



# Impact of Ethnic War on Dynamic Properties of Stock Return in Colombo Stock Exchange of Sri Lanka

U.E.S. Kumara<sup>a</sup>, W.A. Upananda<sup>b</sup>, and M.S.U. Rajib<sup>c</sup>

<sup>a</sup>Faculty of Business Studies and Finance, Wayamba University of Sri Lanka. [emilkumara@yahoo.com](mailto:emilkumara@yahoo.com)

<sup>b</sup>Faculty of Business Studies and Finance, Wayamba University of Sri Lanka. [uwitta@yahoo.com](mailto:uwitta@yahoo.com)

<sup>c</sup>School of Management, Wuhan University of Technology, Wuhan, PR China. [rajib\\_ais@yahoo.com](mailto:rajib_ais@yahoo.com)

## Abstract

Entire Macroeconomic system is adversely affected by an ethnic problem in a country. Experiences of nearly three decades Civil War in Sri Lanka have exposed a continuous economic recession with depressing the reliability of equity investments in the capital market. Stock return volatility is one of the measures of risk of equity investments and degree of volatility is affected by the economic instability of the country. The core objectives of the current study is to scrutinize the differences of Volatility Clustering (Persistence of shocks prevail for longer periods) and Asymmetric Effect (Bad news create more volatility than good news) of the return series during and after the Civil War derived from All Share Price Index of Colombo Stock Exchange. Daily observations of ASPI from 1985 to 2012 have been considered by dividing it in to war period and post-war period. Meanwhile it was investigated Leptokurtic and Risk-return Trade-off conditions of both series. While GARCH (m, s) model was employed for volatility clustering, both TGARCH and EGARCH models were applied for testing the Asymmetric Effect of the series. Tools in descriptive statistics, and GARCH (M) model were for observing the Leptokurtic condition and Risk-return Trade-off respectively. Eventually study found that the existence of volatility clustering for both war period's return and post-war periods' return. However it is relatively higher in the war period's return. It was further revealed that the Asymmetric effect is more critical for the post-war period's return. This indicates that during the period of war, bad news have been more typical. Both return series have satisfied the Leptokurtic condition. Even though there is a positive relationship between risk and return for both series they are not significant in the GARCH (1, 1)-M model.

**Keywords:** *asymmetric effect; leptokurtic; risk-return trade-off; stock return; volatility clustering*

## 1. Introduction

Households postpone their current consumption because of savings. Savings are converted in to investments expecting a higher expected rate of return. Even though there are various sources of investment they are vary each other in terms of risk and return. Stock investment is one of the most popular investment sources where rational investors can earn relatively higher return with higher risk exposure. Risk arises due to the variability of market price of stock, and continuous increase of the market price reduces the risk.

During the recent past finance era has attracted the interest in testing the dynamic properties of financial time series and where volatility clustering has been one of the major properties. Besides Leptokurtic behavior and asymmetric effect (Leverage Effect) have been identified as other properties of financial time series. Price of stock reflects the attributes of financial time series because of its unpredictable behavior. "Bachelier (1900) viewed financial series as the accumulation of independent, identically distributed random variable" (Christian, 1998). Most of diagnostic tests in econometrics suggest that stock return is best suited

in analyzing financial time series rather than stock prices. However most of empirical evidence has supported that return series behaves as a non-normal distribution with a higher peak by its nature. This is the property of “Leptokurtosis” in financial time series.

There is no precise measure to measure the risk of stock in the Finance literature. However in the Capital Assets Pricing Model (CAPM) of Sharpe (1964), expected return was an aggregation of risk free rate and some risk premium. “Volatility means the conditional standard deviation of the underlying asset return” Ruey (2005). Volatility is treated as one of the risk measures in stock investment due to directly unobservable ups and downs in stock prices. Showing a positive relation higher volatility generates higher risk. Therefore accurate prediction of volatility is preferred on the hand of risk averse investors.

Typical attribute of stock prices is its upward and downward movements with the time because supply and demand for stock determines the equilibrium price. In a highly liquid market investors respond instantly for higher volatilities, and they seek less risky assets. After an attentive examination of the behavior of volatility it is realized that the volatilities are characterized by clustering where 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). Investors are very much keen about the persistence of volatility clustering whether it lasts for a short term or long term.

