that the Bangladesh stock market returns exhibit leptokurtosis which is a well-known stylized fact in the finance literature. Jarque-Bera statistics imply that daily distributions of stock market returns are not normally distributed. Therefore, the rejection of the normality test based on Jarque-Bera test gives evidence for the existence of GARCH effects.

3.2 Results of Unit Root Tests

The results of ADF and PP unit root tests in Table 2 reveal that the null hypothesis of unit root is strongly rejected at one percent significant level for the RDSI and RCASPI. It confirms that all the return series are stationary, that is, they do not follow a random walk. Since, both the return series are stationary, we can follow GARCH processes.

3.3 Results of Autocorrelation Test

The volatility clustering nature of DSI and CASPI returns is confirmed by the autocorrelation test that is reported in Table 3. Table 3 shows that there is highly significant autocorrelation for all lags from lag 1 to lag 30 for the returns based on the Ljung -Box Q statistics. This may be seen as evidence for the presence of ARCH effect or volatility clustering in both the returns series. To confirm the results, the autocorrelation coefficient of the DSI and CASPI returns for squared residuals are also calculated. The Ljung-Box Q-statistics associated with the p values of the squared values of RDSI accept the null hypothesis of no autocorrelation up to 30 lags, while the squared values of RCASPI do not accept the null hypothesis at 1% level of significance. Thus, the volatility clustering nature of RCASPI is also established by serial autocorrelation test of squared returns. Since the returns of DSI, and returns and squared returns of CASPI are correlated and not normally distributed, we follow a GARCH process to model our time series.

3.4 Results of the Conditional Mean Equations of GARCH(1,1) and EGARCH(1,1) Models

In order to determine the conditional mean equation of the GARCH(1,1) model that will best fit the data, 36 Autoregressive Moving Average (ARMA) processes of different orders are fitted to avoid generating autocorrelation in the squared residuals of the dependent variable of the variance equation. We choose the optimal model based on Schwarz Information Criteria (SIC) as Enders (2010) argues that SIC always selects a more parsimonious, i.e., lower order model compared to the Akaike Information Criteria (AIC). Given the 36 estimated ARMA models, the ARMA (0,1) model provides the lower value of SIC for RDSI, and ARMA (0,0,) model provides the lower value of SIC for RCASPI. Thus, MA model of order (1) is preferred for the RDSI, while no ARMA term is added for the RCASPI. Table 4 shows the results for the estimated models from which the p-value associated with the MA(1) coefficient is statistically significant for RDSI, and constant coefficient is statistically significant for RCASPI.

The ARCH-LM tests shown in Table 4 evidence that the estimated residuals exhibit autoresgressive heterskedasticity (ARCH effect).

Thus, we then proceed a symmetric MA(1)-GARCH(1,1) model and an asymmetric MA(1)-EGARCH(1,1) model to estimate volatility characteristics of stock returns prevail in the Dhaka Stock Exchange.

Besides, GARCH(1,1) Model and EGARCH(1,1) model are used to estimate the stylized facts of stock returns prevail in the Chittagong Stock Exchange.

3.5 Results of the MA(1)-GARCH(1,1) and GARCH(1,1) Models

In order to assess the well-known stylized facts of stock returns prevailing in the Bangladesh stock market, the MA(1)-GARCH(1,1) model for RDSI and GARCH(1,1) model for RCASPI are used. Table 5 reports the results of the mean and variance equations of the estimated models for all share price indices returns of DSE and CSE. The mean equation of the estimated MA(1)-GARCH(1,1) model shows that the constant μ is close to zero and significant at 10% level, while GARCH(1,1) model shows that the constant μ is close to zero and significant at 1% level. The coefficient of MA(1) is highly significant, indicating that the previous period returns play a vital role in determining the current stock market return in DSE. All the parameters in the variance equations (ω, α and β) have the expected positive signs and more importantly, ω, α and β are highly significant, meaning that the non-negative conditional variancesare found for both the stock markets in Bangladesh.

