Existence and persistence of conditional skewness and kurtosis: Evidence from Sri Lanka

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Abstract

The Colombo Stock Exchange (CSE) currently forms a natural test-bank for comparative stock market studies due to Sri Lanka's recent conflict and reconciliation which partitions the exchange's recent history into conflict and post-conflict periods. Using the daily All Share Price Index (ASPI) returns from 2006 to 2012, we compare the conditional dynamics of the time-varying skewness and kurtosis of the ASPI for two adjacent periods: the conflict period (1st January 2006 to 18th May 2009) and the post-conflict period (19th May 2009 to 2012). Our findings support the existence of conditional skewness and kurtosis for both periods. However, the findings regarding the persistence of conditional skewness and kurtosis were mutually exclusive; with the persistence for conditional kurtosis detected only in the conflict period and the persistence for conditional skewness prevailing only in the post-conflict period. As such, this study links persistence in conditional kurtosis with periods of conflict and persistence in conditional skewness with periods of post-conflict.

Keywords *: Conditional skewness and conditional kurtosis; Gram-Charlier density; GARCHSK; Conflict and post-conflict; Sri Lanka.*

1. Introduction

A necessary condition for the smooth functioning of a stock market is the political and economic stability of the country concerned. Hence, the stock market, via its market index, acts as a barometer of stock market behaviour. The stock market index reflects market direction and indicates day-to-day fluctuations in stock prices. The index acts a precursor of political and economic expectations (see Pathak (2011)). The Colombo Stock Exchange (CSE) forms a unique benchmark for comparative stock market studies due to Sri Lanka's recent past civil war which divides any such dataset into conflict and post-conflict samples (see Coyne, Dempster, and Isaacs, 2010).

The dynamics of arrival of news or shocks during-conflict and post-conflict environments will be quite different as would be expected. Conflict or unstable conditions give rise to greater uncertainty than post-conflict or stable conditions. The perception of risks would also differ quite significantly between the two periods. In the context, the role of conditional higher moments of a return distribution has become increasingly important in the literature mainly because traditional measures based on mean and variance have failed to fully characterise return behaviour (see Campbell and Hentschel, 1992 & Kirchler and Huber, 2007).

Dayaratne (2014) looked at various Sri Lankan accounting and market indicators (sector indices, market capitalisation, key market ratios etc.) and found significant positive differences between the conflict and post-conflict performances in these indicators. His findings 'imply that peace is an essential element for the development of the capital market on Sri Lanka'. Deyshappriya (2014), using OLS and GARCH (1,1) models, tested market return data for day-of-the-week effects and found the conflict period to be more day-of-the-week inefficient than the post-conflict period. Jeyasreedharan (2015), using a modified Kolmogorov-Smirnov statistic, tested the All Share Price Index (ASPI) and 20 stocks for day-of-the-week effects in the conflict and post-conflict periods and found the post-conflict period to be more day-of-the-week inefficient than the conflict period. But the differences were found to be less apparent (for the stocks selected) between the two periods after allowing for Autoregressive Conditional Heteroskedasticity (ARCH) effects, finding Monday and Friday anomalies in both periods. Kumara, Upananda, and Rajib (2014) after studying the dynamic properties of stock returns during and after the ethnic conflict in Sri Lanka concluded that 'during the period of ethnic conflict, stocks returns … deviated more from normality than the post-conflict period' with both periods displaying leptokurtic and asymmetric behaviour.

Given that the empirical distribution of stock returns in Sri Lanka has been observed in both periods to be both asymmetric and leptokurtic but with varying degrees, this paper examines the dynamics of conditional skewness and conditional kurtosis over the conflict and post-conflict periods. In doing so, the paper contributes to the current conflict/post-conflict literature in the following ways. Firstly, this is the first paper to directly examine the existence and persistence of both conditional skewness and conditional kurtosis in the Sri Lankan stock market. Second, it examines the changing behaviour of conditional higher moments under conflict and post-conflict conditions. In Section 2 we discuss the characteristics of the Gram-Charlier GARCHSK model for jointly estimating the time-varying or conditional variance, skewness and kurtosis. Section 3 presents and characterises the data as sampled. Section 4 presents and discusses the empirical results. In Section 5 we conclude with a summary and implications.

2. Method

The Auto regressive Conditional Heteroskedastic (ARCH) model by Engle (1982) enables the conditional variance to change over time as a function of past errors while the unconditional variance remains constant. The generalised ARCH or GARCH was developed by Bollerslev (1986) by adding lagged conditional variance(s) to the equation.

