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Volatility Forecasting, Market Efficiency and Effect of Recession of SRI Indices

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Abstract. *This paper seeks to examine the RWH, return characteristics and various asymmetric effects of the daily returns of the DJSI (SRI) indices during pre-recession, recession, post-recession and the whole periods (December 1998 to March 2015). To achieve these objectives RWM, ARCH, GARCH, EGARCH and TARCH models are applied along with these various tests are done. ARCH measure confirms about the presence of volatility clustering. According to GARCH measure significant asymmetric shocks and persistence of conditional volatilities present in the daily returns of the SRI indices during the entire sub periods as well as the whole period. According to the EGARCH measure shows that the returns of the SRI indices are free from leverage effects except for DJSI Korea index where leverage effect exists during the recession period. For volatility forecasting not a single measure is appropriate based on various criterions (RMSE, MAE & MAPE). Only GARCH measure is appropriate during the post-recession period. It is also found that the standardised residuals are i.i.d. Finally, the returns of the SRI indices follow RWH that means the indices are informationally efficient in their weak forms and no one can predict the SRI stock price movements and earn abnormal profits by technical analysis.*

Keywords: Market Efficiency, RWH, ARCH, GARCH, EGARCH, TARCH, BDS.

JEL Classification: G11, G14, M14

Introduction

A stock market offers an added dimension of investment opportunity to the investors according to their investment needs and thus, the nature and behaviour of stock market returns are of key interest to the researchers. Generally, the researchers are interested to deal with the problems of return forecasting, market efficiency, asymmetric and leverage effects. Volatility occurs due to the uncertainty in the stock market that causes favourable as well as unfavourable effects (Poon, 2005) but risk is exclusively associated with the undesirable events. Although, the variation of the stock prices is not vicious it may be a sign of market efficiency. It is generally assumed that the fluctuation of stock prices hampers market efficiency which causes excess volatility that finally occurs market crashes and or crisis. The relationship between stock prices and its volatility is a long standing issue to the financial researchers. Empirically, volatilities of contemporaneous return and conditional returns are negatively correlated that is often referred to as asymmetric volatility in the financial literature. Most of the traditional time series econometric tools are concerned with modelling the conditional mean of a random variable. However, some interesting economic theories are designed to work with the conditional variance, or volatility.

The problem of volatility clustering in the stock returns attracts the researchers in applying good models to measure and forecast stock return volatilities. Normally, the financial time series data like stocks and exchange rate tends to occur in volatility clusters due to a large and small changes in the market. This type of phenomenon is first observed by Mandelbrot (1963) and Fama (1965), and further described by Baillie et al. (1996), Chou (1988) and Schwert (1989). Hence, various empirical models particularly time series models are employed to study the stock market volatility, leverage effect and market efficiency. The empirical applications of the autoregressive conditional heteroskedasticity (ARCH) model introduced by Eagle (1982) or its extension generalised by Bollerslev (1986) in GARCH model and its various extensions (EGARCH, TARCH, PARCH etc.) by Engle et al. (1987), Glosten et al. (1993), Nelson (1991) tries to forecast stock returns' volatility. Besides that, it is often observed in the stock returns that volatility is found to be higher after getting bad news (negative shocks) rather than getting a good news (positive shocks) of the same magnitude. Hence, volatility is affected asymmetrically by positive and negative shocks. This fact is called leverage effect which is first pointed out by Black (1976) that means changes in stock prices tend to be negatively correlated with the changes in volatility that is also documented by Christie (1982) and Nelson (1991). Engle and Ng (1993) explain news impact curve (IMC) with asymmetric response to both good and bad news. To test the leverage effect (good and bad news), many nonlinear extensions of the GARCH model are developed by Nelson (1991 EGARCH), Threshold ARCH (TARCH), Threshold GARCH (TGARCH) and PARCH which are independently developed by Zakoian (1994) and Glosten, Jagannathan and Runkle (1993). Beside these, large numbers of recent studies have examined different aspects of volatility forecasting in different markets (see Longin, 1997; Gazda and Vyrost, 2003; Chen and Lian, 2005; Brandt and Jones, 2006; Engle et al., 2007; Chang Su, 2010; Goudarzi, 2011; Ameur and Senanedsch, 2014 etc.) and depicted various effects by using a range of volatility measures.

