SRI LANKAN STOCK MARKET VOLATILITY ANALYSIS: AN ARMA-GARCH APPROACH

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Abstract

Beyond its role in capital generation, a stock market is emulated as a facet in economic development indication. Sri Lankan stock market, the Colombo Stock Exchange (CSE) is a languidly developing market known for instability and periodical fluctuations increasing the volatility risk for the investors. Toward market development, it is imperative in attracting and retaining long term investors. Thus, the study aimed to identify the dynamics of the CSE through volatility estimation of the Sri Lankan stock market during a high volatile period. Further, the use of ARMA-GARCH models aims to contribute to the local empirical studies on the applicability of ARMA-GARCH models in the Sri Lankan context.

The study used the daily closing prices of the All-Share-Price Index (ASPI) from January 2018 to December 2022 in log return volatility. Owing to the non-normality and serial dependence conditions inherent in the data, the study developed an ARMA (2,2) mean equation and separate volatility equation applying symmetric models of GARCH, and TGARCH and asymmetric GARCH models of EGARCH, and GJR-GARCH.

The study findings identified that asymmetric GARCH models are more reliable in volatility estimation and forecasting. Further, ASPI indicated a leverage effect where negative information caused idiosyncratic volatility.

Keywords: ARMA-GARCH, GARCH, Leverage Effect, Stock Markets, Volatility

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1. Introduction

A stock market is a proclaimed capital generator of an economy with market indices tracking the performance. However, beyond its role in capital generation, it is a proxy to national economic performance. Thus, beyond its role in stock market performance indication, a market index is emulated as an important facet in economic indication. Hence, the positive or negative fluctuations in a market index indicate the availability of new information that affects the composure of the stock market. Among the global stock markets, developing markets are known for its high volatility risk due to the investor behaviour and government interventions. Thus, market maturity is vital in market development. Herein, the volatility analysis of developing markets aids in investor decisions and policymaking (Wang et al., 2021).

Autoregressive Moving Average (ARMA) was used in stock prediction and modelling in constant volatility environments (Tsay, 2005). However, stock markets gravitate to fluctuation based on the information available. Market volatility depicts the conditional deviation of the asset returns. Generally, rising stock prices are associated with lower volatilities comparative to the higher volatilities' negative movements encountered causing an asymmetric behaviour in the volatility. The influence of volatility on stock markets and investor behaviour makes it imperative to comprehend the volatility variations accurately. Thus, modelling the volatility of the financial markets is identified as an efficient measure of estimating parameters and increasing accuracy of forecasts. Engle in 1982 presented the Autoregressive Conditional Heteroskedasticity (ARCH) models in estimating the variance of asset returns. Following ARCH, a voluminous body of mathematical and statistical models have been presented in measuring volatility of financial assets (Ali, 2013; Maqsood, et al. 2017; Tsay, 2005). However, given the fluctuations in volatility, ARMA models are used in combination with GARCH models to capture the linear dependence of the mean of stock prices and variance adequately. Thus, ARMA estimates a linear combination of the dependence in mean and the conditional variance of the residual are estimated through GARCH. Further, Autoregressive Moving Average - Generalized Autoregressive Conditional Heteroskedasticity (ARMA-GARCH) is identified to exhibit higher accuracy in stock index movement predictions in volatile periods. Additionally, owing to the idealistic assumptions in the GARCH models, the ARMA-GARCH models provide consistent and asymptotically normal forecasts (Francq & Zakoïan, 2000; Ghani & Rahim, 2019; Sans-Cipollitti, 2020; Xiang, 2022) The preeminent Sri Lankan stock market, the Colombo Stock Exchange (CSE) has shown sluggish development despite its protracted history since the establishment in 1896 compared to other peer developing countries in the region. All-Share-Price Index (ASPI) and Standards and Poor Sri Lanka 20 (S&P SL20), the broader market index and the narrow market index respectively are known to be highly volatile in anomalies indicating instability. Thus, efficient volatility analysis can significantly reduce the volatility risk in the market and provide comprehensive insights on development opportunities in promoting market maturity. Further, CSE could benefit from the long-term investment stability.

Thus, study identified the importance of accurate parameter estimations and efficient volatility modelling in comprehending the underlying dynamics of CSE. Consequently, the study aims to determine the applicability of ARMA-GARCH models in volatility prediction of the Sri Lankan stock market through in-sample forecasting. Therein the study aims to identify an appropriate linear combination of the mean and volatility of the stock price movements in ASPI, the broad market index of CSE contributing to an overall overview of the Sri Lankan stock market. Through the study period of January 2018 to December 2022, Sri Lanka experienced quagmire implications. Easter Sunday attack in 2019, global pandemic from 2020 and drastic policy changes owing to an economic crisis in 2022 had significant effects on the Sri Lankan economy (Central Bank of Sri Lanka, 2019; Colombo Stock Exchange, 2020). These implications have been reflected in the stock market owing to the market closure for extended periods. Thus, the study reflects the stock market behaviour through mean and conditional volatility during periods of negative settings. Additionally, the study contributes to timely estimations on the CSE providing conclusive estimations insightful for both investors and policy-makers. Further, applicability of the ARMA-GARCH models in the stock market predictions is limited to the Sri Lankan context of stock market volatility. Consequently, the study aims to identify the applicability of ARMA-GARCH on how both symmetric and asymmetric approach could provide empirical evidence in the Sri Lankan context for the deficiency in literature on this approach.

Later, the study discusses the literature on the approach from volatility determination to ARMA-GARCH approach and its empirical study findings. Preceded by literature, the study methodology, and results on the applicability of ARMA-GARCH models is identified. Subsequently, study conclusion divulges the insights from the study.

2. Literature Review

Volatility of an asset identifies the conditional deviation that its returns would encounter. However, the unobservability of the volatility has increased the difficulty of its estimation and forecasting. Volatility is observed to occur in clusters, have a fixed range of fluctuation and a leverage effect (Tsay, 2005). The leverage effect of volatility allows asymmetric fluctuations in stock markets. On one hand, leverage effect would cause low volatilities in price increments. On the other hand, it would cause high volatilities in negative performances of a stock market (Ali, 2013). Thus, the leverage effect binds volatility to the stock market performance creating highly volatile and unstable market indices (Silva, et al., 2016). Natenberg (2015) identified four types of volatility based on the timely definitions namely, future volatility, historical volatility, forecast volatility and implied volatility.