Given a time series of stock prices, $\{P_0, P_1, \ldots, P_T\}$ the continuously compounded returns r_t at time t is defined as $\ln(P_t) - \ln(P_{t-1})$, t=1,2,…,T. We filter the r_t series to get rid of some weak dynamics in the conditional mean, and obtain the ε_t series as $\varepsilon_t = r_t - \alpha_0 - \alpha_1 r_{t-1}$. The ε_t series can then be taken to be a discrete time stochastic process, and Ω_t the information set (past and present) at time t. The classical GARCH(1,1) process is then expressed as:

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}$$

where h_t is the conditional variance of ε_t and $\varepsilon_t|\Omega_t \sim \sqrt{h_t}\eta_t$ where η_t is independent and identically distributed (iid) with $E_{t-1}(\eta_t)=0$, $E_{t-1}(\eta_t^2)=1$ and density $f(.;\ \theta)$ where θ is a vector of shape parameters. The de facto density function used is generally the normal distribution with the shape parameter, θ=0. However, skewness (asymmetry) and kurtosis (fat-tails) are stylised facts of financial returns data. As consequence, many distributions have appeared in the literature to address the asymmetry or fat-tails or both (see Yan (2005)). The list includes the t-distribution (TD) by Bollerslev (1987) and Hansen (1994), the generalised error distribution (GED) by Nelson (1991), the generalised hyperbolic distribution (GHD) by Eberlein and Keller (1995) and Barndorff-Nielsen (1997), the stable distribution (SD) by McCulloch (1996), the noncentral-t (NCTD) distribution by Harvey and Siddique (1999) and the Gram-Charlier (GCD) distribution by Jondeau and Rockinger (2003).

More flexibility can be introduced by allowing the asymmetry (3rd moment) and/or fat-tails (4th moment) to be conditioned and time-varying just like the variance (2nd moment) equation in a GARCH(1,1) model. As discussed by Yan (2005) this can be implemented via two approaches. In the first approach, an Autoregressive Conditional Density (ARCD) formulation is imposed on the shape parameters and the 'skewness and kurtosis are derived from the time-varying shape parameters' (see Hansen (1994) and Jondeau and Rockinger (2003)). In the second approach, an Autoregressive Conditional Moment (ARDM) formulation is applied directly the skewness or kurtosis and the 'shape parameters are backed out from the skewness and kurtosis' (see Harvey and Siddique (1999) and Brooks, Burke, Heravi, and Persand (2005)). León, Rubio, and Serna (2005) combine both approaches by assuming a Gram-Charlier (GC) series expansion of the normal density function for the error distribution where the shape parameters also double up as the skewness and kurtosis parameters. As this model is also much easier to estimate we adopt León, et al. (2005)'s approach.

León, et al. (2005) augmented the standard GARCH model with skewness and kurtosis equations to obtain the GARCHSK model and is given by:

$$\varepsilon_t = r_t - \alpha_0 - \alpha_1 r_{t-1}$$
$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}$$
$$\eta_t = \varepsilon_t / \sqrt{h_t}$$
$$s_t = \gamma_0 + \gamma_1 \eta_{t-1}^3 + \gamma_2 s_{t-1}$$
$$k_t = \delta_0 + \delta_1 \eta_{t-1}^4 + \delta_2 k_{t-1}$$

where h_t is the conditional variance of ε_t, s_t is the conditional skewness of η_t, k_t is the conditional kurtosis of η_t and $\varepsilon_t|\Omega_t \sim \sqrt{h_t}\eta_t$ where η_t is independent and identically distributed (iid) with a density $f(.;\theta_t)$ where θ_t is a time-varying vector of shape-cum-moment parameters. The conditional distribution of η_t is assumed to follow a Gram-Charlier (GC) series expansion of the standard normal density function and is given by:

$$GC(\eta_t)|\Omega_t = \varphi(\eta_t)[\psi^2(\eta_t)/\Gamma_t],$$

where

$$\varphi(\eta_t) = 1/\sqrt{(2\pi)}[\exp(-\eta_t^2/2)]$$
$$\psi(\eta_t) = 1 + [s_t(\eta_t^3 - 3\eta_t)/6] + [(k_t - 3)(\eta_t^4 - 6\eta_t^2 + 3)/24]$$
$$\Gamma_t = 1 + (s_t^2/6) + [(k_t - 3)^2/24]$$

