Ruhuna Journal of Management and Finance
Volume 1 Number 2 - July 2014
ISSN 2235-9222

Do Dynamic Properties of Stock Return Vary Under Hostile Environment? A Study During and After the Ethnic Conflict in Sri Lanka

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Abstract

Investors' choice in investment is affected by a number of factors such as natural disasters, ethnic conflicts, war, political instability, economic recessions etc. Therefore, socioeconomic stability is important in building trust among investors. Nearly three decade-long ethnic conflict in Sri Lanka during 1983 to 2009 may have influenced the investment environment. Several researchers have already examined the dynamic properties of stock return in Sri Lanka. However, those findings are not consistent when there is an impact from ethnic conflict. Therefore, this study aimed to investigate the behavioural patterns of volatility clustering, asymmetric effect and leptokurtic condition of the return during and after the ethnic conflict. Similarly, risk-return trade-off condition is also tested. Daily observations of All Share Price Index from 1985 to 2012 are categorized into conflict period and post-conflict period. While GARCH (m, s) model is employed for volatility clustering, both TGARCH and EGARCH models are applied for testing the Asymmetric effect. Descriptive statistics and GARCH (M) model are used to assess the leptokurtic condition and risk-return trade-off respectively. The study found that volatility clustering existed for the conflict periods' return as well as for the post-conflict periods' return. However, it was relatively higher during the conflict period. Moreover, the research found that asymmetric effect was more critical for the post-conflict periods' return. Irrespective of the ethnic conflict, stock return has satisfied the leptokurtic condition and positive relationship between risk and return.

Keywords: *dynamic properties; ethnic conflict; investment environment; stock return*

1. Introduction

Households as well as firms postpone their current consumption with the intension of saving. Savings are converted into investments expecting a higher rate of return. Even though there are various sources of investment, they vary from each other in terms of risk and return. Stock investment is one of the most popular mode of investment where rational investors can earn relatively higher return with higher risk exposure. Risk arises due to the variability of market prices of stocks. These price fluctuations are affected by firm specific factors as well as market specific factors. These factors may behave in line with the incidents and contingencies like natural disasters, political instability and economic or financial crises etc. which are beyond the control of human. Nearly three decade-long ethnic conflict in Sri Lanka may have directed the entire macroeconomic system and may have an adverse effect on investment environment. Thus, during 2009 and 2014, with the end of ethnic conflict, the capital market should have reached to a stable position to achieve the expected level of economic growth. Therefore, the key objective of this study is to investigate the behavioural patterns of volatility clustering, asymmetric effect and leptokurtic condition of the return during and after the ethnic conflict. Similarly, risk-return trade-off is also tested.

Since recently, the interest of researchers in testing the dynamic properties of financial time series vastly focused on volatility clustering. Moreover, leptokurtic behaviour and asymmetric effect (leverage effect) have also been tested as other properties of financial time series. Stock price reflects the attributes of financial time series because of its unpredictable behaviour. Christian (1998) viewed the financial time series as the accumulation of independent, identically distributed, random variable. Most of diagnostic tests in econometrics suggest that stock return as the best to analyze the financial time series rather than stock prices. Empirical evidences have supported that return series behaves as a non-normal distribution with a higher peak by its nature. This is the property of leptokurtosis in the financial time series.

There is no agreed method to measure the risk of stock in the literature. In Capital Assets Pricing Model, expected return is an aggregation of risk free rate and risk premium. Volatility is treated as one of the risk measures in stock investment due to directly unobservable fluctuations in stock prices. “Volatility means the conditional standard deviation of the underlying asset return” (Ruey, 2005, p.7). Typically, risk and return has a positive relationship.

Upward and downward movements of stock prices with respect to supply and demand of stocks are the typical attributes of stock prices. In a highly liquid market investors respond instantly for higher volatilities, and seek less risky assets. After a close examination of the behaviour of volatility, it has been realized that volatilities are characterized by a clustering pattern: large changes in stock prices tend to be followed by large changes and small changes tend to be followed by small changes. “The estimate of volatility is highest for large negative returns (shocks) and declines for higher returns” (Christian, 1998, p.16). Thus, the investors are keen about the persistence of volatility clustering whether it lasts for a short or long period.