Volatility models developed are of two purposes namely, to root out functions that regulate the evolution of the volatility and to determine the stochastic function in defining the volatility. Autoregressive Conditional Heteroskedasticity (ARCH) is a time varying variance model introduced by Engle in 1982 in observing the financial markets. Further, studies have identified the effectiveness of ARCH models in variance prediction during high oscillation periods owing to crises (Dinardi, 2020). Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model by Bollerslev in 1986 is an extension of the ARCH explaining the volatile behaviour. ARCH and GARCH models are frequently associated with financial market volatility estimations. Both premeditates the former of the two purposes (Tsay, 2005). ARCH and GARCH model are estimated under normality conditions which contrast the pragmatic financial conditions. Hence, Exponential GARCH (EGARCH), Threshold GARCH (TGARCH), Glosten, Jagannathan and Runkle GARCH (GJR-GARCH) and integration of ARMA-GARCH models are incorporated to match the pragmatic assumptions (Ali, 2013). Whilst GARCH models including TGARCH are identified as symmetric models EGARCH and GJR-GARCH are identified as asymmetric models of GARCH and are used in the leverage effect identification (Ali, 2013 Tsay, 2005).

Among the abundant empirical studies, Maqsood, et al. (2017) determined asymmetric GARCH estimations are a better fit for the Nairobi Stock Exchange whilst Karunanayake and Valadkhani (2011) analysed the influence of United States, United Kingdom, Australian and Singapore stock markets' volatility on one another. Conducting empirical studies on developing and emerging markets, Arsalan, et al., (2022) stated that emerging markets are prone to high volatilities and slower mean reversions compared to the lower volatilities and swifter mean reversions in the developing markets. Among empirical studies on symmetric and asymmetric GARCH modelling, Akhtar and Khan (2016), Arsalan, et al., (2022), Endri, et al. (2020), Kumar (2012), Renggani, et al. (2020), and Vasudevan and Vetrivel (2016) analysed Asian stock markets on stock price and exchange rate volatilities. Further, Epaphra (2017) used symmetric and asymmetric GARCH in determining the exchange rate volatility for Tanzania.

In the Sri Lankan context, Hewamana, et al. (2022), Jahufer (2021), and Jegajeevan (2012) identified asymmetric GARCH models to estimate better volatility fits to stock market volatility given the leverage effect and investor behaviour identified. However, it is contrasting Jaleel and Samarakoon (2009) since no leverage effect is identified in the EGARCH model. However, they concluded that stock market volatility measures are the highest in the liberation period. Silva et. al. (2016) used a GARCH (1,1) model to determine the volatility related to the day of the week effect in CSE. Morawakage and Nimal (2016) identified that TGARCH modelling of the Sri Lankan stock market shows that CSE is highly affected by negative innovations than positive innovation. Therein, these studies conclude contrasting identifications on CSE volatility. Kande Arachchi (2018) used symmetric and asymmetric GARCH models in determining exchange volatility. Further, Alibuhtto (2014), Dilrukshi et al. (2022), used GARCH models in predicting volatility in Colombo Consumer Price Index, coconut retail prices respectively where no leverage effects are identified.

Among many prior studies GARCH applications are found under financial analyses which hoists itself to a prominence. However, empirical studies of Ali (2013) using asymmetric GARCH models in estimating the pathogens of marine recreational sites, Ciarreta, et al., (2017) in using GARCH to estimate the realised volatility of electricity prices, Chen, and et al (2019) using asymmetric GARCH models in forecasting the wind power, and Shanika and Jahufer (2021) modelling asymmetric GARCH in determining volatility of international tourist arrivals to Sri Lanka depict the wide array of GARCH applications.

Francq and Zakoïan (2000) stated that owing to strong assumptions in GARCH estimations, for weak GARCH estimations inherent in serial correlation, GARCH-ARMA models provide more consistent and asymptotically normal forecasts. Further, Grachev (2017) identified that ARMA-GARCH (1,1) consistently yield the best results in stock pricing for within-sample forecasting. Wang, et al. (2021) used ARMA-GARCH models in observing the Chinese market index volatility. Ghani and Rahim (2019) used ARMA-GARCH models to predict rubber prices in Malaysia where Xiang (2022) used the approach in predicting international oil prices with higher accuracy. Further, Sans-Cipollitti (2020) identified that ARMA-GARCH approach comparatively provided higher accuracy in stock index prediction. Kamal and Haque (2016) modeled the volatility of the Indian, Bangladesh and Sri Lankan stock markets in ARMA-GARCH to determine the fact that in the South Asian markets' volatility subsided promptly post crisis. Locally, Zhang and Nadarajah (2018) analysed CSE returns from 1985 to 2017 to conclude that the ARMA-APARCH modelling is efficient in forecasting volatility of the Sri Lankan market based on its log likelihood. Consequently, a limited ARMA-GARCH approach on predicting stock market volatility can be identified in the Sri Lankan context. ARMA-GARCH estimations of Perera and Rathnayake (2019), and Thevakumar and Jayathilaka (2022) determinde the exchange rate sensitivity through volatility parameters. Beyond financial analysis, De Silva and Herath (2016), and Hettiwaththa and Abeygunawardana (2018) modeled ARIMAX-GARCH models in determining vegetable pricing volatility and measuring flood risks in Rathnapura district respectively.

Farther, empirical studies identified appropriateness of the quadratic variation theory in forecasting high frequency and highly volatile data (Andersen et al., 2007). Marcucci (2005) identified Markov – Switching GARCH (MRS-GARCH) can increase the forecasting efficiency of volatility estimations.

3. Methodology

The current study uses the daily closing prices of ASPI from 1st January 2018 to 31st December 2022 obtained from the Colombo Stock Exchange. The log returns of the closing prices of 1160 daily closing price observations are calculated for the study and the analysis was conducted for the log returns of ASPI. However, the study uses a turmoil period of the stock market. CSE had several extensive closures and the closing prices in these periods were omitted from the readings to avoid the outliers in closing prices. Thus, the study would reflect the repercussions of the periods through the log closing prices.

The initial analysis of the daily returns identified a presence of non-normality and hurst exponent nearly equal to zero that reflected the mean reverting nature of the data (Appendix: Figure 1) (Gospodinov et al, 2019). Further, the ARCH-GARCH models developed showed weakness due to the serial correlations present among the data consistent with the findings of Tsay (2005) on daily stock returns and serial correlations. Hence, an ARMA-GARCH combination was used in the volatility analysis of the model. ARMA and GARCH models of the combination were expected to represent the mean and the volatility of the stock prices.