An important and unique property of the GC density function is that the expected values for its first four moments are as follows: $E_{t-1}(\eta_t)=0$, $E_{t-1}(\eta_t^2)=1$, $E_{t-1}(\eta_t^3)=s_t$, $E_{t-1}(\eta_t^4)=k_t$ with the coefficients of skewness and kurtosis as explicit shape parameters (see Corrado and Su (1996)). After omitting irrelevant constants, the log-likelihood function for any observation corresponding to the conditional distribution $\varepsilon_t|\Omega_t \sim \sqrt{h_t}\eta_t$ and whose density function is $\sqrt{h_t}[GC(\eta_t)|\Omega_t]$, is given by:

$$l(\theta_t) = -\ln(h_t)/2 - \eta_t^2/2 + \ln[\psi^2(\eta_t)] - \ln(\Gamma_t)$$

where θ_t is a time-varying vector of shape-cum-moment parameters and $l(\theta_t)$ is the conditional log-likelihood function. The parameters of the GARCHSK model need to be constrained to ensure that the conditional variance and kurtosis are positive and all three higher moments are stationary. We use the Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton optimization algorithm for the numerical maximisation of the log-likelihood function (see Dennis and Moré (1977) for details). We denote the above model specification as a GARCHSK (3,3,3) model, where the numbers within brackets define to the number of parameters to be estimated in the variance, skewness and kurtosis equations respectively. Note that the previous GARCH(1,1) model is nested as an GARCHSK (3,0,0) model (with s_t=0 and k_t=3) within the GARCHSK(3,3,3) specification.

3. Data

The closing daily prices for the All Share Price Index (ASPI) were downloaded from Datastream, a division of Thomson Reuters. The sample period studied is from 1st January 2006 to 31st December, 2012 (1826 days). The sample period is further sub-divided into two periods: the conflict period (1st January 2006 to 18th May 2009) and the post-conflict period (19th May 2009 to 31st December 2012). The daily close-to-close log-returns were computed for all trading days. The number of trading days for the conflict period was 876 days and for the post-conflict period was 941 days.

Figure 1 illustrates the time-varying nature of the standardised daily returns over both sample periods. There is a definite downward trend over the conflict period, with a positive trend and high volatility during the penultimate stages of the conflict followed by a more volatile post-conflict period. Figure 2 summarises the unconditional statistics for the return series. The histogram depicts a non-normal distribution of returns with some positive skewness (0.3452, likely due to some very extreme and/or outlying

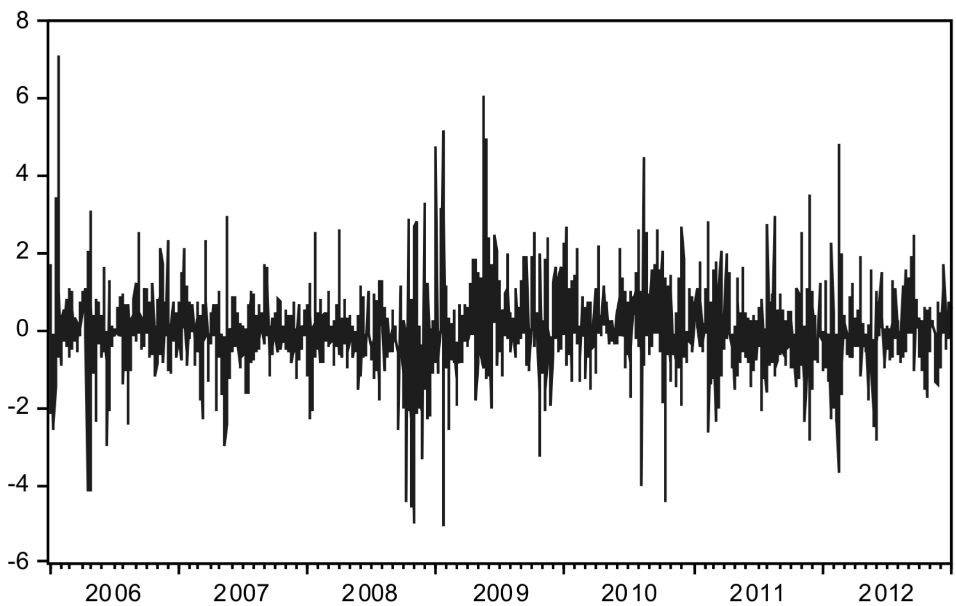

Figure 1 Daily Returns of ASPI (2006-2012)