Black (1976) and Christie (1982) have discussed the leverage effect for stock returns. Accordingly bad news creates more volatility than good news. As stated by Efficient Market Hypothesis if share prices of a capital markets fully reflect available information, which is an attribute of an efficient capital market. Whenever new information is available in the market place rational investors adjust their stock price estimates. However there may be some certain information for which stock prices may respond instantly than others. The degree of responsiveness may vary to the extent that the investors perceive that information as critical, and they respond for bad news and good news differently. Return volatility is affected by good news as well as bad news. However there may be some markets where return may respond for good news and bad news asymmetrically. “Good news have the same impact on volatility as bad news, if they imply the same absolute return” Christian (1998).

As a measure of risk, volatility plays a prominent role in the risk analysis of stock investment. It could be used to measure the market efficiency as well. Volatility estimates enable investors to predict the price behavior in the future and ultimately they could identify the risk and return relationship. Financial researchers have long interested in testing the properties of return series of developed markets as well as emerging markets. Sri Lanka, as an emerging market studies on dynamic properties of stock return are rare. Those studies had been carried out before the ethnic war and testing those properties after the war has not yet been done. However current study is carried out as a comparative study for the war period and post-war period. Accordingly objectives of the study are to investigate the differences of volatility clustering and asymmetric effects of both periods, and to test for Leptokurtosis and Risk Return trade off conditions.

Macro economy is a complex dynamic system (Christian, 1998). Macroeconomic factors fluctuate in line with the local trends as well as international trends. If there is an ethnic problem in a country the behavior of these factors cannot be predicted, and it may create more bad news than good news. Empirical studies have found that macroeconomic factors direct the behavior of the capital market extensively. Accordingly nature of stock return volatility and the way of responding for good news and bad news may vary during the period of war and with its end. In fact during a period of civil war bad news may be typical. Therefore bad news may not create more volatility in share prices. Hence study addresses “How did the ethnic war of Sri Lanka affect the dynamic properties of stock return of Colombo Stock Exchange”. In addressing this, Risk-return trade-off conditions of return series are also tested.

## 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). Volatility means the conditional standard deviation of the underlying asset return (Ruey, 2005). Too much volatility is considered as a symptom of an inefficient stock market. Higher the volatility, higher the risk. Low volatility is preferred as it reduces unnecessary risk borne by investors (Mittal & Goyal, 2012). Correct estimation and prediction of volatility is most important for major financial institutes, because volatility is directly related to usual risk measures. Risk factor depends on the volatility of the individual assets. The risk factor however is not only a volatility measure (Christian, 1998).

Another typical property of security price changes, namely the clustering of volatilities. 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). 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). 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). It is well known that in financial markets large changes tend to be followed by large changes and small changes (Zivot & Wang, 2003).

Black (1976) and Christie (1982) first noted that the leverage effect for stock returns, it is an empirical fact that volatility of financial assets is asymmetric (Christian, 1998). Many recent investigations show that standard GARCH models can be severely misspecified, particularly in the case of stock market data. Observed features such as the "Leverage Effect: first noted by Black (1976) and Christie (1982) could only be modeled by following for asymmetry in the volatility equation (Christian, 1998). There are some features of the financial time series data which cannot be captured by symmetric ARCH and GARCH models. The most interesting feature not addressed by these models is the "Leverage Effect" where the conditional variance tends to respond asymmetrically to positive and negative shocks in returns (Mittal & Goyal, 2012). Outside events which the economists called shocks cannot be neglected (Christian, 1998). Compared to emerging market economies, developed markets are not considerably affected by asymmetric behavior or any leverage effect in their equity markets.

The two main properties of security price changes or returns- leptokurtic distribution and volatility clustering (Christian, 1998). Leptokurtosis is characterized with fat tails as compared to normal distribution (Mittal & Goyal, 2012). Recent results for many different financial time series suggest that the limit distribution for increasing time intervals is normal. This stands in contradiction to the early result of Fama (1965), who found a non-normal stable distribution to be a closer description of stock market returns (Christian, 1998). 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).

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, then the ARCH model is unnecessary and misspecified" (Zivot & Wang, 2003). "If the ARCH effect is found, we will have to use Generalized Least Squares" (Gujarati, Porter & Gunasekar, 2012). "The basic idea of ARCH models is that 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)". Accordingly he 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). Instead Bollerslev (1986) has proposed Generalized ARCH

(GARCH) model with ARCH and GARCH parameters as an extension for ARCH. “Usually GARCH coefficient is found to be around 0.9 for many weekly or daily financial time series” (Zivot & Wang, 2003). Engle, Lilien and Robins (1987) propose 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, 2003). In finance, the return of a security may depend on its volatility. To model such phenomenon, one may consider the GARCH-M model (Ruey, 2005). The general Exponential GARCH (EGARCH) model was introduced by Nelson in 1991, to overcome some drawbacks of the GARCH model and which can be applied for testing the leverage effects. TGARCH model developed by Glosten, Jagannathan and Runkle (1993) and Zakoian (1994) is also applied to handle the leverage effects of financial time series.