Figure 1: Daily closing prices of ASPI

Source: Authors' calculations based on CSE published data

The volatility models were developed to capture the returns of the ASPI market at time t based on the information available in time (t-1). Hence the mean and the variance of the returns (r_t) are as follows (Tsay, 2005).

$$Mean\ of\ returns\ (\mu_t) = E(r_t|F_{t-1}) \rightarrow \text{Equation (1)}$$

$$Variance\ of\ returns(\sigma_t^2) = Var(r_t|F_{t-1}) \rightarrow \text{Equation (2)}$$

The stationarity of the data was checked through an Augmented Dickey Fuller (ADF) and Phillip-Perron (P-P) tests. The tests assumed the null hypothesis of the log returns of ASPI containing a unit root for the overall period.

The presence of serial dependence among the daily returns necessitates the modelling of the mean equation through an ARMA (p, q) model where p, and q are non-negative integers with a_t, a shock or an innovation on the stock index in time t (Equation 3) (Tsay, 2005).

$$\mu_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i r_{t-i} - \sum_{i=1}^{q} \theta_i a_{t-i} \rightarrow \text{Equation (3)}$$

Further, residuals of the ARMA model were checked to identify significance of the ARCH effect present in the residuals. ARCH tests by Engle in 1982 is a Lagrange Multiplier test to identify the presence of significant dependence. Hence the null hypothesis assumes no correlations present in the residuals of the ARMA model. The presence of significant ARCH effects requires the development of the volatility model. The study used five GARCH models jointly with the ARMA mean equation to in comparing the accuracy of the model forecasts.

Initially, the study used a GARCH (1,1) model in estimating the volatility present (Equation 4). The model assumes normal distribution conditions. However, the inherent heavy tailed nature of GARCH (1,1) necessitates the estimation of a GARCH (t) (1,1) model with skewed Student's t innovation (Tsay, 2005).

$$\sigma_t^2 = \omega + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad 0 \leq \alpha_1, \beta_1 \leq 1; (\alpha_1 + \beta_1) < 1 \rightarrow \text{Equation (4)}$$

$$Unconditional\ vatiance\ (\sigma) = \frac{\omega}{1-\alpha-\beta} \rightarrow \text{Equation (4.1)}$$

Further, the non-normal nature of the residuals necessitates the modelling of asymmetric GARCH models to overcome the weaknesses inherent in the GARCH (1,1) models. Thus, an exponential GARCH model (EGARCH (1,1)) is estimated. EAGRCH (1,1) proposes a conditional variance in log linear form as the volatility of the ASPI returns (Equation 5). B is the lag operator such that $Bg(a_t) = g(a_{t-1})$ (Bollerslev, 2008; Tsay, 2005).

$$a_t = \sigma_t a_t, \quad \ln(\sigma_t^2) = \omega + \frac{1+\beta_1 B}{1-\alpha_1 B} g(a_{t-1}) \rightarrow \text{Equation (5)}$$

$$Unconditional\ vatiance\ (\sigma) = \frac{\omega}{1-\beta} \rightarrow \text{Equation (5.1)}$$

Subsequently, a Zakoian Threshold GARCH model (TGARCH) (at times abbreviated as ZGARCH) was estimated for the asymmetric returns of ASPI. It estimated the volatility through standard deviation instead of variance (ζ) in the TGARCH (1,1) model estimated (Equation 6) (Ali, 2013; Bollerslev, 2008).

$$\zeta_t^2 = \omega + \alpha_1(|\varepsilon_{t-1}| - \gamma_1 a_{t-1}) + \beta_1 \zeta_{t-1} \rightarrow \text{Equation (6)}$$

$$Unconditional\ vatiance\ (\sigma) = \frac{\omega}{1-\alpha-\beta} \rightarrow \text{Equation (6.1)}$$

Decisively, a Glosten, Jagannathan and Runkle GARCH model (GJR-GARCH) was further estimated to depict the asymmetric nature of the ASPI returns. Model is corresponding a TGARCH. However, the GJR-GARCH (1,1) model used the skewed Student's t distribution in the estimations (Equation 7) (Ali, 2013). N_{t-1} is a negative indicator of negative innovation of the returns (Ali, 2013; Tsay, 2005).

$$\zeta_t^2 = \omega + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 N_{t-1} a_{t-1}^2;\ N_{t-1} = \begin{cases} 1 & if a_{t-1} < 0 \\ 0 & if a_{t-1} < 0 \end{cases} \rightarrow \text{Equation (7)}$$

$$Unconditional\ vatiance\ (\sigma) = \frac{\omega}{1-\alpha-\frac{\gamma}{2}-\beta} \rightarrow \text{Equation (7.1)}$$

Post analysis, Ljung-Box test was conducted to identify serial autocorrelations present in the estimations. It would hold the null hypothesis of no serial correlations are present in m-lags considered. Further, a 45-day rolling window forecast was taken to identify the accuracy of the estimated models in forecasting volatility of the ASPI returns. Owing to the inherent errors in forecasting out-of-sample, Error estimations of mean squared error (MSE), mean absolute error (MAE) and the root mean squared error (RMSE) were calculated in the error estimations of the forecasts.

4. Findings

The study considered log closing prices of ASPI, the broad market index of CSE in the analysis. The descriptive data are shown in Table 1 for the daily closing prices of ASPI and the log returns of the market index. The Jarque-Bera tests for normality in residuals indicate the non-normality of the residual in both closing prices and stock returns at 95 percent confidence level. Further, the data depicts a nearly zero hurst exponent with a negative skewness suggesting a mean reverting behaviour and fat tails in the residuals (Appendix- Figure 1).

Table 1: Descriptive statistics

Data	Obs.	Mean	Std.	J-B Statistic	J-B p-value
Closing	1160	7110.401	1864.465	422.170	2.125e-92
Returns	1160	0.024	1.307	2829.449	0.000

Source: Authors' calculations based on CSE published data

Table 2: Stationary tests

Test	With constant	With constant and trend
ADF	-7.145	-7.159
	(0.000)	(0.000)
P-P	-26.978	-26.955
	(0.000)	(0.000)
	ADF/ P-P critical values	
	With Constant	With constant and trend
1%	-3.44	-3.97
5%	-2.86	-3.41
10%	-2.57	-3.13

Source: Authors' calculations

ADF and P-P tests indicate the stationarity of the log returns of ASPI are stationary at a 95 percent confidence level rejecting the null hypothesis. Hence, the stock returns did not require differencing. However, the autocorrelations plot (ACF) and the partial autocorrelations plot (PACF) indicate serial dependence of the stock returns (Appendix: Figure 3). Thus, ACF and PACF lags greater than the 95 percent confidence level are used in the ARMA model parameter determination.