As stated in Efficient Market Hypothesis, stock prices fully reflect available information in an efficient capital market. Whenever new information is available in the market, rational investors adjust their stock price estimates. However stock prices may respond for certain information instantly. The degree of responsiveness may vary with the perception of investor about the information and respond for bad news and good news differently. “Good news has the same impact on volatility as bad news, if they imply the same absolute return” (Christian, 1998, p.105). Further as cited in Christian (1998), Black (1976) and Christie (1982) have contended that bad news creates more volatility than good news. In contrast, return volatility may be equally affected by good news as well as bad news and in some markets, return may respond for good news and bad news asymmetrically.

During the recent past, the volatility plays a prominent role in the risk analysis of stocks. It can be used to measure the market efficiency as well. Volatility estimates enable investors to predict the price behaviour to establish risk and return relationship. Financial researchers are interested in testing the properties of return of both developed and emerging markets. However, few prior studies on dynamic properties of stock return have been conducted in emerging markets like Sri Lanka. Few studies have been carried out in the Sri Lankan context to determine the behavioural patterns of the properties during the period of ethnic conflict. However, similar studies carried out as a comparative study, during and after the ethnic conflict could not be found. Therefore, this study focuses on investigating the variations of volatility clustering, asymmetric effect, leptokurtosis and risk-return trade-off during and after the ethnic conflict of Sri Lanka.

2. Literature Review

The distribution of financial time series shows certain characteristics such as leptokurtosis (i.e. fat tails as compared to normal distribution), volatility clustering (i.e. strong autocorrelation in returns where large changes tend to be followed by large changes and small changes tend to be followed by small changes) and heteroskedasticity (i.e. non-constant variance).

"Volatility refers to the ups and downs in the stock prices" (Mittal & Goyal, 2012, p.2). Ruey (2005, p.97) defines volatility as the "conditional standard deviation of the underlying asset return". As described by Mittal and Goyal (2012), higher volatility is a feature of an inefficient stock market. Higher volatility leads to a higher risk. Investors prefer low volatility because it leads to low risk. As per Christian (1998), correct estimation and prediction of volatility are very important for major financial institutes, because volatility is one of the major risk measures. As per Christian (1998, p. 93), "Correct estimation and prediction of volatility are very important for major financial institutes, because volatility is one of the major risk measures. Risk factor depends on the volatility of the individual assets and however, risk factor is not only a volatility measure".

As cited in Christian (1998), Mandelbrot (1963) has determined clustering of volatilities as another typical property of stock price changes. "It was observed that large changes of either sign tend to be followed by large ones and small changes by small ones. Thus, price changes were no longer considered to be independent" (Christian, 1998, p. 2). "Although volatility is not directly observable, it has some characteristics that are commonly seen in asset returns. First, there exist volatility clusters (i.e. volatility may be high for certain time periods and low for other periods). Second, volatility evolves overtime in a continuous manner. Third, volatility does not diverge to infinity. Fourth, volatility seems to react differently to a big price increase or a big price drops" (Ruey, 2005, p.98-99). "The stylized fact was the observation that volatilities tend to cluster: Large and small price changes of either sign both tend to persist" (Christian, 1998, p.93). "It is well known that in financial markets, large changes tend to be followed by large changes, and small changes tend to be followed by small changes" (Zivot & Wang, 2006, p.223).

"Black (1976) and Christie (1982) first noted about the leverage effect for stock returns and it is an empirical fact that volatility of financial assets is asymmetric" (Christian, 1998, p.13). Christian (1998) further said that, as per the recent investigations, standard Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models can be severely mis-specified, particularly in terms of stock market data. Accordingly, leverage effect can only be modelled by following for asymmetry in the volatility equation. Mittal and Goyal, (2012) have stated that some features of the financial time series data cannot be captured by symmetric Autoregressive Conditional Heteroskedasticity (ARCH) and GARCH models. Accordingly, leverage effect is the most interesting feature that was not addressed by the aforementioned models.