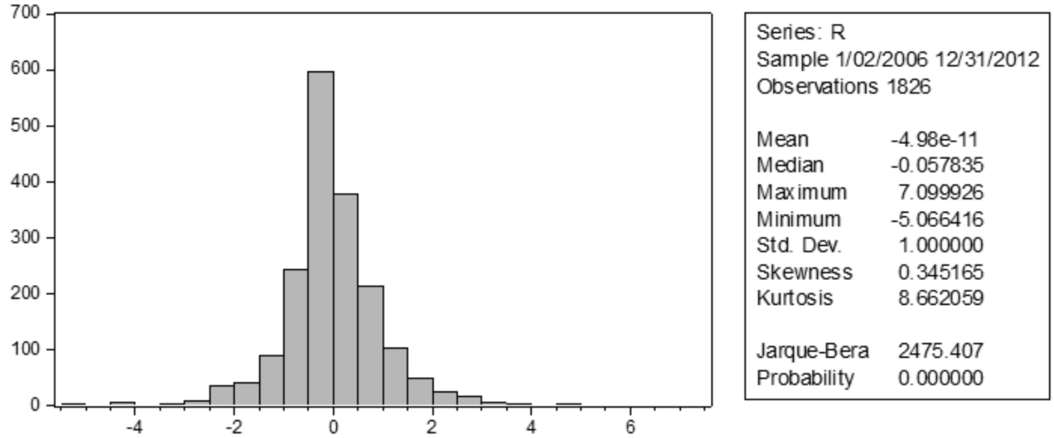

Figure 2 Histogram and Descriptive Statistics of Daily Returns (R) of ASPI (2006-2012)

observations) and a high kurtosis (8.662, likely due to the high number of extreme and/or outlying observations). Note that the return series is has been standardised and thus the average volatility over the sample period is 1.0 as depicted in Figure 2. The normal distribution for the returns is clearly rejected by the high Jarque-Bera statistic of 2475.407 with p-value 0.0000).

4. Results

Four GARCHSK models were fitted for the return series over the conflict and non-conflict periods separately to uncover differences, if any, in the conditional moments between the two periods. Given that the log-likelihood function for the Gram-Charlier density function is non-linear, we follow León, et al. (2005) in choosing the starting values for the estimation procedure. We first, estimate the GARCHSK(3,0,0) model using the normal distribution as the error density. We then estimate the GARCHSK(3,1,1) model using the estimates from the GARCHSK(3,0,0) run as the starting values and repeating the same for the GARCHSK (3,3,1) model and finishing up with the GARCHSK (3,3,3) estimates.

The results for the four GARCHSK models and the two sample periods are given in Tables 1 and 2 separately. All the estimates satisfy the model parameter constraints and stationary conditions.

We first examine the results for the conflict period in Table 1. In the GARCHSK (3,0,0) or GARCH (1,1) model all the parameters are significant with the except of the constant in the mean equation. The results also indicate the estimated GARCHSK(3,0,0) model is stationary. The high short-run parameter $\beta_1 = 0.2079 > 0.1$ and the low long-run parameter $\beta_2 = 0.7348 < 0.9$ indicates a market in the conflict period that is very "jumpy or nervous" as shown by the variance(H) plot in the top-right panel in Figure 3 (see Alexander (2008)). The conditional variance is also semi-strong persistent as indicated by ($0.9 < \beta_1+\beta_2 = 0.9210 < 0.95$). This finding is augers with the findings by Jegajeevan (2010) whose "in-depth analysis on daily return using symmetric GARCH model has supported the fact that the daily return shows time-varying volatility with high persistence" for the ASPI from 1998 to June 2009.

The GARCHSK (3,1,1) model has significant higher moment parameters, highlighting the relevance of unconditional skewness and kurtosis in return fluctuations, with the kurtosis parameter indicating near normal with a skewness of -0.0999 and kurtosis of 2.4615. The same for the GARCHSK (3,3,1) model though the skewness parameters are not significant. The GARCHSK (3,3,3) model, however, confirms this by a shift in significance from conditional skewness to conditional kurtosis. None of the parameters in the skewness equation is significant in contrast to the very significant parameters in the kurtosis equation. The long-run parameter in the variance equation drops slightly when the kurtosis equation is included in the model, indicating the relevance of conditional kurtosis to the return dynamics. The results for the GARCHSK (3,3,3) model highlights the dominance of kurtosis over skewness during the conflict period. Moreover the kurtosis equation as estimated indicates semi-strong persistence in the conditional fourth moment in the conflict return generation process.