With the purpose of examining the behavior of stock market volatility, persistence of volatility for a long time, asymmetric volatility in stock return, and risk-return trade-off, Jegajeevan (2012) has carried out a study on Colombo Stock Exchange (CSE) of Sri Lanka. Daily observations of All Share price Index (ASPI) has been considered for return calculation and which does not include observations after the Civil War. This return series has not been in a normal distribution and has exhibited an ARCH effect. Therefore study has moved to a GARCH analysis. Accordingly GARCH (4, 4) model and EGARCH (1, 1) model have confirmed that the existence of volatility clustering and leverage effect for daily return series respectively. Whereas 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 contributed more to the Sri Lankan literature being one and only study focused this era. However these findings may or may not valid for today because economy is now free of war effects.

As a similar study in the south Asian region Goudarzi and Ramanarayanan (2011) have attempted to model only the asymmetric volatility in the Indian Stock market during the period of global financial crisis. Both EGARCH (1, 1) and TGARCH(1,1) have been employed upon BSE 500 stock index and they have revealed that the presence of the leverage effect indicating bad news has been more dominant in the Indian stock market in increasing volatility than good news during that period. A different study has been undertaken by T.U.I. Peiris and T.S.G. Peiris (2011) to examine how macroeconomic 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 to 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.

Properties of return series of Saudi Arabia have been investigated by Freedi, Shamiri and Isa (2012) applying both symmetric and asymmetric GARCH models. Study has been carried out as a comparative study considering period of local crisis and post-crisis period. It has been provided evidence further to the finance literature being a non-normal distribution of the return series. Persistence of volatility has been higher during the period of crisis and after the crisis than before the crisis. Moreover it could also be examined an asymmetric effect on stock return of Saudi Arabia. This asymmetric effect has been further ensured by industrial economies in the Asian region as per the study carried out by Hassan and Shamiri (2007) to model and forecast the volatility of Malaysian and Singaporean stock indices considering daily observations for fourteen years. Besides AR (1)-GJR 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.

From the developed market context, it could have been seen a weak relationship between mean returns on a stock portfolio and its conditional variance or standard deviation in United States measured by GARCH in mean models. Therefore Baillie and DeGennaro (1990) have suggested to investors to apply another measure of risk in managing their 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 only 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 almost similar to the study of “Modeling Stock Returns Volatility in Nigeria Using GARCH Models” conducted by Emenike in 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 civil war on dynamic properties of stock return, Leptokurtic Behavior, Volatility Clustering and Asymmetric Effect are taken as those properties of the return series. In addition risk factor is also considered to test its relationship with stock return. Daily observations of ASPI of CSE from January 1985 to December 2012 are gathered in the study by dividing it in to war period and post-war period. Stock return is defined as the natural logarithm of the ratio of the ASPI at time  $t$  and  $t-1$ .

Descriptive statistics; Skewness, Kurtosis and Jarque-Bera Statistic are employed for both series to ensure that they follow a leptokurtic behavior and where the following hypotheses are tested at 5 percent significant level. If the probability value ( $p$ -value) is less than 0.05 the null hypothesis would be rejected.

$$H_0: \text{Sample is drawn from a normally distributed population;} \quad H_1: H_0 \text{ is not true}$$

Ordinary Least Squares (OLS) with an ARCH (Autoregressive Conditional Heteroskedasticity) problem generates spurious results for OLS estimations. To examine the existence of an ARCH effect following hypotheses are tested at 5 percent significant level. If the respective  $p$ -value for ARCH (1) is less than 0.05, the null hypothesis would be rejected.

$$H_0: \alpha_1=0 ; \quad H_1: H_0 \text{ is not true}$$

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

$$a_t = \sigma_t \epsilon_t; \quad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \dots + \alpha_m a_{t-m}^2$$

$$\sigma_t = \text{Positive square root of } \sigma_t^2$$

$\epsilon_t = A \text{ sequence of independent and identically distributed random variables with mean 0 and variance 1}$

To ensure that the ARCH effect has left the series ARCH-LM test is employed. If the results of the ARCH-LM test provide enough evidence not to reject the above null hypothesis, it could be concluded that the non-existence of an ARCH effect. ARCH model with free of ARCH effect can be extended for GARCH (Generalized ARCH) and its modifications. Volatility clustering of the return series is tested by following GARCH (m, s) model proposed by Bollerslev (1986), and where  $m$  and  $s$  stand for the ARCH term and GARCH term respectively.