But this study doesn't focus on the traditional stock markets. It exclusively analyses the various asymmetric effect of socially responsible stock indices (SRI stock Index). Most of the earlier studies have analysed the financial performance of socially responsible investments (SRI) and very few among them have empirically examined the performance of SRI indices (see Statman, 2000; Kurtz and Di Bartolomeo, 1996, 1999; Garz et al., 2002; Schroder, 2005; Consolandi et al., 2008; Managi, 2012 etc.). It is very common to evaluate and compare performance of SRI funds with the conventional indices and SRI indices with the conventional indices. But, it is quite uncommon to analyse the various asymmetric effects of SRI indices and compare this with other SRI indices. At this ground, the present study has tried to examine the various asymmetric effects of the SRI indices during three sub-periods (pre-recession, during recession and post-recession) and the whole period that is expected to add new evidence in the existing literature.

Besides these, there are no such studies on random walk hypothesis (RWH) to test the SRI market efficiency. Generally, the stock returns are predictable when RWH is rejected based on its own lagged values that means stock market is not efficient in its weak form. Although, the empirical evidences have shown a mixed result regarding random walk hypothesis which is efficient in its weak form. Conrad and Juttner (1973) argue that random walk hypothesis is inappropriate to explain the price changes. Moreover, Frennberg and Hansson (1993) shows that stock prices don't follow random walk (see Lo and Mackinlay, 1987; Poterba and Summers 1988; Mun et al., 2008 etc.). But, Cooper (1982) shows that stock market follows random walk hypothesis that support to the efficient market hypothesis (see also Kendal, 1953; Fama, 1965a, 1965b; Granger and Morgenstern, 1963; Godfrey et al., 1964; Sharma and Kennedy, 1977). On the other hand, Panas (1990) argues that stock market is efficient in its strong form. Fama (1970) says a market is said to be efficient if the stock prices fully reflect all the available information that means there is no opportunities for investors to make abnormal profits by manipulating information contained in the history of fundamental data. The present study analyses whether the SRI stock indices follow random walk or not.

The study is designed as follows; in section 2 describes the objective. Section 3 deals with data and study period. Section 4 provides methodology. Section 5 analyses the result and finally, section 6 ends with a conclusion and recommendation.

Objective of the study

The study is designed to achieve the following objectives:

1. To analyse the statistical properties of daily returns
2. To examine whether the SRI indices follow RWH.
3. To examine the diverse asymmetric effects of SRI indices returns during different sub periods
4. To measure the persistence of volatility of daily SRI index return.
5. To evaluate the dynamic forecasts of the conditional mean and variance of the daily returns

6. To examine whether the conditional variances are identically independently distributed (i.i.d.)

Data and study period

The study considers the daily SRI closing index value and transforms the values into a series of continuously compounded percentage return $R_{sri,t} = \log(I_t/I_{t-1})$ where I_t is the index value at the current period t and I_{t-1} is the price at the previous period. The price of the indices ranges between December 1998 and March 2015. The study is basically divided into three sub periods (Before recession: up to December 2007, during recession: From January 2008 to February 2009 and after recession: From March 2009 to March 2015) and examines the various effects of the sub-periods. Here, 11 SRI indices are considered namely DJSI US, DJSI World, DJSI World Ex All, DJSI North America, DJSI World Enlarged, DJSI World Enlarged Ex All Ex AE, DJSI Europe, DJSI Euro Zone, DJSI Asia Pacific, DJSI Korea and DJSI Emerging Market. Here, the year of inception of DJSI Emerging Market index is 2012 (After recession) also taken into consideration for analysis. All the indices follow best-in-class approaches and maintain long term economic, environmental and various social criteria. The raw data is collected from the websites of www.spdji.com, www.robecosam.com and other related sources.

Methodology

The study uses daily closing index price. The daily return of the SRI indices is computed as follows:

$$R_{sri,t} = \log(I_t/I_{t-1}) \tag{1}$$

Where, I_t is the current period price at time t and I_{t-1} is the price at the previous period.

To observe the pattern of distribution of the time series data, skewness and kurtosis are computed. The zero value of skewness indicates the distribution is symmetry. The kurtosis measures the peakedness of a distribution relative to the normal distribution. Hence, the study applies Jarque-Bera test statistic to observe whether the time series data of the SRI indices is normal or not. The J-B test statistic is computed as under:

$$J - B = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right] \tag{2}$$

Where, n is the number of observation, S and K denote skewness and kurtosis respectively.