In Figure 3 we graphically illustrate the implications of our GARCHSK(3,3,3) model estimates for the conflict period. The skewness (S) plot shows no persistence and is supported by the corresponding low parameter estimates ($\gamma_1+\gamma_2 = 0.1337 << 0.8$) in Table 1. The kurtosis (K) plot depicts a semi-strong persistence and is confirmed by ($0.9 < \delta_1+\delta_2 = 0.9215 < 0.95$) from the kurtosis equation in Table 1. The kurtosis (K) plot spikes upward and then decays away slowly until there is another spike. The average half-life of both the conditional variance and conditional kurtosis is around 8 days, indicating the conditional uncertainties during the conflict periods carry over into the weekends, supporting Deyshappriya (2014)'s findings of high volatility Mondays during a similar window of the conflict period in Sri Lanka. An additional point to note that the spikes in the kurtosis plot coincide (near perfectly) with the spikes in the skewness plot for the same (conflict) period highlighting the common influence of large or extreme shocks on the higher conditional moments.

Table 1 GARCHSK Estimates for Conflict Period (2006-18 May, 2009). The reported coefficients are ML estimates of the four equations in the GARCHSK model.

Parameters	GARCHSK(3,0,0)	GARCHSK(3,1,1)	GARCHSK(3,3,1)	GARCHSK(3,3,3)
α_0	0.015685	0.028187	-0.056870	**-0.071546**
	(0.5649)	(0.0939)	(0.0019)	**(0.0002)**
α_1	0.202557	0.243036	0.155956	0.106183
	(0.0000)	(0.0000)	(0.0000)	(0.0002)
β_0	0.068968	0.069016	0.069016	0.063207
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_1	0.207928	0.247590	0.213499	0.247231
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_2	0.734756	0.653582	0.711813	0.672870
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_0	0.000000	-0.099999	-0.299296	-0.250988
		(0.0000)	(0.0261)	(0.1809)
γ_1			0.005357	0.006955
			(0.4202)	(0.3688)
γ_2			-0.237438	**0.126721**
			(0.6700)	**(0.8466)**
δ_0	3.000000	2.461474	2.461474	0.202072
		(0.0000)	(0.0000)	(0.0000)
δ_1				0.001505
				(0.0000)
δ_2				**0.919977**
				(0.0000)
Log-likelihood	-330.5856	-376.4349	-397.6957	**-307.5979**

The boxplots of Figure 4 further depict the distribution of the conditional moments during the conflict period. The distribution of the standardised GARCH residuals (E in Figure 3) is symmetric and near normal with a skewness of -0.0999 and kurtosis of 2.4615 (as per GARCHSK (3,1,1) model in Table 1) as compared to the filtered sample skewness and kurtosis of 0.1893 and 9.9319 respectively for the conflict period (not tabulated). This indicates that taking into account the influence of conditional higher moments (above the second moment) begets near normal residuals. The distribution of the conditional variance and kurtosis are asymmetric and widely dispersed. The distribution of the conditional skewness is symmetric though with some large outliers.

We next examine the results for the post-conflict period in Table 2. In the GARCHSK (3,0,0) or GARCH (1,1) model all the parameters are significant. The results also indicate the estimated GARCHSK(3,0,0) model is stationary. The high short-run parameter $\beta_1 = 0.1598 > 0.1$ and the low long-run parameter $\beta_2 = 0.7504 < 0.9$ indicates a market that is still "jumpy or nervous" as shown by the variance (H) plot in the top-right panel in Figure 5. The conditional variance is however only weakly persistent as indicated by $(0.80 < \beta_1 + \beta_2 = 0.8740 < 0.90)$.

The GARCHSK (3,1,1) model has all its parameters significant, highlighting the relevance of unconditional skewness and kurtosis