Thus, the estimated MA(1)-GARCH(1,1) and GARCH(1,1) models give the impression to capture volatility clustering in our data quite precisely.

The sum of the ARCH and GARCH coefficients is less than 1 ($\alpha + \beta = 0.98$ for CSE, and $\alpha + \beta = 0.60$ for DSE) which implies that the unconditional variance of ε_t or h_t^2 is stationary. The sum of the ARCH and GARCH coefficients measures the persistence of volatility, and this is not very close to 1 for DSE means that a shock to the Dhaka stock exchange volatility would not last a long time, while the sum of the ARCH and GARCH coefficients for CSE is nearly close to 1 means that a shock to the Chittagong stock exchange volatility is likely to last a long time. The significant GARCH term β proves that MA(1)-GARCH(1,1) and GARCH(1,1) are the appropriate model to account volatility on the DSE and CSE respectively, and that volatility in the present period influences volatility in the next period, while the highly significant ARCH term α indicates a positive relationship between shocks and volatility in the Bangladesh stock market. Table 5 also reports that α is lower than β, which implies that the volatility of the stock markets in Bangladesh is affected by past volatility more by related news from the past period. With regard to diagnostic fit, the estimated MA(1)-GARCH(1,1) model satisfies all conditions of the GARCH theory based on Ljung -Box Q statistics and ARCH-LM tests.

3.6 Results of the MA(1)-EGARCH (1,1) Model and EGARCH (1,1) Model

The basic GARCH model is symmetric and does not capture the asymmetric effect that is inherent in most stock market returns data, which is also known as the leverage effect. In financial economics, the asymmetric or leverage effect refers to the characteristics of time series on asset prices that bad news tends to increase volatility more than good news.

In order to estimate the level of asymmetric volatility of stock returns prevailing in the DSE, the MA(1)-EGARCH(1,1) model is used, while EGARCH (1,1) model is used for CSE. Table 6 reports results of the mean and variance equations of the estimated models for the all share price returns of Dhaka Stock Exchange and Chittagong Stock Exchange.

The asymmetry term γ is positive and insignificant for CSE suggesting that the volatility spill-over mechanism is not asymmetric in Chittagong stock exchange. The mean and variance equations of the estimated MA(1)-EGARCH(1,1) model for DSE show that all the parameters are highly significant at 1% level. This is a strong indication for a leverage effect in DSE. The positive coefficient of ABS(RESID(−1)/ SQRT(GARCH(−1))) implies that positive innovations (unanticipated price increases) are more destabilizing than negative innovations. In fact, the asymmetry term γ is negative and highly significant for DSE. This implies that negative shock has a greater impact on volatility rather than the positive shocks of the same magnitude in Dhaka stock exchange. The significance of negative shocks persistence or the volatility asymmetry in DSE indicates that investors of DSE are more prone to the negative news in comparison to the positive news. In terms of diagnostic fit presented in Table 6, the estimated model for DSE satisfies all conditions of the GARCH theory based on Ljung -Box Q statistics and ARCH-LM tests, while EGARCH(1,1) model for CSE fails to satisfy all conditions of the GARCH theory.