According to Christian (1998), the two main properties of changes in security price or returns are leptokurtic distribution and volatility clustering. Mittal and Goyal (2012) stated leptokurtosis as fat tails as compared to normal distribution. "Recent results for many different financial time series suggest that the limit distribution for increasing time intervals is normal. This stands in contradiction with the early results of Fama (1965), who found a non-normal stable distribution to be a closer description of stock market returns" (Christian, 1998, p.3). "A traditional assumption made in financial study is that the simple returns are independently and identically distributed as normal with fixed mean and variance. However normality assumption is not supported by many empirical asset returns which tend to have a positive excess kurtosis" (Ruey, 2005, p.14).

GARCH and its extensions are used in testing the properties of financial time series. Before applying GARCH, existence of an ARCH effect in the series is tested. "Before estimating a full ARCH model for a financial time series, it is usually good practice to test for the presence of ARCH effects in the residuals. If there are no ARCH effects in the residuals, the ARCH model is unnecessary and misspecified" (Zivot & Wang, 2006, p. 228). "If the ARCH effect is found, we will have to use GLS (Generalized Least Squares)" (Gujarati, Porter, & Gunasekar, 2012, p.842). "The basic idea of ARCH models is the shock of an asset return is serially uncorrelated and the dependence of shock can be described by a simple quadratic function of its lagged values" (Ruey, 2005, pp.102-103). Accordingly Ruey proposes an ARCH (m) model.

"Although the ARCH model is simple, it often requires many parameters to adequately describe the volatility process of an asset return" (Ruey, 2005, p.113). Instead, GARCH model with ARCH and GARCH parameters are applied as an extension for ARCH. "Usually the GARCH coefficient b_1 is found to be around 0.9 for many weekly or daily financial time series" (Zivot & Wang, 2006, p.230). "Engle, Lilien and Robins (1987) proposed to extend the basic GARCH model so that the conditional volatility can generate a risk premium which is part of the expected returns. This extended GARCH model is often referred to as GARCH-in-the-mean (GARCH-M) model" (Zivot & Wang, 2006, p.250-251). "In finance, the return of a security may depend on volatility. To model such phenomenon, one may consider the GARCH-M model" (Ruey, 2005, p.123). As cited in Ruey (2005), General Exponential GARCH (EGARCH) model, which was introduced by Nelson (1991), can be applied to conquer the drawbacks of GARCH model and to test the leverage effects.

Jegajeevan (2012) has carried out a study on Colombo Stock Exchange (CSE) of Sri Lanka with the purpose of examining the behaviour of stock market volatility, persistence of volatility for a long time, asymmetric volatility in stock return and risk- return trade-off. Daily observations (during the conflict period) of All Share Price Index (ASPI) have been considered for return calculation. This return series has not been in a normal distribution and has exhibited an ARCH effect. Therefore, the study has moved to a GARCH analysis. Accordingly GARCH (4, 4) model and EGARCH (1, 1) model have confirmed the existence of volatility clustering and leverage effect for daily return series respectively. Further, there had been a positive insignificant risk-return relationship as per EGARCH (2,1)-M model. These findings have proved that daily return of CSE exhibits empirically confirmed attributes of financial time series, and have contributed to the Sri Lankan literature, being one and only study focused on this era. Yet, the post-conflict context is not explored.

Similarly, Hojatallah and Ramanarayanan (2011) have attempted to model only the asymmetric volatility in the Indian stock market during the global financial crisis (2008-2009). Both EGARCH (1, 1) and TGARCH (1,1) have been employed upon BSE 500 stock index and they have revealed the presence of leverage effect indicating bad news has been more dominant in the Indian stock market in increasing volatility than good news during that period. Further Peiris and Peiris (2011) has examined how macro economic factors affect on volatility, considering monthly time series data of twenty industrial sectors of CSE. The volatility of composite stock return fitted by GARCH (1, 1) model has been regressed against both narrow and broad money supply, inflation, and interest rate. They have found that, apart from the sectors like footwear and textile, motors, oil palm, and services, other sectors are volatile. Further changes in interest rate and inflation have affected the volatility of stock return.

GARCH models including both symmetric and asymmetric models have been applied on daily returns of Khartoum Stock Exchange (KSE) of Sudan by Ahmed and Suliman (2011) to capture the volatility clustering and leverage effect. While GARCH (1, 1) and GARCH-M (1, 1) models tested symmetry effect, EGARCH (1, 1), TGARCH (1, 1) and PGARCH (1, 1) for the asymmetric effect. Daily return of KSE has shown a non-normal distribution, and conditional heteroskedasticity has existed in the residual series. In line with the GARCH (1, 1) model, an explosive volatility has existed and symmetric volatility could have been observed. GARCH-M (1, 1) has suggested that the presence of a positive relationship between volatility and expected return.