Table 3: ARMA (2,2) model – Mean equation

	ARMA (2, 2) Model (Mean Model)			
	Coefficient	Standard error	t-statistic	p-value
AR (1)	0.790	0.096	8.222	0.000
AR (2)	0.136	0.068	1.987	0.047
MA (1)	-0.509	0.095	-5.372	0.000
MA (2)	-0.359	0.058	-6.148	0.000
Sigma	1.571	0.030	52.424	0.000
	Residual diagnostics			
	Test statistic		p-value	
Ljung-Box test	43.080		0.000	
Jarque-Bera	4647.310		0.000	
Skewness	-0.280		Kurtosis	11.080

Source: Authors' calculations

Table 3 depicts the ARMA (2,2) model and at 95 percent confidence level all parameters of the model are significant. The stock returns from the autoregressions are influencing the future values of the stock returns in a positive and decreasing manner. Contrastingly, innovations of the model are negative and negatively decreasing suggesting the decreasing impact from the innovations or system shocks on the future stock returns. The behaviour of returns and innovations estimated are complementary to the findings of Kamal and Haque (2016) on Sri Lankan stock market behaviour post crisis. Moreover, the rapid decline of the prior returns and innovation on future stock returns provide confirmation to the findings of Arsalan, et. al., (2022) on developing countries requiring less time to return to its mean reverting position. Further, the coefficients further suggest the stationarity of the AR (2) and MA (2) models considering its characteristic equation (Tsay, 2005). However, the tests on normality and autocorrelations for the ARMA estimation rejects their null hypotheses at 95 percent confidence level to reveal the underlying non-normal and serial dependence conditions of the model. Estimated ARMA model can be defined to explain the mean equation of the volatility model as follows (Equation 3.1).

$$\mu_t = 1.571 + 0.79r_{t-1} + 0.136r_{t-2} - 0.509a_{t-1} - 0.359a_{t-2} \rightarrow \text{Equation (3.1)}$$

Table 4: ARCH effects test

Lag	Test statistic	p-value
Lag 1	165.916	9.37e-37
Lag2	96.776	1.388e-39

Source: Authors' calculations

The presence of the ARCH effect is determined through Lagrange-Multiplier test. The test accepts the null hypothesis at a 95 percent confidence level confirming the serial dependence of the residuals in the mean equation. Thus, volatility is analysed from mean zero GARCH model estimations. Table 5 depicts the GARCH models estimated for the residuals of the ARMA model in estimating the ASPI stock return volatility.

Table 5: GARCH estimations- volatility models

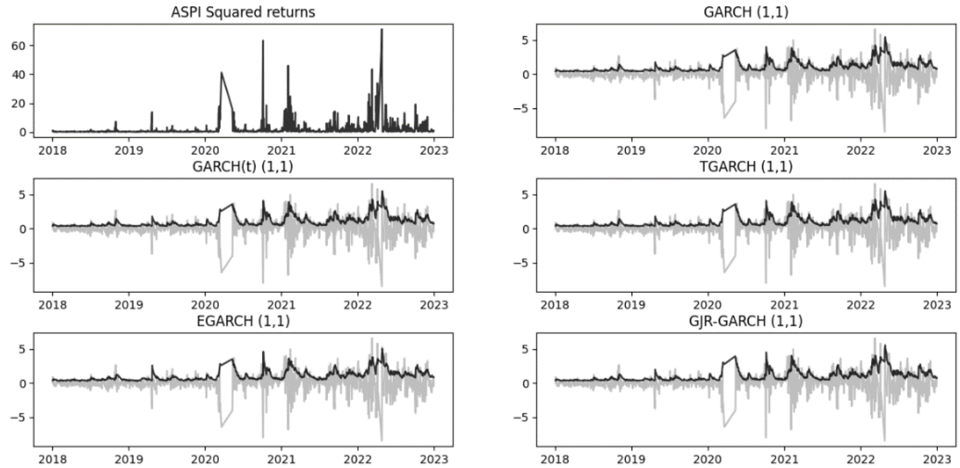
Model	Volatility equation				Parameter estimates		
	Omega (ω)	Alpha (α)	Beta (β)	Gamma (γ)	Log likelihood	AIC	BIC
GARCH (1,1)	0.025** (0.038)	0.214** (0.000)	0.786** (0.000)		-1503.48	3012.96	3028.13
GARCH (t) (1,1)	0.019** (0.007)	0.226** (0.000)	0.774** (0.000)		-1426.41	2862.83	2888.11
EGARCH (1,1)	0.016 (0.246)	0.378** (0.000)	0.970** (0.000)	-0.038* (0.063)	-1427.85	2865.70	2890.98
TGARCH (1,1)	0.019** (0.007)	0.226** (0.007)	0.774** (0.007)		-1426.61	2861.22	2881.45
GJR-GARCH (1,1)	0.021** (0.008)	0.177** (0.000)	0.772** (0.000)	0.103** (0.022)	-1424.17	2858.35	2883.63

Source: Authors' calculations
Notes: **-95 percent significance; *- 90 percent significance

The study estimates a symmetric GARCH models namely, GARCH (1,1), a GARCH (1,1) using skewed t distribution, a TGARCH model with students' T distributional estimates. The asymmetric models used in the study are EGRACH (1,1) and GJR-GARCH (1,1) models. Comparatively, all models estimated have a volatility persistence closer to one indicating a finite volatility persistence for all the models.

Comparing the symmetric models, the parameter estimators Akaike information criterion (AIC) and the Bayesian information criterion (BIC) suggest that the TGARCH model is more efficient in forecasting volatility among the models considered. Further, GARCH (1,1) model show the least efficiency in determining the volatility evolution of ASPI market index. Among the asymmetric models, the parameter estimations identify the superior efficiency of GJR-GARCH (1,1) comparative to the EGARCH model in volatility estimation. The findings correspond to the findings of Hewamana, et. al. (2022), Jahufer (2021), and Jegajeevan (2012). Study findings further contribute to the findings of Zhang and Nadarajah (2018) in expanding the empirical evidence on ARMA-GARCH applications in market index volatility determination.