4. Conclusion

In the above analysis, we investigate the stylized facts of stock returns for Dhaka Stock Exchange and Chittagong Stock Exchange. The study uses GARCH models to arrive at the objectives of the study employing daily return series of DSI from DSE and CASPI from CSE for the period of 02 January 1993 to 27 January 2013 and 01 January 2004 to 20 August 2015 respectively.The excess kurtosis impliesthat the Bangladesh stock market returns exhibit leptokurtosis which is a well-known stylized fact in the finance literature. Since the returns of DSI and CASPI are stationary, correlated and non-nomally distributed, we follow a GARCH process to model our time series. Using Box-Jenkings procedure, the study proceeds a symmetric MA(1)-GARCH(1,1) model and an asymmetric MA(1)-EGARCH(1,1) model for Dhaka Stock Exchange, while GARCH(1,1) model and EGARCH(1,1) model for Chittagong Stock Exchange. The results of the estimated MA(1)-GARCH(1,1) and GARCH(1,1) models reveal that the stock market of Bangladesh captures volatility clustering. The sum of the ARCH and GARCH coefficients reveals that the volatility of DSE is moderately persistent, while the volatility of CSE is extremely persistent. Considering the existence of the asymmetric effects of shocks on the return volatility in the Bangladesh stock markets, we also fit the data with the MA(1)-EGARCH(1,1) and EGARCH(1,1) models. The results indicate that the volatility spill over mechanism is not asymmetric in Chittagong stock exchange. The negative and highly significant γ indicates that the asymmetric shocks or leverage effect exists in the Dhaka Stock Exchange. That is, bad news (negative shocks) has a larger impact on DSI return volatility than good news (positive shocks). With regard to diagnostic fit, the estimated models for DSE satisfy all conditions of the GARCH theory based on Ljung -Box Qand Q^2 statistics as the estimated models are free from serial autocorrelation up to 36 lags. Moreover, the ARCH LM test supports that the models succeed in removing conditional heteoskedasticity up to 36 lags. In contrast, the GARCH models are inadequate in modeling the volatility of Chittagong stock market return as Ljung-Box Q and Q^2 tests suggest that the estimated models are not free from serial autocorrelation up to 36 lags. Additionally, GARCH(1,1) model for CSE fails in removing conditional heteroskedasticity up to 12 lags, while EGARCH(1,1) model up to 36 lags. The minimum AIC, SIC and the maximum Log Likelihood values of the MA(1)-GARCH(1,1) model for DSE indicate that it is adequate in modeling the volatility of Dhaka stock market returns. We believe that this study would be of assistance to investors and policy makers at Bangladesh and overseas. Future studies can find out whether macroeconomic variables volatility has any impact on the stock returns volatility in Bangladesh.

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Table 1: Descriptive Statistics for Daily Returns ofRDSI and RCAPSI

	RDSI	RCASPI
Mean	0.046789	0.077694
Median	0.000757	0.062487
Maximum	59.90334	13.07073
Minimum	-24.95818	-7.764455
Std. Dev.	1.844108	1.388456
Skewness	7.709156	0.091001
Kurtosis	257.5930	9.723853
Jarque-Bera	13073409*	5338.712*
Observations	4823	2832

Note: * indicates significance at 1% percent level.

Table 2: Results of Augmented Dickey Fuller (ADF) andPhillips-Peron (PP) Test

Return Series	None	Intercept	Intercept with trend	Remarks
ADF Test				
RDSI	-62.77181 (-2.565442)	-62.80204 (-3.431524)	-62.79559 (-3.959941)	No Unit Root
RCASPI	-50.82473 (-2.565779)	-50.96763 (-3.432469)	-51.04995 (-3.961284)	No Unit Root
PP Test				
RDSI	-63.20936 (-2.565442)	-63.17421 (-3.431524)	-63.16799 (-3.959941)	No Unit Root
RCASPI	-51.40720 (-2.565779)	-51.37853 (-3.432469)	-51.36163 (-3.961284)	No Unit Root

Note: MacKinnon 1% critical values for the ADF and PP statistics are in brackets.

Table 3: Tests for Serial Correlation in Daily DSI and CAPSIReturns and Squared Returns

Lags	Q (Returns)				Q^2(Returns)			
	RDSI		RCASPI		RDSI		RCASPI	
	Q-stat	P	Q-stat	P	Q-stat	P	Q-stat	P
1	48.204	0.000	5.1499	0.023	0.3603	0.548	474.33	0.000
5	57.009	0.000	12.889	0.024	0.6090	0.988	969.91	0.000
10	69.149	0.000	23.476	0.009	0.7600	1.000	1765.4	0.000
15	74.532	0.000	41.592	0.000	0.8471	1.000	2150.6	0.000
20	77.719	0.000	50.643	0.000	1.1439	1.000	2618.5	0.000
25	89.812	0.000	65.848	0.000	1.3229	1.000	3108.1	0.000
30	96.341	0.000	67.248	0.000	2.4026	1.000	3309.6	0.000