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

The  $\alpha_i$  and  $\beta_j$  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 represents the following form.

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

The conditional variance of  $a_t$  at time  $t$  depends on both the squared error term in the previous time period and its conditional variance in the previous time period. Taking different combinations of ARCH term and GARCH term, it is expected to choose the most appropriate model to describe the volatility clustering and 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 ( $\alpha$ ) and GARCH coefficient ( $\beta$ ) closes to unity.

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

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

$\alpha_i, \gamma_i$  and  $\beta_j$  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  $a_{t-i}$  indicates “good news”, negative  $a_{t-i}$  is for “bad news”. Based on the Gamma ( $\gamma$ ) value of above TGARCH and EGARCH models, existence of an asymmetric effect is determined. If  $\gamma$  is positive in the TARCH model or  $\gamma$  is negative in EGARCH model, an Asymmetric Effect exists.

GARCH (M) model of Engle, Lilien and Robins (1987) is to be examined 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.

$$r_t = \mu + c\sigma_t^2 + a_t, \quad a_t = \sigma_t \epsilon_t,$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

While  $\mu$  and  $c$  stand for constants the parameter  $c$  indicates the risk premium. The relationship between return and its volatility will be stated upon the sign of  $c$  and following hypotheses are also to be tested.

$$H_0: \beta=0 \quad ; \quad H_1: H_0 \text{ is not true}$$

#### 4. Results and Findings

In this section, the behavior of the properties of stock return during the period of civil war and after the civil war is examined separately. Accordingly Leptokurtosis, Volatility Clustering, Asymmetric Effect, and Risk-return Trade-off are discussed respectively for each sample period.

**Properties of Stock Return during the Period of Civil War**

Jarque-Bera statistics of 308803.7 is higher than the critical chi-square value of 5.99 at 5 percent significance level and two degrees of freedom, and it rejects the null hypothesis of “Sample is drawn from a normally distributed population” because respective P-value is less than 0.05 at 5 percent significant level. Coefficient of skewness (0.813980) indicates a positively skewed distribution, and coefficient of Kurtosis (38.66932) is far away with a higher peak from the rule of thumb of normal distribution i.e. 3.

In estimating volatility models using OLS method, it is needed for testing the existence of an ARCH effect for the return series. 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 ( $\alpha$ ) = 0, because probability i.e. Zero, is less than 0.05 at 95 percent significant level. 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 due to there are enough evidence not to reject the null hypothesis at 5 percent significant level due to P-value (0.1515) is higher than 0.05. 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 support for a GARCH analysis. ARCH model with free of ARCH effect has extended in to 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 period of civil war. The summation of its ARCH coefficients and GARCH coefficients is 0.9927 and which is very close to unity. GARCH (1, 1) model with a sum of 0.9673 is also applicable to explain the volatility clustering.

Table 1: GARCH (m, s) Model

<b>m</b>		<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>
<b>s</b>						
1	AIC	-6.796957	-6.819558	-6.835374	-6.836160	-6.836027
	MLL	19760.36	19827.04	19874.01	19877.30	19877.91
2	AIC	-6.800333	-6.834598	-6.835999	-6.835862	-6.837371
	MLL	19771.17	19871.76	19876.83	19877.43	19882.82
3	AIC	-6.808482	-6.837468	-6.837502	-6.840259	-6.837006
	MLL	19795.85	19881.10	19882.20	19891.21	19882.76
4	AIC	-6.820283	-6.837450	-6.837786	<b>-6.841168</b>	-6.834719
	MLL	19831.15	19882.05	19884.02	<b>19894.85</b>	19877.11
5	AIC	-6.825561	-6.833011	-6.839740	-6.829282	-6.801926
	MLL	19847.49	19870.15	19890.70	19861.31	19782.80