It is assumed that time series data must be stationary that means its mean, variance and co-variance don't change over time. But in reality it is not so happened. Thus, the regression result is obtained by using such non stationary data is spurious because usual "t" test cannot be applied to test the significance of the coefficients. To test the stationary or random walk hypothesis of the time series data of the SRI indices, a non-parametric approach proposed by Phillips and Perron (1988) is applied for non-augmented DF test equation that can be written as:

$$\Delta y_t = \alpha y_{t-1} + \chi_t \delta + e_i \tag{3}$$

It modifies the "t" ratio of the coefficient so that serial correlation doesn't affect the asymptotic distribution of the test statistic. The PP test is based on the following statistic:

$$\tilde{t}_\alpha = t_\alpha \left(\frac{\gamma_0}{f_0} \right)^2 - \frac{T(f_0 - \gamma_0)(se(\hat{\alpha}))}{2 f_0^{1/2} s} \tag{4}$$

Where, $\hat{\alpha}$ is the estimate and t_α is the t ratio of α, $se(\hat{\alpha})$ is the coefficient of standard error and s is the standard error of the test regression. γ_0 is a consistent estimate of the error variance (computed as, $(T-K)s^2/T$ where k is the number of regressors), f_0 is an estimator of the residual spectrum at frequency zero. The Mackinnon (1996) critical value calculations are used to compare the computed t value and if p value is significant then there is no unit root problem in the time series data.

In General, financial time series such as stock prices, exchange rate and inflation rate often exhibit the happening of volatility clustering that means there are periods of wide swings in prices for an extended time period followed by a period of relative calm. Philip Hans Franses (1998) says "that financial time series data reflect the trading among buyers and sellers where various sources of information and other exogenous factors may have an impact on the time series pattern of asset prices. Different type of information leads to various interpretations and sometime specific economic information may cause wide market fluctuation. We often observe that large positive and negative observations in financial time series tend to appear in volatility clustering. Mandelbrot (1993) observes that "large changes in stock prices tend to be followed by small changes of either sign whereas small changes tend to be followed by small changes of either sign". If there is volatility clustering in the time series data then there is a possibility to exist a strong autocorrelation in squared return. To detect such clustering Box-Pierce Q statistic is computed.

$$Q = n \sum_{k=1}^{m} pk \approx \chi^2{}_m \tag{5}$$

Where, n is the sample size and m is the lag length. Here, daily data is used and therefore a lag length up to 24 is considered. The reason behind to consider 24 is that there might be at most 24 trading days in a month. If the value of Q statistic is significant then accept the null hypothesis or in other words presence of autocorrelation.

A great deal of macro econometric work examines the variability of stock market. The investors are also likely to be affected by the volatility of stock prices that means uncertainty may make huge losses or gains. Hence, the question is that how do we model financial time series to forecast SRI index values that might experience uncertainty. The financial time series follows random walk (RWH), i.e., they are non-stationary but its first difference become stationary. Hence, the first differenced series also often exhibit wide swings or volatility that means the variance of the time series varies over time. To model such varying variance so called Autoregressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982) becomes popular. In ARCH model it is assumed that heteroskedasticity or unequal variance has no autoregressive structure, that means heteroskedasticity observed over different periods is autocorrelated that specifies ARCH effect is present, i.e., there is volatility clustering in time series data.

To test the ARCH effect the following regression equation (OLS) is estimated:

$$R_{sri,t} = \beta_1 + \beta_2 R_{sri,t-1} + \beta_3 R_{sri,t-2} + \ldots + \beta_p R_{sri,t-p} + e_t \quad (6)$$

It is assumed that $e_t \sim N(0, \alpha_0 + \alpha_1 e^2_{t-1})$, i.e., e_t is normally distributed with 0 mean and variance $\alpha_0 + \alpha_1 e^2_{t-1}$. Here, the variance of e at time t depends on squared distributions at t-1 that causes serial correlation problem. Hence, the variance of e at time t may depend not only on one lagged squared disturbance term but also on several lagged squared disturbance terms that may be written as follows:

$$\mathrm{Var}(\mu_t) = \sigma^2_t = \alpha_0 + \alpha_1 e^2_{t-1} + \alpha_2 e^2_{t-2} + \ldots + \alpha_p e^2_{t-p} \quad (7)$$