Freedi, Shamiri, and Isa (2012) have investigated the properties of return series of Saudi Arabia by applying both symmetric and asymmetric GARCH models in a comparative study by considering the periods of local crisis and post-crisis. This study is a case with a non-normal distribution of the return series. Persistence of volatility is higher during the crisis and after the crisis than before the crisis. Moreover, it has examined an asymmetric effect on stock return of Saudi Arabia. This asymmetric effect is further ensured by industrial economies in the Asian region as per Hassan and Shamiri (2007) concerning the volatility of Malaysian and Singaporean stock indices considering daily observations for fourteen years. Besides AR (1)-GJR (Glosten-Jagannathan-Runkle) model has been the best model in forecasting the volatility in Malaysian stock market and AR (1) - EGARCH has provided a better estimation for Singapore. Leptokurtic condition has also been satisfied by both indices.

In developed markets, a weak relationship can be seen between mean returns on a stock portfolio and its conditional variance or standard deviation in US measured by GARCH in mean models. Therefore, Baillie and DeGennaro (1990) have suggested to apply another measure of risk in managing the portfolio rather than variance. Value weighted monthly excess stock returns with no dividends data from February 1928 to December 1984 has been used in the study. However application of GARCH models has been limited to identify the risk and return relationship of return series in this study. Apart from this risk-return trade off condition, other objectives of this study are similar to Emenike (2010). GARCH (1, 1) model, GJR-GARCH (1, 1) and Generalized Error Distribution (GED) shape test have provided evidence on the presence of volatility clustering, leverage effects and leptokurtic returns distribution for the return series.

3. Methods

In investigating the effect of ethnic conflict on dynamic properties of stock return, leptokurtic behaviour, volatility clustering and asymmetric effect are taken as properties of the return series. In addition to those properties, the risk factor is also considered in identifying its relationship with the stock return. In this study, daily observations were gathered on ASPI of CSE from January 1985 to December 2012. This period was divided into conflict period and post-conflict period. Stock return is the natural logarithm of the ratio of the ASPI at time t and t-1.

Descriptive statistics such as skewness, kurtosis and Jarque-Bera statistic were employed for both series to ensure that they follow a leptokurtic behaviour. Following hypotheses were formulated and tested at five per cent significant level.

H_0: Sample is drawn from a normally distributed population
H_1: H_0 is not true

Ordinary Least Squares (OLS) with an ARCH problem generates spurious results for OLS estimations. To examine the existence of an ARCH effect following hypotheses were tested at five per cent significant level. If the respective *p*-value for ARCH (1) is less than 0.05, the null hypothesis is rejected.

H_0: $\alpha_1 = 0$
H_1: $\alpha_1 \neq 0$

If the ARCH effect exists for OLS, following ARCH (m) model proposed by Ruey (2005) is applied.

$$a_t = \sigma_t \in_t, \qquad \sigma_t^2 = \alpha_0 + \alpha_1 \alpha_{t-1}^2 + \ldots + \alpha_m a_{t-m}^2$$

σ_t = Positive square root of σ^2_t
ϵ_t = A sequence of independent and identically distributed random variable with mean 0 and variance 1.

To ensure that the ARCH effect has left the series, ARCH-LM test is executed. If the results of the ARCH-LM test provide enough evidence to not reject the above null hypothesis, non-existence of an ARCH effect can be confirmed. ARCH model free of ARCH effect can be extended for GARCH and its modifications. Volatility clustering of the return is tested by GARCH (m, s) model proposed by Bollerslev (1986) as cited in Ruey (2005), where *m* and *s* stand for the ARCH term and GARCH term respectively.

$$a_t = \sigma_t \in_t, \qquad \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2$$

The α_i and β_j are the ARCH and GARCH parameters of the model respectively. While *m* is the lagged terms of the squared error term, *q* represents the lagged conditional variances. Ultimately the simplest GARCH (1, 1) model is represented as,

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \qquad 0 \leq \alpha_1, \beta_1 \leq 1, (\alpha_1 + \beta_1) < 1$$

Conditional variance of *a* at time *t* depends on both the squared error term in the previous time period and its conditional variance. Taking different combinations of ARCH term and GARCH term, it is expected to choose the most appropriate model to describe the volatility clustering where both Maximum Log Likelihood (MLL) value and minimum Akaike Information Criterion (AIC) are considered as model selection criteria. Volatility clustering exists if the aggregation of ARCH coefficient (*α*) and GARCH coefficient (*β*) closes to unity.