Figure 2: Conditional volatility of GARCH models on ASPI returns



Source: Authors’ calculations

Further, asymmetric models can be used in the identification of the leverage effect. In EGARCH (1,1) the leverage effect is weakly significant at 90 percent confidence level and the impact it causes would be asymmetric ($\gamma \neq 0$) (Kamal & Haque, 2016). Leverage effect identification through EGARCH is akin to Hewamana, et. al. (2022), Jahufer (2021), and Jegajeevan (2012). However, the model does not specify the effect of the information through its coefficient. GJR-GARCH (1,1) provides more insights to the leverage model. Akin to EGARCH, GJR-GARCH indicates asymmetric impact from the leverage effect on ASPI volatility. Comparatively, GJR-GARCH model indicate a significant leverage effect with negative news causing a deferential effect on the volatility of the market index. The findings provide evidence for Kumar (2012) that less mature markets are heavily relying on information. However, leverage effect identification on both models contrast to the study findings of Jaleel and Samarakoon (2009). The findings strengthen the conclusions of Hewamana et. al. (2022) that irrational investors cause idiosyncratic volatility with negative speculation.

Table 6: Ljung-Box test statistics

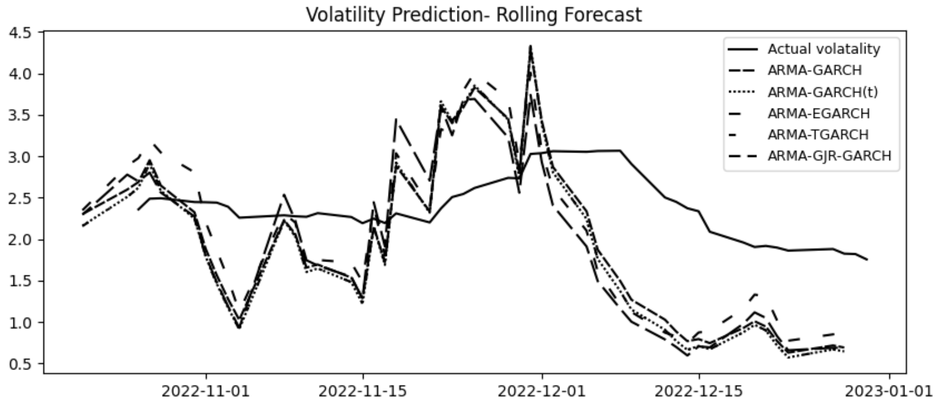
Lag	Statistic	p-value
1	0.010	0.921
2	0.629	0.730
3	0.841	0.840
4	2.085	0.720
5	5.833	0.323

Source: Authors' calculations

The model diagnostics conducted reveal that the residuals are not serially correlated rejecting the null hypothesis at 95 percent confidence level. Further, the diagnostics strengthen the claims on the applicability of ARMA-GARCH models in volatility estimation when serial correlation is detected in financial data. The study findings further provide empirical evidence to the findings of Francq and Zakoïan (2000) on the two-step estimation to gain consistency in forecasting for asymptotically normal data.

Moreover, study findings on symmetric and asymmetric GARCH modelling for volatility are comparable to the stock market volatility patterns of peer developing nations in the region including India and Pakistan (Akhtar & Khan 2016; Arsalan, et. al., 2022; Endri, et. al., 2020; Kumar, 2012; Vasudevan & Vetrivel 2016).

Figure 3: 45-day rolling window volatility prediction of GARCH models



Source: Authors' calculations

The study used a 45 day in-sample forecasting on volatility of ASPI. Thus, the GARCH models forecasted the volatility forecasts for the final 45 trading days of year 2022. Thus, the actual and predicted volatility (Figure 3) are the forecasted and actual ASPI volatility from 21st October 2022 to 28th December 2022. Forecasts of the models approach a similar behaviour which challenges the selection of a better model. Thus, the error terms of each forecast were calculated to gain quantitative insights to the accuracy of volatility prediction, beyond graphic depictions.

Table 7: Forecasting errors of GARCH models

	ARMA-GARCH (1,1)	ARMA-GARCH(t) (1,1)	ARMA-EGARCH (1,1)	ARMA-TGARCH (1,1)	ARMA-GJR-GARCH (1,1)
MSE	0.901	1.026	0.874	1.11	1.064
MAE	0.809	0.861	0.799	0.892	0.875
RMSE	0.949	1.013	0.935	1.054	1.031
Mean	1.975	1.916	2.065	1.697	1.933

Source: Authors' calculations

Table 7 demonstrates the accuracy of forecasts of each GARCH model. Comparatively, EGARCH has the highest accuracy in in-sample 45-day rolling forecasts in contrast to Morawakage and Nimal (2016). Symmetric GRACH models of GARCH (1,1) and GARCH (t) (1,1) respectively have the accuracy after EGARCH. The finding contradicts the study findings of Renggani, et. al. (2020) where GARCH (1,1) is identified as a better model in forecasting volatility. The findings further indicate that based on the parametric estimations, the ARMA-GJR-GARCH model would explain the underlying dynamics and the evolution of conditional volatility of ASPI. However, the model predictions of EGARCH model are more reliable in forecasting volatility. Hence it could be concluded that compared to symmetric GARCH models, asymmetric GARCH models are superior in volatility explanation and in volatility forecasting. Further, evidently the study findings observe the applicability of GARCH models in volatility estimations with ARMA representation in the Sri Lankan context.

5. Conclusion

Sri Lankan stock market is acknowledged to be an unstable market with periodical fluctuations increasing the volatility risk. CSE is a developing stock market with sluggish development comparatively to its peers. Thus, market maturity is vital for market development and the economic development. To stimulate long term investments, CSE needs to attract long term investors and institutions with favourable policy implementations. Thus, the study aimed to identify the dynamics of the CSE through volatility estimation of the Sri Lankan stock market during a highly turmoil period. Further, the use of ARMA-GARCH models would contribute to the local empirical studies on the applicability of ARMA-GARCH models and provide timeliest findings.

The study uses the daily closing prices of ASPI from January 2018 to December 2022 estimate the volatility parameters. Owing to the non-normality and serial dependence conditions inherent in the data, the study develops an ARMA (2,2) mean model and separate volatility models for the residuals with symmetric and asymmetric GARCH models.

The study findings identify asymmetric models to be more reliable in volatility estimation and forecasting than symmetric models owing to the parametric estimations and the forecasting error estimations on the models. Further, ASPI indicates a leverage effect where negative information causes high volatility in the market in both EGARCH and GJR-GARCH models with significant leverage coefficients. This coincides with several Sri Lankan and other developing and emerging market findings.