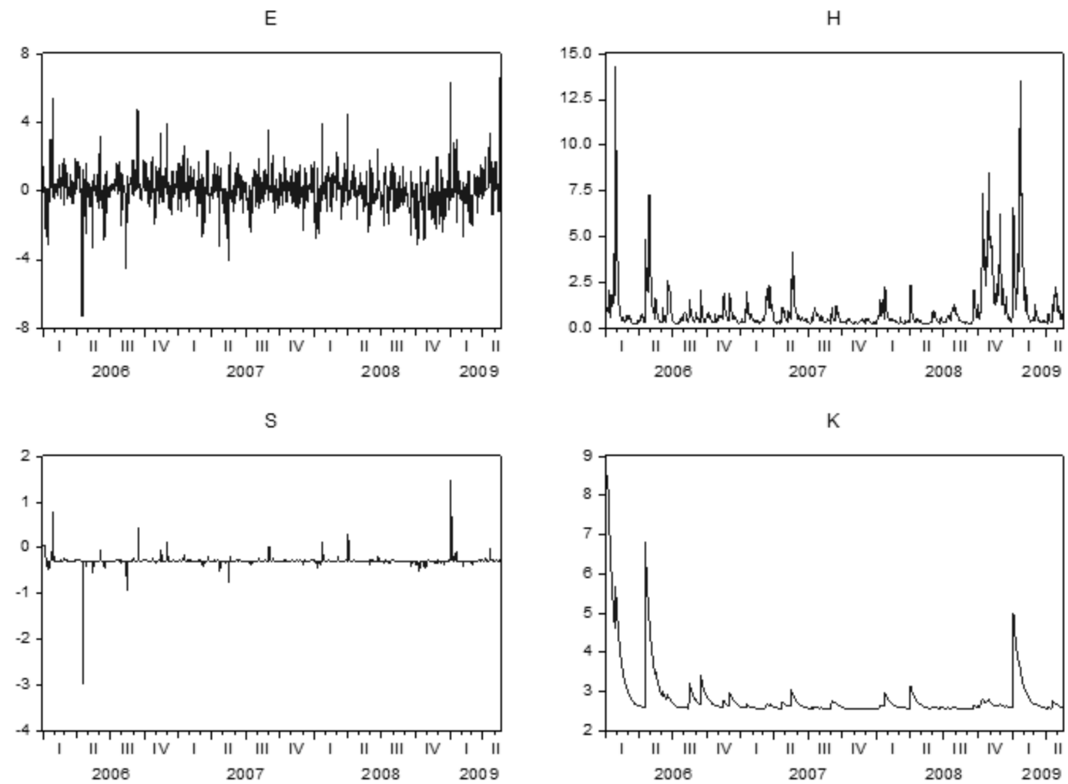

Figure 3 Plots of GARCHSK residuals (E), variance(H), skewness(S) and kurtosis (K) Conflict Period

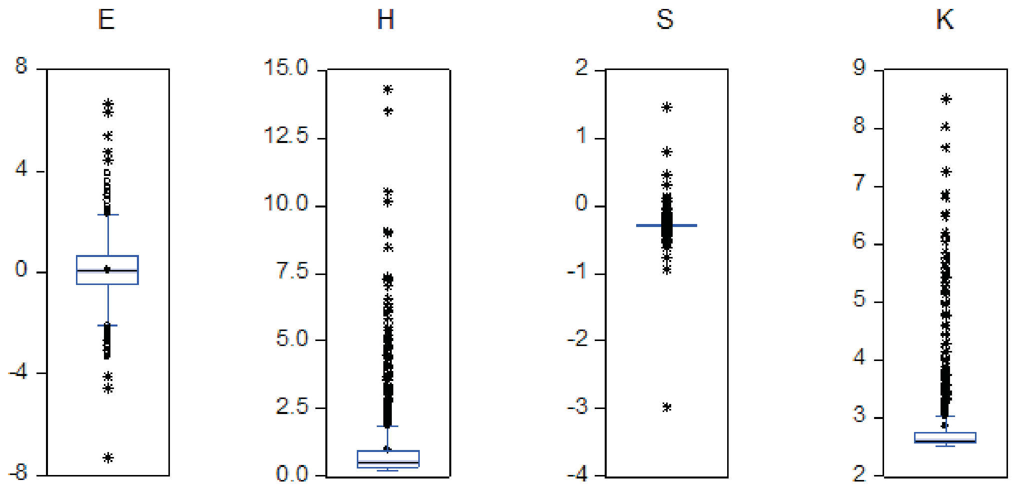

Figure 4 Boxplots of residuals(E), volatility(H), skewness(S) and kurtosis(K) - Conflict Period

Table 2 GARCHSK Estimates for Post-Conflict Period (19 May, 2009-2012). The reported coefficients are ML estimates of the four equations in the GARCHSK model.

Parameters	GARCHSK(3,0,0)	GARCHSK(3,1,1)	GARCHSK(3,3,1)	GARCHSK(3,3,3)
α_0	0.087839	0.074388	0.076363	0.057752
	(0.0027)	(0.0008)	(0.0003)	(0.0324)
α_1	0.223682	0.246880	0.240271	0.245954
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_0	0.082855	0.068644	0.069273	0.082107
	(0.0000)	(0.0000)	(0.0000)	(0.0007)
β_1	0.159787	0.105632	0.105967	0.121508
	(0.0000)	(0.0000)	(0.0000)	(0.0003)
β_2	0.750443	0.774142	0.771611	0.752520
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_0	0.000000	-0.053461	-0.001063	0.001085
		(0.0006)	(0.0005)	(0.3365)
γ_1			0.000450	-0.001564
			(0.2489)	(0.1039)
γ_2			0.985350	0.993963
			(0.0000)	(0.0000)
δ_0	3.000000	2.390142	2.397706	2.304800
		(0.0000)	(0.0000)	(0.0855)
δ_1				0.011733
				(0.0013)
δ_2				0.333020
				(0.3800)
Log likelihood	-366.1424	-431.4108	-430.6934	-341.5948

in return fluctuations, with the constant kurtosis parameter of 2.390 being nearer to that of the normal distribution. The same is true for the GARCHSK (3,3,1) model with a significant difference in the parameters of the skewness equation as compared to the conflict period. The