Here, equation 6 represents the ARCH model of order p. The presence of ARCH is tested by examining the validity of the null hypothesis H_0: $\alpha_1 = \alpha_2 = \ldots = \alpha_p = 0$. To test this hypothesis Engle proposed to run the auxiliary regression (Regressed Squared Standardized Residuals on a constant) at p lags.

$$e^2{}_t = \alpha_0 + \alpha_1 e^2{}_{t-1} + \alpha_2 e^2{}_{t-2} + \ldots\ldots\ldots + \alpha_p e^2{}_{t-p} \quad (8)$$

Where, $e_t = R_{sri,t} - \hat{R}_{sri,t}$ the series for e_t is obtained from OLS regression equation 3. Now, the null hypothesis can be tested by applying the usual F-test or by Engle's LM test statistic that asymptotically distributed as a $\chi^2(p)$. If F-statistic and LM statistic are found to be significant then reject H_0 that means ARCH effect is present in the time series. If there is no ARCH effect in the residuals then the ARCH model is needless and mis-specified. After checking for unit root and ARCH effect we can specify asymmetric GARCH model to test the leverage effect.

One of the limitations of the ARCH specification (equation 4) is that it looks more like a moving average specification than the autoregression. From this lacuna a new idea is developed that includes the lagged conditional variance terms as autoregressive terms. The model is developed by Bollerslev in 1986 popularly known as GARCH model. The model is based on the assumption that forecasts of variance changing in time depend on the lagged variance of the capital assets. An unexpected up and down of returns of SRI at time t will generate more volatility in the periods to come. This model can be generalised to a GARCH (p,q) model where there will be p lagged terms of squared error and q terms of the lagged conditional variances as follows:

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i e^2{}_{t-i} + \sum_{i=1}^{q} \beta_i \sigma^2{}_{t-i} + v_i \quad (9)$$

Where, α_0 is the mean. P is the degree of ARCH process and q is the degree of GARCH process. V_t is the random process with the properties of white noise. Since equation 6 expresses the dependence of the variability of returns in the current period data from previous periods that implies conditional variability. The degrees of p and q are determined on the same principles like the ARIMA method (see Box-Jenkins, 1970). The simplest and most widespread GARCH(1,1) model can be written as:

$$\sigma^2{}_t = \alpha_0 + \alpha_1 e^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1} + v_t \tag{10}$$

As the variance is expected to be positive then we can assume that the regression coefficient α_0, β_1 and α_1 will be always positive, while the stationarity of the variance is preserved, if the coefficient β_1 and α_1 are smaller than 1.

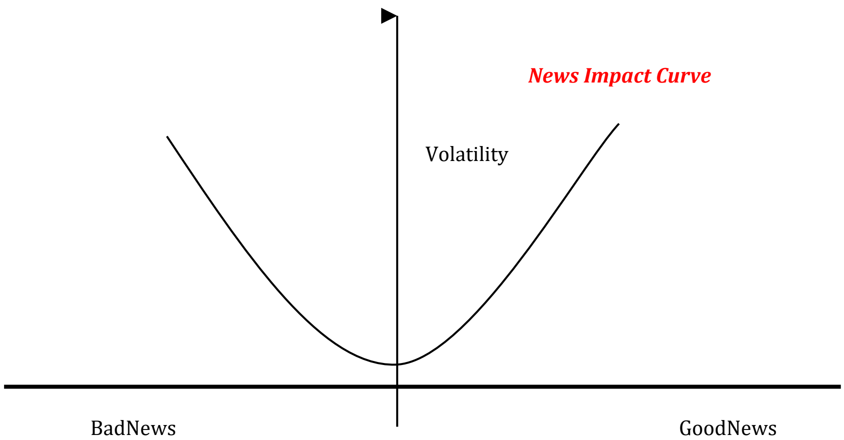
The conditional variability of SRI returns is defined in equation 7 that consist of three effects:

1. The constant part α_0
2. The part of volatility expressed by the relationship $\alpha_1 e^2{}_{t-1}$ designated as ARCH effect.
3. The part given by the predicted variability from the previous period and expressed by the relationship $\beta_1 \sigma^2{}_{t-1}$ that termed as GARCH effect.

Here, the sum of regression coefficients (α_1+β_1) expresses the influence of the variability of SRI indices from the previous period on the current value of the variability and this value is usually close to 1, which is a sign of increased inertia in the effects of shocks on the variability of returns on SRI.