Further, it is observed that the volatility of the Sri Lankan stock market in comparison to many developing markets are highly dependent on information and commonly idiosyncratic volatilities are caused by immature investor behaviour. Complementary to developing stock markets, the study findings show that ASPI the broader market index of CSE swiftly move in tandem with its mean reverting position. Thus, the study identifies the necessity of implementing policies and regulations in promoting market maturity in the CSE. Further long-term investors are imperative for developing market maturity. Thus, favourable market conditions are vital to be simulated in this endeavour.

Declaration

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References

Akhtar, S., & Khan, N. (2016, August 01). Modeling volatility on the Karachi Stock Exchange, Pakistan. Retrieved March 14, 2023, from https://www.emerald.com/insight/content/doi/10.1108/JABS-05-2015-0060/full/html

Ali, G. (2013). EGARCH, GJR-GARCH, TGARCH, AVGARCH, NGARCH, IGARCH and APARCH Models for Pathogens at Marine Recreational Sites. *Journal of Statistical and Econometric Methods, 2*(3), 57-73.

Alibuhtto, M. (2014). Analysing Volatility of Colombo Consumer Price Index using GARCH Models. In *Fourth International Symposium 2014*. Sri Lanka: South Eastern University of Sri Lanka.

Andersen, T. G., Bollerslev, T., & Diebold, F. X. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *Review of Economics and Statistics, 89*(4), 701-720. doi:10.1162/rest.89.4.701

Arsalan, T., Chishty, B. A., Ghouri, S., & Ansari, N. U. (2022). Comparison of volatility and mean reversion among developed, developing, and emerging countries. *Journal of Economic and Administrative Sciences*. doi:10.1108/jeas-01-2022-0009

Bollerslev, T. (2008). Glossary to arch (GARCH). *SSRN Electronic Journal,* 1-46. doi:10.2139/ssrn.1263250

Central Bank of Sri Lanka. (2019). (rep.). *Annual report 2019* (pp. 186–187). Colombo, Sri Lanka: Central bank of Sri lanka. Retrieved from https://www.cbsl.gov.lk/sites/default/files/cbslweb_documents/publications/annual_report/2019/en/13_Box_09.pdf

Chen, H., Zhang, J., Tao, Y., & Tan, F. (2019). ASYMMETRIC GARCH type models for asymmetric volatility characteristics analysis and wind power forecasting. *Protection and Control of Modern Power Systems, 4*(1). doi:10.1186/s41601-019-0146-0

Chong, C. W., Ahmad, M. I., & Abdullah, M. Y. (1999). Performance of GARCH models in forecasting stock market volatility. *Journal of Forecasting, 18*(5), 333-343. doi:10.1002/(sici)1099-131x(199909)18:5<333::aid-for742>3.0.co;2-k

Ciarreta, A., Muniain, P., & Zarraga, A. (2017). Modeling and forecasting realized volatility in German-austrian continuous intraday electricity prices. *Journal of Forecasting*, *36*(6), 680-690. doi:10.1002/for.2463

Colombo Stock Exchange. (2020). Retrieved from https://cdn.cse.lk/pdf/company-articles/local-stock-market-remains-resilient-continues-progress-beyond-pre-covid-19-levels.pdf

De Silva, S., & Herath, H. (2016). Assessing the Market Price Volatility of Vegetable in Sri Lanka. In *Proceedings of 15th Agricultural Research Symposium* (pp. 41-45). Makandura, Sri Lanka: Wayamba University of Sri Lanka. Retrieved March 14, 2023, from http://repository.wyb.ac.lk/bitstream/handle/1/854/PROCEEDINGS-2016-41.pdf?sequence=2&isAllowed=y

Dilrukshi, K. B., Jayalath, K. V., Dissanayake, S. N., & Perera, S. M. (2022). Retail price volatility: The case of coconut in Sri Lanka. *Sri Lankan Journal of Agricultural Economics*, *23*(1), 22. doi:10.4038/sjae.v23i1.4659

Dinardi, F. B. (2020). *Forecasting the stock market using ARIMA and ARCH/GARCH approaches* (Doctoral dissertation, NOVA Information Management School (NIMS), 2020) (pp. 1-50). Portugal: Universidade Nova de Lisboa. Retrieved March 14, 2023, from https://run.unl.pt/handle/10362/109749.

Endri, E., Abidin, Z., Simanjuntak, T., & Nurhayati, I. (2020). Indonesian Stock Market Volatility: GARCH model. *Montenegrin Journal of Economics, 16*(2), 7-17. doi:10.14254/1800-5845/2020.16-2.1

Epaphra, M. (2017). Modeling exchange rate volatility: Application of the GARCH and EGARCH models. *Journal of Mathematical Finance, 07*(01), 121-143. doi:10.4236/jmf.2017.71007

Francq, C., & Zakoïan, J. (2000). Estimating weak GARCH representations. *Econometric Theory*, *16*(5), 692-728. doi:10.1017/s0266466600165041

Ghani, I. M., & Rahim, H. A. (2019). Modeling and forecasting of volatility using ARMA-GARCH: Case Study on malaysia natural rubber prices. *IOP Conference Series: Materials Science and Engineering*, *548*(1), 1–13. doi:10.1088/1757-899x/548/1/012023

Gospodinov, M., Gospodinova, E., & Georgieva-Tsaneva, G. (2019). Mathematical methods of ECG data analysis. *Healthcare Data Analytics and Management,* 177-209. doi:10.1016/b978-0-12-815368-0.00007-5

Grachev, O. Y. (2017). *Application of Time Series Models (ARIMA, GARCH, and ARMA- GARCH) for Stock Market ForecastingGARCH) for Stock Market Forec* (Doctoral dissertation, Northern Illinois University, 2017) (pp. 1-51). Illinois, USA: Northern Illinois University. doi:https://huskiecommons.lib.niu.edu/studentengagement-honorscapstones/177/?utm_source=huskiecommons.lib.niu.edu%2Fstudentengagementhonorscapstones%2F177&utm_medium=PDF&utm_campaign=PDFCoverPages

Hettiwaththa, H. W., & Abeygunawardana, R. A. (2018). Measuring flood risk in Ratnapura Town area in Sri Lanka. *International Conference on Climate Change, 2*(2), 31-41. doi:10.17501/2513258x.2018.2203

Hewamana, H. M., Siriwardhane, D. R., & Rathnayake, R. M. (2022). Nexus between asymmetric information and stock market volatility: Evidence from Sri Lanka. *Sri Lanka Journal of Economic Research, 9*(2), 83. doi:10.4038/sljer.v9i2.164