Table 4: Estimated Models and ARCHHeteroskedasticity Tests

Variable	RDSI		RCASPI	
	ARMA (0,1) Model		**ARMA (0,0) Model**	
	Coefficient	P-Value	Coefficient	P-Value
C	0.046791	0.1089	0.077694*	0.0029
MA(1)	0.104706*	0.0000	-	-
ARCH-LM Heteroskedasticity Tests				
F-statistic	1.760839**	0.0489	568.4766*	0.0000
Obs*R-squared	21.09887**	0.0490	473.6920*	0.0000

Notes: * means significance at 1% level and ** means significance at 5% level.

Table 5: Estimates of the MA(1)-GARCH(1,1) Model and GARCH(1,1) Model

	RDSI			**RCASPI**		
Variable	Coefficient		P-value	Coefficient		P-value
Constant (μ)	0.061298**		0.0667	0.116722*		0.000
MA(1) Term θ	0.181711*		0.000	-		-
Constant (ω)	1.570802*		0.000	0.044002*		0.0000
ARCH (1) Term α	0.255310*		0.000	0.146354*		0.0000
GARCH (1) Term β	0.340166*		0.000	0.835581*		0.0000
Loglikelihood, AIC, SIC	-9397.41, 3.89899, 3.905710			-4440.26, 3.13860, 3.14700		
Residual Diagnostic Fitting						
	RDSI			**RCASPI**		
Lags	Q	Q^2	ARCH LM F-Test	Q	Q^2	ARCH LM F Test
1	-	0.002 (0.96)	0.001 (0.96)	5.05 (0.02)	13.08 (0.00)	13.11 (0.00)
6	10.27 (0.06)	0.015 (1.00)	0.002 (1.00)	19.24 (0.00)	18.18 (0.00)	2.94 (0.00)
12	16.81 (0.11)	0.024 (1.00)	0.002 (1.00)	27.02 (0.00)	22.26 (0.03)	1.78 (0.04)
36	38.56 (0.31)	0.19 (1.00)	0.005 (1.00)	52.72 (0.03)	48.73 (0.07)	1.21 (0.18)

Notes: P-values are in brackets. * means significance at 1% and ** means significance at 10%.

Table 6: Estimates of the MA(1)-EGARCH(1,1) Model and EGARCH(1,1) Model

	RDSI		RCASPI	
Variable	Coefficient	P-value	Coefficient	P-value
Constant (μ)	0.183234*	0.000	0.106447*	0.000
MA(1) Term θ	0.179563*	0.000		
Constant (ω)	0.400580*	0.000	-0.210265*	0.0000
EARCH (1) Term α	0.338628*	0.000	0.290650*	0.0000
EARCH-a (1) Term γ	-0.049494*	0.000	0.002054	0.8122
EGARCH (1) Term β	0.489489*	0.000	0.965221*	0.0000
Loglikelihood, AIC, SIC	-9500.93, 3.942332, 3.950395		-4437.549, 3.137393, 3.147896	

Residual Diagnostic Fitting

	RDSI			RCASPI		
Lags	Q	Q^2	ARCH LM F-Test	Q	Q^2	ARCH LM F Test
1	-	0.00 (0.98)	0.00 (1.00)	4.76 (0.02)	22.53 (0.00)	22.66 (0.00)
6	8.60 (0.12)	0.00 (1.00)	0.00 (1.00)	17.90 (0.00)	27.50 (0.00)	4.45 (0.00)
12	15.33 (0.16)	0.01 (1.00)	0.00 (1.00)	25.44 (0.01)	31.49 (0.00)	2.49 (0.00)
36	37.96 (0.33)	0.17 (1.00)	0.00 (1.00)	50.55 (0.05)	58.11 (0.01)	1.42 (0.04)

Notes: P-values are in brackets. * means significance at 1%.