TARCH (Threshold ARCH) or TGARCH model developed by Glosten, Jaganaathan and Runkle (1993) and Zakoian (1994), and EGARCH model proposed by Nelson (1991) are simultaneously deployed for testing the asymmetric effect of both series. Accordingly TGARCH (m, s) model and EGARCH model take the following forms respectively.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{s} (\alpha_i + \gamma_i N_{t-i}) a_{t-i}^2 + \sum_{j=1}^{m} \beta_j \sigma_{t-j}^2$$

Where a_i, γ_i, and β_j are non-negative parameters of the model and zero is used as its threshold to detach the impacts of past shocks.

$$ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{s} \alpha_i \frac{|a_{t-i}| + \gamma_i a_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{m} \beta_j ln(\sigma_{t-j}^2)$$

While positive α_{t-i} indicates good news, negative α_{t-i} denotes bad news. Based on the Gamma *(γ)* value of above TGARCH and EGARCH models, existence of an asymmetric effect is determined. If γ is positive in the TARCH model or γ is negative in EGARCH model, an asymmetric effect exists.

As cited in Christian (1998), GARCH (M) model of Engle et al., (1987) is used to examine the nature and the significance of the relationship between risk and stock return, and the proposed simple GARCH (1,1)-M model is as follows.

$$r_t = \mu + c\sigma_t^2 + a_t, \qquad a_t = \sigma_t \in_t,$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

While μ and *c* stand for constant, the parameter *c* indicates the risk premium. The relationship between return and its volatility is stated upon the sign of *c* and following hypotheses were also tested. If the *p*-value of relevant coefficient is less than 0.05 the null hypothesis is rejected at 5 percent significant level.

$H_0: \beta = 0$
$H_1: \beta \neq 0$

4. Results and Discussion

The behavior of the properties of stock return during the period of ethnic conflict and after the ethnic conflict is examined separately. Accordingly leptokurtosis, volatility clustering, asymmetric effect, and risk-return trade-off are discussed respectively for both periods.

Properties of Stock Return during the Period of Ethnic Conflict

The Jarque-Bera statistic (308803.7) is significant ($p<0.05$). Thus, the null hypothesis of sample is drawn from a normally distributed population is rejected (further, skewness=0.814 and kurtosis=38.669).

In estimating volatility models using OLS method, existence of an ARCH effect for the return series needs to be tested. Therefore, stock return is regressed against the previous period's return in the OLS, and ARCH effect is tested for the same regression using ARCH test with lag one. Results of the hetroskedasticity revealed that ARCH problem existed for the residuals rejecting the null hypothesis, i.e. ARCH coefficient (α) = 0, at 95 percent level of significance. Therefore, OLS is not good for volatility estimations and instead ARCH method was applied. After applying the ARCH method, ARCH-LM test was applied to see whether there is an ARCH effect in the return series further. Accordingly, the ARCH effect has left the series and the null hypothesis cannot be rejected at 5 percent significance level (p = 0.15). Results of ARCH-LM test provide a good indication that before applying ARCH-LM test there had been an ARCH effect for the return series. Existence of an ARCH effect in the residuals is a perquisite for the application of GARCH models.

Existence of an ARCH effect for OLS and a non-normal distribution supports for a GARCH analysis. ARCH model with free of ARCH effect has been extended into GARCH model with different combinations of ARCH term and GARCH term to test the property of volatility clustering in the return series (table 1). Both AIC and MLL indicate that GARCH (4, 4) model is the best model to explain the volatility clustering during the ethnic conflict period. The summation of its ARCH coefficient and GARCH coefficient is very close to unity (i.e., 0.99). GARCH (1, 1) model with a sum of 0.967 is also applicable to explain the volatility clustering.