Jahufer, A. (2021). Choosing the best performing GARCH model for Sri Lanka stock market by Non-Parametric Specification Test. *Journal of Data Science, 13*(3), 457-472. doi:10.6339/jds.201507_13(3).0003

Jaleel, F. M., & Samarakoon, L. P. (2009). Stock market liberalization and return volatility: Evidence from the emerging market of Sri Lanka. *Journal of Multinational Financial Management, 19*(5), 409-423. doi:10.1016/j.mulfin.2009.07.006

Jegajeevan, S. (2012). Return volatility and asymmetric news effect in Sri Lankan stock market [Abstract]. *Staff Studies, 40*(1), 37. doi:10.4038/ss.v40i1.4680

Kamal, J. B., & Haque, A. E. (2016). Dependence between stock market and foreign exchange market in South Asia: A copula-GARCH approach. *The Journal of Developing Areas, 50*(1), 175-195. doi:10.1353/jda.2016.0010

Kande Arachchi, A. K. (2018). Comparison of Symmetric and Asymmetric GARCH Models: Application of Exchange Rate Volatility. *American Journal of Mathematics and Statistics, 8*(5), 151-159. doi:10.5923/j.ajms.20180805.08

Karunanayake, I., & Valadkhani, A. (2011). Asymmetric Dynamics in stock market volatility. *Economic Papers: A Journal of Applied Economics and Policy, 30*(2), 279-287. doi:10.1111/j.1759-3441.2011.00101.x

Kumar, D. R. (2012). Empirical analysis of stock return volatility by using Arch-Garch models: The case of indian stock market. *International Journal of Scientific Research, 2*(2), 202-206. doi:10.15373/22778179/feb2013/68

Maqsood, A., Safdar, S., Shafi, R., & Lelit, N. J. (2017). Modeling stock market volatility using GARCH models: A case study of nairobi securities exchange (NSE). *Open Journal of Statistics, 07*(02), 369-381. doi:10.4236/ojs.2017.72026

Marcucci, J. (2005). Forecasting stock market volatility with regime-switching GARCH models. *Studies in Nonlinear Dynamics & Econometrics, 9*(4), 1-42. doi:10.2202/1558-3708.1145

Morawakage, P. S., & Nimal, P. D. (2016). Equity market volatility behavior in Sri Lankan context. *Kelaniya Journal of Management, 4*(2), 1–9. doi:10.4038/kjm.v4i2.7496

Natenberg, S. (2015). The four types of volatility and how to evaluate them. *Option Volatility Trading Strategies*, 67-79. doi:10.1002/9781119204473.ch5

Perera, A., & Rathnayake, R. (2019). The effect of selected macroeconomic factors on exchange rate volatility in Sri Lanka. Retrieved March 15, 2023, from http://dr.lib.sjp.ac.lk/bitstream/handle/123456789/12495/FHSS%20-%20The%20effect%20of%20selected%20macroeconomic%20factors%20on%20exchange%20rate%20volatility%20in%20Sri%20Lanka.pdf?sequence=1

Perera, K. (2016). Effects of exchange rate volatility on stock market return volatility: Evidence from an emerging market. *International Journal of Science and Research (IJSR), 5*(1), 1750-1755. doi:10.21275/v5i1.nov153206

Renggani, P., Made Sumertajaya, I., Afendi, F. M., & Budiarti, R. (2020). Comparison of symmetric and asymmetric GARCH models in the futures contract of Robusta Coffee in Jakarta Futures Exchange. *International Journal of Scientific and Research Publications (IJSRP), 10*(11), 157-166. doi:10.29322/ijsrp.10.11.2020.p10717

Sans Cipollitti, R. (2020). Comparative effectiveness of the ARMA-GARCH over simple strategies.

Shanika, A., & Jahufer, A. (2021). Volatility analysis of international tourist arrivals to Sri Lanka using GARCH models. In *10th Annual Science Research Session 2021* (pp. 111-115). Sri Lanka: South Eastern University of Sri Lanka.

Silva, S., Tilakaratne, C., & Munasinghe, R. (2016). Impact of day of the week effect on all share price index (ASPI) and a comparison of forecastability of GARCH and NARX models. *2016 Sixteenth International Conference on Advances in ICT for Emerging Regions (ICTer),* 311-320. doi:10.1109/icter.2016.7829936

Thevakumar, P., & Jayathilaka, R. (2022). Exchange rate sensitivity influencing the economy: The case of sri lanka. *PLOS ONE, 17*(6). doi:10.1371/journal.pone.0269538

Tsay, R. S. (2005). Conditional Heteroscedastic Models. In *Analysis of Financial Time Series* (2nd ed., pp. 97-149). Hoboken, New Jersey: John Wiley & Sons.

Vasudevan, R. D., & Vetrivel, S. C. (2016). Forecasting stock market volatility using GARCH models: Evidence from the Indian Stock Market. *Asian Journal of Research in Social Sciences and Humanities, 6*(8), 1565. doi:10.5958/2249-7315.2016.00694.8

Wang, Y., Xiang, Y., Lei, X., & Zhou, Y. (2021). Volatility analysis based on GARCH-type models: Evidence from the Chinese Stock Market. *Economic Research-Ekonomska Istraživanja, 35*(1), 2530-2554. doi:10.1080/1331677x.2021.1967771

Xiang, Y. (2022). Using ARIMA-GARCH model to analyze fluctuation law of International Oil Price. *Mathematical Problems in Engineering*, 1–7. doi:10.1155/2022/3936414

Zhang, Z., & Nadarajah, S. (2018). A statistical analysis of the Colombo Stock Returns. *Global Business Review, 22*(1), 101-118. doi:10.1177/0972150918797196

Appendix

Figure 1: Correlogram log returns of ASPI.