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

Table 2: TARCH Model

	TARCH Models				
	TARCH (1,1,1) <sup>1</sup>	TARCH (4,4,1)	TARCH (4,4,2)	TARCH (4,4,3)	TARCH (4,4,4)
$\alpha_1$	-0.468145	0.482396	0.578726	0.492313	0.308170
$\gamma_1$	-0.115775	0.001517	-0.224687	-0.011195	-0.056618
$\alpha_2$	-	-	-0.287914	0.167930	0.113096
$\gamma_2$	-	-	0.214979	0.035340	0.037270
$\alpha_3$	-	-	-	-0.145868	0.072599
$\gamma_3$	-	-	-	-0.011225	-0.068611
$\alpha_4$	-	-	-	-	-0.047333
$\gamma_4$	-	-	-	-	-0.051965
AIC	-6.798523	-6.837335	-6.840030	-6.843085	-6.780244
MLL	19765.91	19884.71	19893.55	19903.43	19721.78

<sup>1</sup>TARCH(ARCH Term, GARCH Term, Threshold Level)

Findings of the TARCH model are further ensured by the EGARCH models in the 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.

Table 3: EGARCH Model

	EGARCH Models				
	EGARCH (1,1,1) <sup>1</sup>	EGARCH (4,4,1)	EGARCH (4,4,2)	EGARCH (4,4,3)	EGARCH (4,4,4)
$\gamma_1$	0.038880	-0.002216	0.001757	0.015843	0.085253
$\gamma_2$	-	-	0.004278	0.010681	-0.046588
$\gamma_3$	-	-	-	-0.005334	0.089207
$\gamma_4$	-	-	-	-	-0.024639
AIC	-6.774202	-6.827237	-6.812405	-6.825440	-6.817655
MLL	19695.22	19855.37	19813.25	19852.14	19830.51

<sup>1</sup> EGARCH(ARCH Term, GARCH Term, Asymmetric Order)

GARCH (M) models in table 4 reveals the relationship between risk and stock return. A positive relationship between risk and return exists as per all the models. However relationship is insignificant under GARCH (1, 1)-M model because its P value is higher than 0.05 at 5 percent significant level rejecting the null hypothesis. GARCH (4, 4)-M model determines relatively significant trade-off between risk and return than other models.

Table 4: GARCH (M) Model

	GARCH(1,1)-M	GARCH(4,3)-M	GARCH(4,4)-M	GARCH(5,5)-M
Coefficient	0.010417	0.054740	0.067705	0.062414
P	0.7589	0.0371*	<b>0.0191*</b>	0.0254*
AIC	-6.796627	-6.832519	-6.841770	-6.844276
MLL	19760.4	19869.72	19897.60	19906.89

\* Significant at 5 percent level

### Properties of Stock Return during the Post-Civil War Period

Descriptive statistics recommend that the return series after civil war does not follow a normal distribution. Especially Jarque-Bera statistics (319.5836) is higher than the critical chi-square value of 5.99 at 5 percent significance level and two degrees of freedom, rejecting the null hypothesis. Whereas, it's P value is also less than 0.05 at 5 percent significant level. Both coefficients of Skewness (0.337744) and Kurtosis (5.889584) indicate the non-normality of the distribution.

Rejecting the null hypothesis of “ARCH problem does not exist” at 5 percent significant level, results of the OLS method ensures its weaknesses in volatility estimations. This is due to the respective probability value i.e. Zero, 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 have revealed that ARCH effect has left the return series as per the respective probability value of 0.9121 which is higher than the 0.05. Therefore this provides enough evidence not reject the null hypothesis 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.

Table 5: GARCH (m, s) Model

<b>m</b>		<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>
1	AIC	-6.541394	-6.540058	-6.539985	-6.537959	-6.538352
	MLL	2853.777	2854.195	2855.163	2855.281	2856.452
2	AIC	-6.539557	-6.538345	-6.537783	-6.536641	-6.536981
	MLL	2853.977	2854.449	2855.205	2855.707	2856.855
3	AIC	-6.543721	-6.541735	-6.539442	-6.537365	-6.535180
	MLL	2856.790	2856.925	2856.927	2857.023	2857.071
4	AIC	-6.541749	-6.541141	-6.538847	-6.536660	-6.532959
	MLL	2856.932	2857.667	2857.668	2857.715	2857.104
5	AIC	-6.539467	-6.538848	-6.539655	-6.550564	-6.548496
	MLL	2856.938	2857.668	2859.020	2864.771	2864.870
6	AIC	-6.538090	-6.536495	-6.554329	<b>-6.557573</b>	-6.538032
	MLL	2857.338	2857.643	2866.410	<b>2868.823</b>	2861.313
7	AIC	-6.535558	-6.534397	-6.552136	-6.536995	-6.544282
	MLL	2857.236	2857.730	2866.455	2860.861	2865.035