Asymmetric effect

Although, the GARCH model suffers from its unsuitability for modelling the frequently observed asymmetric effect, when a different volatility is recorded systematically in a positive (good news) and negative (bad news) shocks. According to the martingale models, decrease and increase of returns can be interpreted as bad and good news respectively. If a decrease (negative shocks) in returns is accompanied by an increase in volatility greater than the volatility induced by an increase in returns termed as leverage effect. This asymmetric effect is measured by EGARCH and TGARCH models.



EGARCH measure

Let $R_{sri,t}$ is the return of SRI index at time t.

$$R_{sri,t} = \sigma'_{sri} I_{sri,t-1} + \xi_{sri,t} \tag{11}$$

$$\xi_{sri,t} = \sigma_{sri,t} Z_{sri,t} \tag{12}$$

$$Z_{sri,t} / \Omega_{t-1} \sim \Psi(0,1,v) \tag{13}$$

Now the conditional variance may be expresses as follows:

$$\log \sigma^2 = \omega + \sum_{i=1}^{p} \alpha_i \left| \frac{e_{t-1}}{\sigma_{t-1}} \right| + \sum_{j=1}^{q} \beta_j \log(\sigma^2{}_{t-1}) + \sum_{k=1}^{r} \gamma_k \frac{e_{t-1}}{\sigma_{t-1}} + v_t \tag{14}$$

Equation 11 indicates that conditional variance is an exponential function of the SRI returns that automatically ensures its positive character. Where, $\sigma^2{}_t$ is the conditional variance. $Z_{sri,t}$ is the standardized residual. Ψ(.) marks a conditional density function and v denotes a vector of parameters needed to specify the probability density function because equation 8 describes variance. ω, α, β and γ are the parameters to be estimated. The significant advantage of EGARCH model is that even if the parameters are negative then $\sigma^2{}_t$ will be positive. Here, parameter α represents the symmetric effect of the model or in other words ARCH effect. β measures the persistence in conditional volatility irrespective of anything happening in the market (GARCH Effect). If the β value is relatively large, then volatility takes a long time to die out following a crisis in the market (see Alexander 2009). An asymmetric effect is indicated by the non-zero value γ and the presence of leverage effect is given by its negative value. If γ = 0, then the model is symmetric. When $\gamma<0$, then positive shocks (good news) generate less volatility than negative shocks (bad news) and when $\gamma>0$, it indicates that positive innovations are more destabilizing than negative innovations.

TARCH or TGARCH or GJR model

In financial stock market it is often observed that positive and negative shocks have different effects on volatility, in the sense that negative shocks are followed by higher volatilities than positive shocks of the same magnitude (Engle and Ng, 1993). To deal with this phenomenon, Glosten, Jagannathan and Runkle (1993) and Zakoian (1994) introduced independently the Threshold ARCH or TARCH model(1) or TGARCH model that allows for asymmetric shocks to volatility by adding an additional term to capture for possible asymmetries. The TARCH(1,1) model is expressed by an equation for the modelling of a conditional variance:

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i e^2{}_{t-i} + \sum_{j=1}^{q} \beta_j \sigma^2{}_{t-j} + \sum_{k=1}^{r} \gamma_k e^2{}_{t-k} I_{t-k} \tag{15}$$

Where,

(a) $I_{t-1} = 1$, if $e_{t-1}<0$ or negative (bad news)

(b) $I_{t-1} = 0$, if $e_{t-1}>0$ or positive (good news)

This model is based on the assumption that unexpected change in the returns of the SRI index $R_{sri,t}$ expressed in terms of e_t, have different effects on the conditional variance of the SRI index returns. An unforeseen increase in volatility occurs with a bad news ($e_{t-1}<0$) and to fall with good news ($e_{t-1}>0$). Good news has an impact of α_i while bad news has an impact on $\alpha_i+\gamma_k$. This model is also concerned with the leverage effect. If ($\gamma>0$) the value of gamma coefficient is greater than 0, then the leverage effect exists. If $\gamma \neq 0$, then the shock is called asymmetric, and if $\gamma = 0$, the shock is symmetric. Moreover, the persistence of shocks to volatility is given by $\alpha_i+ \beta_j + \gamma_k/2$.