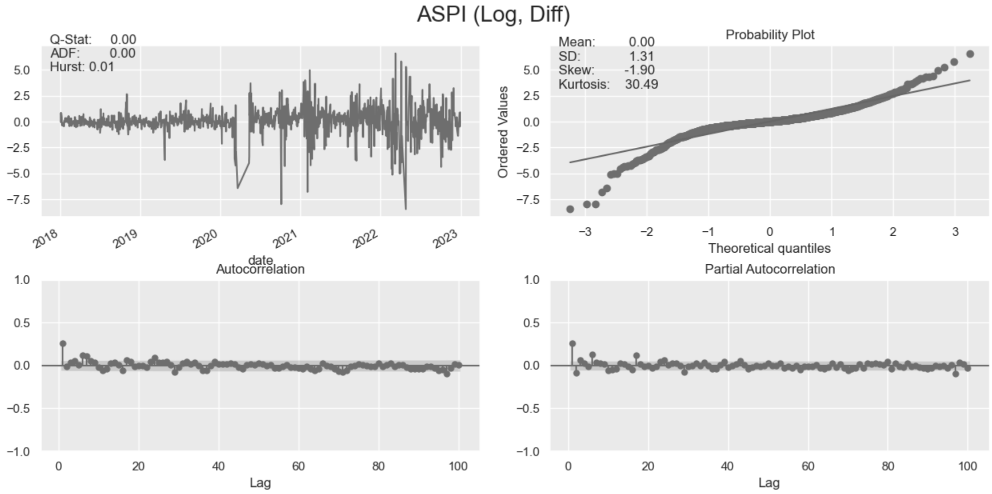

Figure 2: Residuals of the weak GARCH (1,1) model

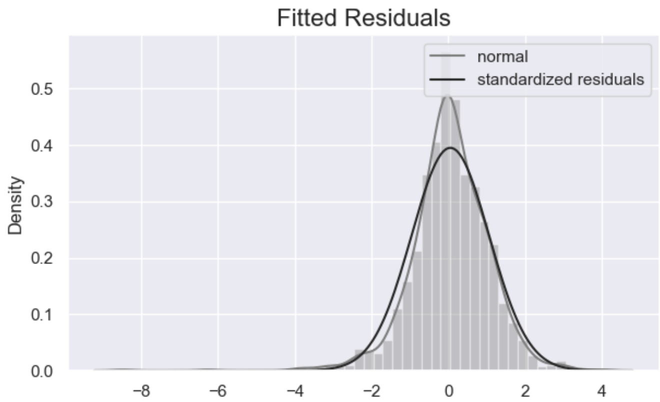

Figure 3: Autocorrelations plot (on left) and Partial Autocorrelation plot (on right) for log returns of ASPI

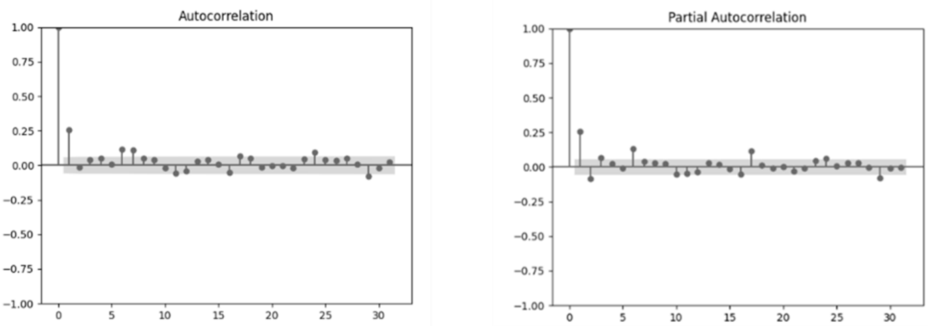

Figure 4: ARMA (2,2) Residual diagnostics

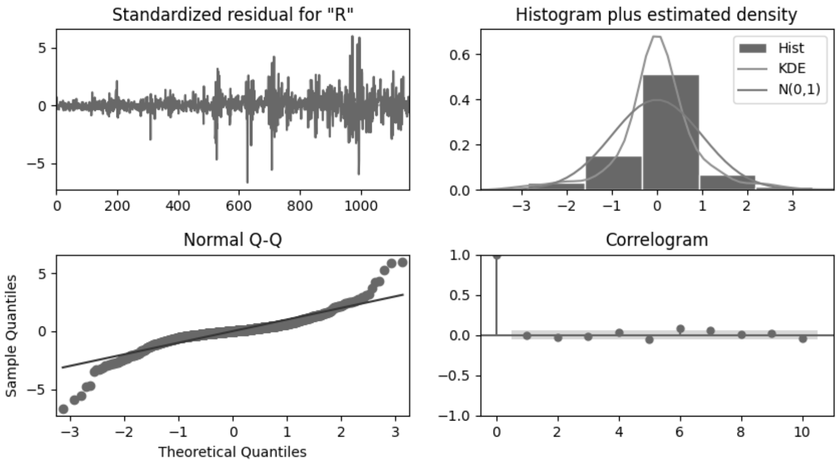

Table 1: ARMA-GARCH models estimated

ARMA (2, 2) Model (Mean Model)				
	Coefficient	**Standard error**	**t-statistic**	**p-value**
AR (1)	0.79	0.096	8.222	0
AR (2)	0.136	0.068	1.987	0.047
MA (1)	-0.509	0.095	-5.372	0.000
MA (2)	-0.359	0.058	-6.148	0.000
Sigma	1.571	0.030	52.424	0.000
Residual diagnostics				
	Test statistic		**p-value**	
Ljung-Box test	43.080		0.000	
Jarque-Bera	4647.310		0.000	
Skewness	-0.280		**Kurtosis**	11.080
Volatility Models				
ARMA-GARCH (1,1)				
Variance parameter	**Coefficient**	**Standard error**	**t-statistic**	**p-value**
omega	0.025	0.012	2.074	0.038
alpha	0.214	0.040	5.387	0.000
beta	0.786	0.026	30.159	0.000
ARMA-GARCH(t) (1,1)				
Volatility parameter	**Coefficient**	**Standard error**	**t-statistic**	**p-value**
omega	0.019	0.007	2.684	0.007
alpha	0.226	0.034	6.589	0.000
beta	0.774	0.035	22.178	0.000

ARMA-EGARCH (1,1)				
Volatility parameter	**Coefficient**	**Standard error**	**t-statistic**	**p-value**
omega	0.016	0.014	1.160	0.246
alpha	0.378	0.046	8.202	0.000
beta	0.970	0.010	99.136	0.000
gamma	-0.038	0.021	-1.860	0.063
ARMA-TGARCH (1,1)				
Volatility parameter	**Coefficient**	**Standard error**	**t-statistic**	**p-value**
omega	0.019	0.007	2.714	0.007
alpha	0.226	0.034	6.558	0.000
beta	0.774	0.035	22.188	0.000
ARMA-GJR-GARCH (1,1)				
Volatility parameter	**Coefficient**	**Standard error**	**t-statistic**	**p-value**
Omega	0.021	0.008	2.661	0.008
alpha	0.177	0.033	5.388	0.000
beta	0.772	0.035	22.209	0.000
gamma	0.103	0.045	2.296	0.022