To capture the volatility clustering feature of the return series, more combinations of ARCH term and GARCH term have been taken in to account in table 5. Basically volatility clustering was found in even GARCH (1, 1) model with the sum of ARCH coefficient (0.194630) and GARCH coefficient (0.714445) being to 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 6: TARCh Model

	<b>TARCh Models</b>				
	<b>TARCh (1,1,1)</b>	<b>TARCh (4,6,1)</b>	<b>TARCh (4,6,2)</b>	<b>TARCh (4,6,3)</b>	<b>TARCh (4,6,4)</b>
$\gamma_1$	0.140661	0.016849	0.036931	0.111417	0.119813
$\gamma_2$	-	-	0.020763	-0.098520	-0.018931
$\gamma_3$	-	-	-	0.197976	0.112614
$\gamma_4$	-	-	-	-	0.130128
AIC	-6.549447	-6.554175	<b>-6.552655</b>	-6.546698	-6.543316
MLL	2858.284	2868.343	<b>2868.681</b>	2867.087	2866.614

Based on the most fitted GARCH model i.e. GARCH (4, 6), extensions of different TARCh models with different threshold levels are presented in the table 6, in addition to the TARCh(1,1,1) model to determine the leverage effect of the return series. Accordingly 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) could also be used to examine the asymmetric effect because its Gamma coefficient has been a positive value.

Even though whatever the suggestions given by the AIC and MLL, table 7 purely 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.

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)
$\gamma_1$	-0.064000	0.008531	0.001757	-0.006486	-0.073622
$\gamma_2$	-	-	0.004278	0.017434	0.005785
$\gamma_3$	-	-	-	-0.126551	-0.054192
$\gamma_4$	-	-	-	-	-0.068958
AIC	-6.552672	-6.549734	-6.812405	-6.567190	-6.553094
MLL	2859.689	2866.409	19813.25	2876.011	2870.872

Risk and return trade-off is best explained by the GARCH (4, 8)-M model according to the table 8 and where relationship has been positive and significant at 5 percent significant level due to P- value is less than 0.05. However, the relationship has been insignificant for GARCH (1, 1)-M model. Coefficients of other models presented are significant at only 10 percent level.

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
Coefficient	0.109044	0.278115	0.195152	0.173805	0.196298
P	0.4646	<b>0.0025*</b>	0.0619**	0.0932**	0.0606**
AIC	-6.539770	-6.546415	-6.546405	-6.539255	-6.544110
MLL	2854.070	2866.964	2866.959	2864.845	2866.960

\*Significant at 5 percent level; \*\*Significant at 10 percent level

## 5. Conclusions

Descriptive statistics conclude that the Stock return derived from ASPI of CSE does not follow a normal distribution during the period of civil war and post-war period. Higher peakedness and the fat-tails that associate with less density in the middle are the attributes of the distributions of both series showing a Leptokurtic behavior. This ensures the findings of the finance literature in relation to the financial time series. However during the period of civil war stock return series is more away from the normality than the post-war period.

Stock return in both periods confirms the presence of an ARCH effect for the residuals. GARCH (4, 4) model is the most appropriate model to describe the persistence in volatility during the period of civil war than GARCH (1, 1) model. However both models are in an accepted level. Volatility clustering of post-war period's return is not best captured by the GARCH (1, 1) model, and GARCH (4, 6) is the most applicable model. Accordingly a strong autocorrelation in return could be seen during the period of civil war. In sum irrespective whether the period, large changes in stock return of CSE tend to be followed by large changes, and small changes tend to be followed by small changes during the entire sample period. This also confirms the property of volatility clustering in financial time series. However the degree of the persistence in volatility has varied during the civil war period and post-war period.

Even though TAR(4, 4) with threshold order 1 and TAR(4, 6) with order 2 are the best model for explaining the asymmetric effect for both return respectively, TAR(1, 1) with order 1 is also enough to capture this effect after the civil war. These findings indicate that as a whole during the entire sample period stock return of CSE has responded more for bad news rather than good news. However this asymmetric effect has been significant after the civil war. This may be due to bad news are more typical during a period of civil war. 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 to the existing literature a positive relationship between risk and stock return could have been examined irrespective whether the periods of concern. During the period of civil war, 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 best explained by the GARCH (4, 8)-M model during the post-war period. However, the relationship has been positive but insignificant for GARCH (1, 1)-M model.

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