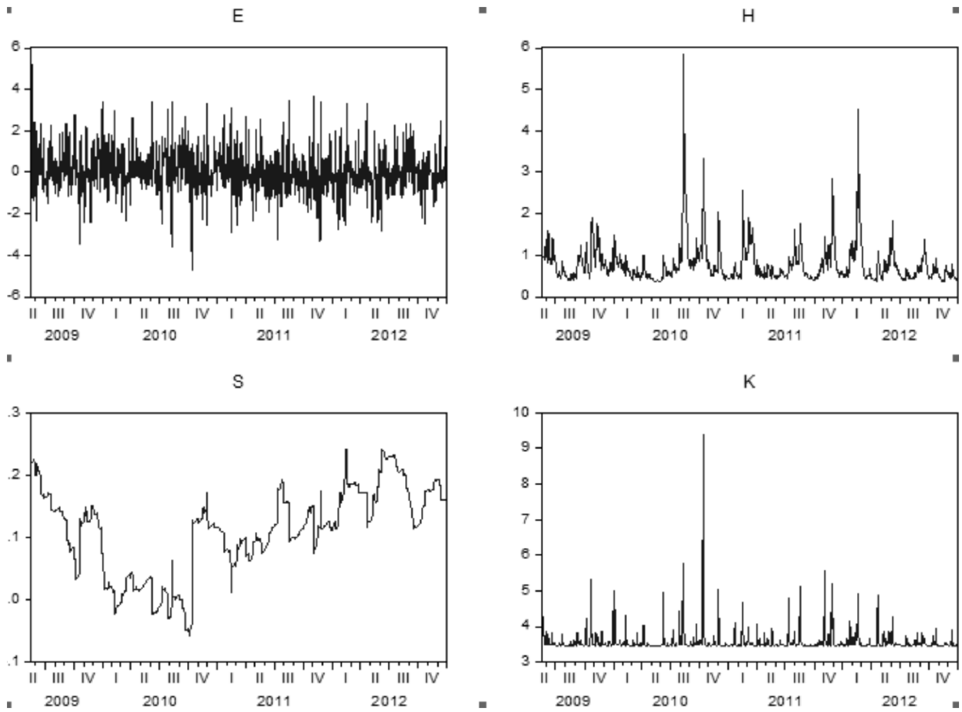

Figure 5 Plots of GARCHSK residuals(E), variance(H), skewness(S) and kurtosis(K) Post-Conflict Period

GARCHSK (3,3,3) model confirms this shift in the focus from conditional kurtosis to conditional skewness. The long-run loading in the variance equation does not drop significantly when the kurtosis equation is included in the model. The results for the GARCHSK (3,3,3) model highlight the dominance of conditional skewness over conditional kurtosis during the non-conflict period. Furthermore, the parameters of the skewness equation as estimated ($0.95 < \gamma_1+\gamma_2 =0.9924 < 1.0$) indicate a strong persistence in the conditional third moment in the GARCHSK (3,3,3) model during the non-conflict period.

In Figure 5 we then graphically illustrate the implications of our GARCHSK(3,3,3) model estimates for the post-conflict period. The skewness (S) plot shows strong trends and is supported by the very high γ_2 parameter estimate of 0.9939 in Table 2. The kurtosis plot has no long run persistence and is indicated by ($\delta_1+\delta_2 = 0.3448 << 0.80$) from the coefficients of the kurtosis equation in Table 2. The half-life of the conditional skewness during the post-conflict period is about 90 days, confirming the trend displayed in the conditional skewness (S) plot (in Figure 5). This means that a full decay is unlikely in the near future under post-conflict conditions and corroborates the findings by Collier and Hoeffler (2002) "that post-conflict deviations from the normal growth relationship follow a inverted-U pattern over the first post-conflict decade" i.e. the first portion of an inverted-U pattern is strongly persistent and has positive skewness. The half-life of the conditional variance is 5 days (weak persistence) and the conditional kurtosis is less than a day (no persistence).