TGARCH model extends the GARCH model used to determine the asymmetric effect of the return series. As per table 2, in addition to the TARCH (1, 1, 1) model, the fitted model, (i.e. GARCH (4, 4) model) with different threshold levels has been taken into consideration. Both AIC and MLL suggest that TARCH (4, 4, 2) and TARCH (4, 4, 3) are the best models in terms of asymmetric effect. However some of Gamma coefficients are negative. Therefore TARCH (4, 4, 1) model with a positive Gamma value can be taken as the best model. An asymmetric effect is not explained by TARCH (1, 1, 1) model because its Gamma coefficient is negative.

Table 1: GARCH (m, s) Model

m s		1	2	3	4	5
1	AIC	-6.7970	-6.8196	-6.8354	-6.8362	-6.8360
	MLL	19760.3600	19827.0400	19874.0100	19877.3000	19877.9100
2	AIC	-6.8003	-6.8346	-6.8360	-6.8359	-6.8374
	MLL	19771.1700	19871.7600	19876.8300	19877.4300	19882.8200
3	AIC	-6.8085	-6.8375	-6.8375	-6.8403	-6.8370
	MLL	19795.8500	19881.1000	19882.2000	19891.2100	19882.7600
4	AIC	-6.8203	-6.8375	-6.8378	**-6.8412**	-6.8347
	MLL	19831.1500	19882.0500	19884.0200	**19894.8500**	19877.1100
5	AIC	-6.8256	-6.8330	-6.8397	-6.8293	-6.8019
	MLL	19847.4900	19870.1500	19890.7000	19861.3100	19782.8000

Table 2: TARCH Model

	TARCH Models				
	TARCH (1,1,1)[a]	**TARCH (4,4,1)**	**TARCH (4,4,2)**	**TARCH (4,4,3)**	**TARCH (4,4,4)**
α_1	-0.4681	0.4824	0.5787	0.4923	0.3082
γ_1	-0.1158	0.0015	-0.2247	-0.0112	-0.0566
α_2	-	-	-0.2879	0.1679	0.1131
γ_2	-	-	0.2150	0.0353	0.0373
α_3	-	-	-	-0.1459	0.0726
γ_3	-	-	-	-0.0112	-0.0686
α_4	-	-	-	-	-0.0473
γ_4	-	-	-	-	-0.0520
AIC	-6.7985	-6.8373	-6.8400	-6.8431	-6.7802
MLL	19765.9100	19884.7100	19893.5500	19903.4300	19721.7800

[a] TARCH (ARCH Term, GARCH Term, Threshold Level)

Findings of the TARCH model are further ensured by the EGARCH models given in table 3. EGARCH (4, 4, 1) with a negative gamma value is the best suited model to capture the asymmetric effect satisfying the AIC and MLL criteria. Here, also EGARCH (1, 1, 1) model does not support for asymmetric effect.

Coefficients (α) of GARCH (M) models in table 4 reveal the relationship between risk and stock return. A positive relationship exists between risk and return as per all models. However relationship is insignificant ($p>0.05$) under GARCH (1, 1)-M model rejecting the null hypothesis. GARCH (4, 4)-M model determines relatively significant trade-off between risk and return than other models.

Table 3: EGARCH Model

	EGARCH Models				
	EGARCH (1,1,1)[a]	**EGARCH (4,4,1)**	**EGARCH (4,4,2)**	**EGARCH (4,4,3)**	**EGARCH (4,4,4)**
γ_1	0.0389	-0.0022	0.0018	0.0158	0.0853
γ_2	-	-	0.0043	0.0107	-0.0466
γ_3	-	-	-	-0.0053	0.0892
γ_4	-	-	-	-	-0.0246
AIC	-6.7742	-6.8272	-6.8124	-6.8254	-6.8177
MLL	19695.2200	19855.3700	19813.2500	19852.1400	19830.5100

[a] EGARCH (ARCH Term, GARCH Term, Asymmetric Order)

Table 4: GARCH (M) Model

	GARCH(1,1)-M	**GARCH(4,3)-M**	**GARCH(4,4)-M**	**GARCH(5,5)-M**
α	0.0104	0.0547	0.0677	0.0624
P	0.7589	0.0371*	**0.0191***	0.0254*
AIC	-6.7966	-6.8325	-6.8418	-6.8443
MLL	19760.4000	19869.7200	19897.6000	19906.8900

*Significant at 5 percent level

Properties of Stock Return during the Post-ethnic Conflict Period

Descriptive statistics recommend that, the return series after ethnic conflict does not follow a normal distribution (skewness=0.337 and kurtosis=5.889). Especially Jarque-Bera statistics (319.584) suggest rejecting the null hypothesis.

The null hypothesis that ARCH problem does not exist is rejected at 5 percent significant level. Thereby results of the OLS method show its weaknesses in volatility estimations because the respective probability value is less than 0.05. Therefore, there is a need of applying ARCH method instead of OLS method. With the application of ARCH method, results of the ARCH-LM test revealed that ARCH effect has left the return series as per the respective probability value of 0.91 which is higher than 0.05. Therefore, the null hypothesis cannot be rejected at 5 percent significant level. This indicates that existence of an ARCH effect has been an inherent attribute of the return series. This provides a base for moving to GARCH models.

To capture the volatility clustering feature of the return series, more combinations of ARCH term and GARCH term have been taken into account in table 5. Basically, volatility clustering was found in even GARCH (1, 1) model with the sum of ARCH coefficient (0.195) and GARCH coefficient (0.714) being 0.91. However, the best model to explain the volatility clustering has been GARCH (4, 6) as per AIC and MLL and its aggregation of ARCH coefficient and GARCH coefficient is 0.97 being very close to unity.

Table 5: GARCH (m, s) Model

m / s		1	2	3	4	5
1	AIC	-6.5414	-6.5401	-6.5400	-6.5380	-6.5384
	MLL	2853.7770	2854.1950	2855.1630	2855.2810	2856.4520
2	AIC	-6.5396	-6.5383	-6.5378	-6.5366	-6.5370
	MLL	2853.9770	2854.4490	2855.2050	2855.7070	2856.8550
3	AIC	-6.5437	-6.5417	-6.5394	-6.5374	-6.5352
	MLL	2856.7900	2856.9250	2856.9270	2857.0230	2857.0710
4	AIC	-6.5417	-6.5411	-6.5388	-6.5367	-6.5330
	MLL	2856.9320	2857.6670	2857.6680	2857.7150	2857.1040
5	AIC	-6.5395	-6.5388	-6.5397	-6.5506	-6.5485
	MLL	2856.9380	2857.6680	2859.0200	2864.7710	2864.8700
6	AIC	-6.5381	-6.5365	-6.5543	**-6.5576**	-6.5380
	MLL	2857.3380	2857.6430	2866.4100	**2868.8230**	2861.3130
7	AIC	-6.5356	-6.5344	-6.5521	-6.5370	-6.5443
	MLL	2857.2360	2857.7300	2866.4550	2860.8610	2865.0350

Table 6: TARCH Model

	TARCH Models				
	TARCH (1,1,1)	**TARCH (4,6,1)**	**TARCH (4,6,2)**	**TARCH (4,6,3)**	**TARCH (4,6,4)**
γ_1	0.1407	0.0168	0.0369	0.1114	0.1198
γ_2	-	-	0.0208	-0.0985	-0.0189
γ_3	-	-	-	0.1980	0.1126
γ_4	-	-	-	-	0.1301
AIC	-6.5494	-6.5542	**-6.5527**	-6.5467	-6.5433
MLL	2858.2840	2868.3430	**2868.6810**	2867.0870	2866.6140

Table 7: EGARCH Model

	EGARCH Models				
	EGARCH (1,1,1)	**EGARCH (4,6,1)**	**EGARCH (4,6,2)**	**EGARCH (4,6,3)**	**EGARCH (4,6,4)**
γ_1	-0.0640	0.0085	0.0018	-0.0065	-0.0736
γ_2	-	-	0.0043	0.0174	0.0058
γ_3	-	-	-	-0.1266	-0.0542
γ_4	-	-	-	-	-0.0690
AIC	-6.5527	-6.5497	-6.8124	-6.5672	-6.5531
MLL	2859.6890	2866.4090	19813.2500	2876.0110	2870.8720