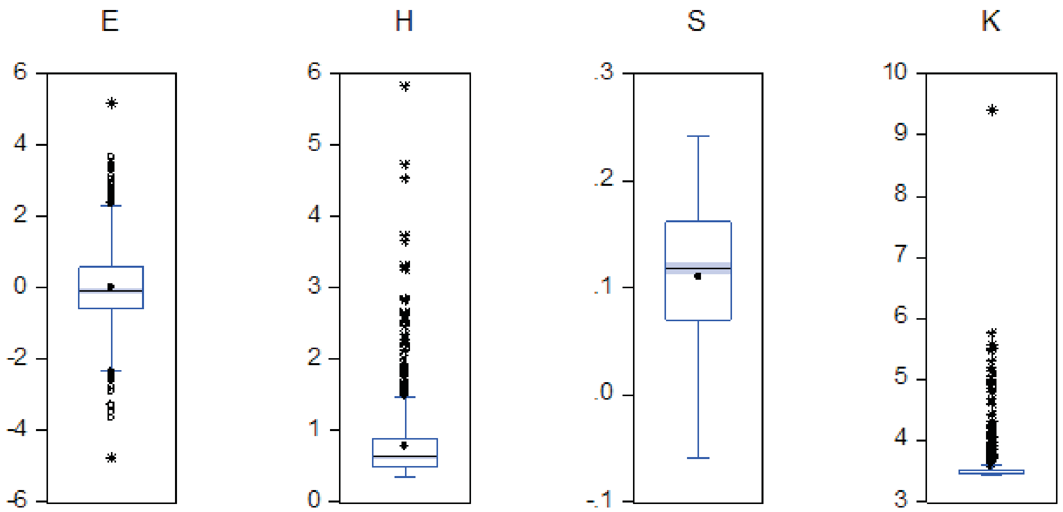

Figure 6 Boxplots of residuals(E), volatility(H), skewness(S) and kurtosis(K) Post-Conflict Period

In the box plots of Figure 6 we then depict the distribution of the conditional moments during the post-conflict period. The distribution of the standardised GARCH residuals is symmetric and near normal with a skewness of -0.05346 and kurtosis of 2.3901 (as per GARCHSK (3,1,1) model of Table 2) as compared to the filtered sample skewness and kurtosis of 0.3025 and 4.5801 respectively (not tabulated). This indicates that taking into account the influence of conditional higher moments (above the second moment) begets near normal residuals. The distribution of the conditional variance and kurtosis are asymmetric and less dispersed than the conflict period. The distribution of the conditional skewness is symmetric and without outliers.

The log-likelihood values for the four GARCHSK models for both periods find the GARCHSK (3,3,3) model the best-fit in both periods, as listed in Tables 1 and 2. The likelihood values were computed starting from the GARCHSK (3,3,3) model and by progressively restricting the parameters according to the sub-model, thus nesting the sub-models within the encompassing 11-parameter GARCHSK (3,3,3) model. The results show that the intermediate GARCHSK models are sub-optimal. The intermediate models, however, were necessary but not sufficient in themselves in the GARCHSK modelling sequence.

5. Conclusion

The findings in this paper highlight the existence and persistence of conditional skewness and/or conditional kurtosis in the Sri Lankan stock market; particularly in times of conflict and post-conflict. All the higher moments considered displayed differences between the two periods selected. The parameters of the variance equation indicate a semi-strong persistence in the conflict period and a weak-from persistence in the post-conflict period. In addition the variance process was twice as spiky and twice as large during the conflict period when compared to the post-conflict period. This is as expected in times of extreme uncertainty as was during the conflict period.

A more significant finding was the switch in the persistence between the third and fourth conditional moments over the two periods. The conflict period displayed a semi-strong persistent relationship for the conditional kurtosis equation and had no persistence for the conditional skewness equation. This finding was inverted for the post-conflict period with a strong persistence in the conditional skewness properties and no persistence in the conditional kurtosis. These findings support the hypothesis that quite different conditional distributional relationships (as depicted by the differing conditional higher moment relationships) hold in times of conflict and post-conflict. The findings indicate that conditional kurtosis plays a very important role in times of conflict and conditional skewness appears to dominate during times of post-conflict. A possible explanation would be that though uncertainty (via conditional volatility) is to be found in both periods, it is the dynamics of the conditional kurtosis that depicts the ambiguity around conflicts. The conditional skewness equation in our study is probably picking up the trending bullish market in Sri Lanka for the post-conflict period.

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