Table 8: GARCH (M) Model

	GARCH (1,1)-M	**GARCH (4,8)-M**	**GARCH (5,7)-M**	**GARCH (5,8)-M**	**GARCH (6,7)-M**
α	0.1090	0.2781	0.1952	0.1738	0.1963
P	0.4646	**0.0025***	0.0619**	0.0932**	0.0606**
AIC	-6.5398	-6.5464	-6.5464	-6.5393	-6.5441
MLL	2854.0700	2866.9640	2866.9590	2864.8450	2866.9600

*Significant at 5 percent level

**Significant at 10 percent level

Based on the most fitted GARCH model, i.e. GARCH (4, 6), in addition to the TARCH (1, 1, 1) model, extensions of different TARCH models with different threshold levels are presented in table 6, to determine the leverage effect of the return series. Accordingly, the TARCH (4, 6, 2) model is the best model in terms of capturing the asymmetric effect as suggested by both AIC and MLL. However one of the good indications here is that even TARCH (1, 1, 1) can be used to examine the asymmetric effect because its Gamma coefficient has been a positive value.

Despite the suggestions given by AIC and MLL, table 7 indicates that EGARCH (1, 1, 1) can only be chosen to describe the asymmetric effect of the return series because it has only negative Gamma value compared to others. Therefore the findings of the TARCH model are further ensured by the EGARCH models in this sense.

Risk and return trade-off is clearly explained by the GARCH (4, 8)-M model according to table 8 and relationship has been positive and significant at 5 percent significance level. However, the relationship has been insignificant for GARCH (1, 1)-M model. Coefficients of other models presented are significant only at 10 percent level.

5. Conclusion

Stock return derived from ASPI does not follow a normal distribution during the period of ethnic conflict and post-conflict period. Higher peakedness and the fat-tails associated with less density in the middle are the attributes of the distributions of both series showing leptokurtic behaviour. Therefore, findings of this study are consistent with, for example, Christian (1998) and Ruey (2005) in relation to assets' return. However, during the period of ethnic conflict, stock return has deviated more from the normality than the post-conflict period.

Stock return in both periods confirms the presence of an ARCH effect for the residuals. GARCH (4, 4) model is more appropriate model to describe the persistence of volatility during the period of ethnic conflict than GARCH (1, 1) model. However, results obtained from both models were in an acceptable level. Volatility clustering of return in post-conflict period is not properly captured by the GARCH (1, 1) model. However, it is captured by the GARCH (4, 6) model. Accordingly a strong autocorrelation in return could be seen during the period of ethnic conflict. Irrespective of the periods large changes in stock return of CSE tend to be followed by large changes, and small changes tend to be followed by small changes. These findings are inconsistent with the findings of similar studies like Jegajeevan (2012) and Emenike (2010) on volatility clustering of financial time series although the degree of the persistence of volatility is different during the ethnic conflict period and post-ethnic conflict period.

Even though TARCH (4, 4) with threshold order 1 and TARCH (4, 6) with order 2 are the best model for explaining the asymmetric effect of both return, TARCH (1, 1) with order 1 is good enough to capture this effect after the ethnic conflict. This finding indicates that during the entire period, stock return of CSE has responded more for bad news than good news. However this asymmetric effect has been significant after the ethnic conflict. This may be due to the typical bad news during the period of ethnic conflict. EGARCH (4, 4) with asymmetric order 1 and EGARCH (4, 6) with order 5 have also supported for the above findings. In sum, stock return of CSE satisfies the property of asymmetric effect of financial time series.

Supporting the arguments of Jegajeevan (2012), and Ahmed and Suliman (2011) a positive relationship between risk and stock return could be observed irrespective of the periods of concern. During the period of ethnic conflict, GARCH (4, 4)-M model determines a positive significant relationship between risk and return. However, GARCH (1, 1)-M model gives a positive insignificant relationship among them. Risk and return trade-off is well explained by the GARCH (4, 8)-M model during the post-conflict period. However, the relationship is positive but insignificant for GARCH (1, 1)-M model.

As a whole, the ethnic conflict is not a matter for the stock return of CSE. During the period of study, a deviation of stock return from the normal distribution was detected and it indicates very small and very large changes of stock return had been occurring more often, whereas, stock return was highly volatile and found to be clustered. CSE has responded more for bad news than good news, and those who had taken a higher risk had earned a relatively higher return. Therefore, dynamic properties of stock return are common to CSE.

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