BDS independence test

To detect nonlinear pattern i.e., the existence of potentially forecastable structure, the most popular and useful BDS test is applied which is due to Brock et al. (1987, revised 1996). This test is applied on standardised residuals of estimated equation 12 to check whether the residuals are independent and identically distributed (i.i.d.). This test is based on the correlation integral as the test statistic. According to the Brock et al. (1996), a sample of i.i.d. observations $\{x_t: t = 1, 2, 3, ..., n\}$ can be shown as follows:

$$BDS = \sqrt{n-m+1}\,\frac{b_{m,n}(\xi)}{\sigma_{m,n}(\xi)} \rightarrow N(0,1) \tag{16}$$

Where, $b_{m,n}(\xi) = C_{m,n}(\xi) - C_{1,n-m+1}(\xi)^m$, $C_{m,n}(\xi)$ and $C_{1,n-m+1}(\xi)^m$ are the correlation integrals. $\sigma_{m,n}(\xi)$ is the standard error of $b_{m,n}(\xi)$. ξ is the distance and m is the dimension. Here, $\xi = 0.7$, and m = 2 to 6 are considered. The testable hypothesis (H_0): the series is i.i.d., that means for a given ξ and m >1, $C_{m,n}(\xi) - C_{1,n-m+1}(\xi)^m = 0$. If the computed value of BDS test statistic is significant at 1% level then the null hypothesis would be rejected and the series is not i.i.d.

Result and discussion

The descriptive statistics of the daily returns of the SRI indices are reported in Table 1. A wide fluctuation in the daily returns of the SRI indices is observed. The mean returns of the indices are positive. The highest mean return is provided by DJSI Emerging market Index (0.0281). The standard deviation of the DJSI Euro Zone Index is the highest as compared to the other indices. Here, the negative skewness values of seven SRI indices indicate that data are skewed left (leptokurtic) as compared to the right one and positive excess kurtosis means that the returns distribution of the SRI indices have fatter tails than a normal distribution. Finally, the JB test statistics (Jarque-Bera) of the returns distribution of the SRI indices are very large and the probability of obtaining such statistics under the normality assumption is significantly zero (at the 99% confidence interval) that confirms rejection of null hypothesis (H_0: Normal distribution).

Table 1. *Descriptive statistics*

SRI Screens	OB	Mean	Median	Max	Min	Std. Dev	Skew	Kurt	JB	P-Value
DJSI US	5042	0.0146	0.0000	10.0770	-8.449	1.145	0.083	11.559	15393.35	0.0000
DJSI World	5040	0.0084	0.0000	9.2402	-7.480	1.029	-0.091	12.465	18814.57	0.0000
DJSI World ex All	5040	0.0081	0.0000	9.2145	-7.349	1.024	-0.083	12.449	18751.29	0.0000
DJSI North America	5065	0.0153	0.0000	9.9085	-8.6087	1.1341	-0.0086	11.4844	15191.76	0.0000

To check the stationarity problem of the daily return series of the SRI indices ADF and PP tests are used. Here, the null hypothesis is that the time series has a unit root and is thus non-stationary against the alternative hypothesis. If it is found that the time series have a unit root, then accept the null hypothesis that the time series is non-stationary. Similarly, if the time series data is free from unit root then reject the null hypothesis and then the time series is stationary. The results of these tests are given in Table 2. It is observed that the computed ADF and PP test statistics of the SRI indices are statistically significant at all significance levels (1%, 5% and 10%) with their corresponding probabilities that confirms rejection of null hypothesis (H_0: $\delta = 0$ or $\rho = 1$) that means the time series don't appear to have a unit root that concludes that the time series of the SRI indices is stationary and follow the random walk fashion. Hence, it may be concluded that the SRI indices are informationally efficient at their weak forms which implies that the returns of the SRI indices cannot be predicted or the price movements of the SRI indices may not be determined through technical analysis.

On the other hand, the autocorrelation problem of the residuals is tested with the help of Box-Pierce Q statistic and with a variant of Ljung-Box LB statistic (Only result is interpreted and the table is not given here due to restricts pages). It is found from the Q statistics of the squared residuals of the SRI indices are lower than the critical values (insignificant) at any significance level (1%, 5% and 10%) up to 24 lags and the probability of obtaining such a LB value under the null hypothesis is practically different from zero in all cases that means rejection of null hypothesis (H_0: $\rho_k = 0$) and conclude absence of autocorrelation problem in the time series returns data of the SRI indices.

Table 2. *ADF and PP tests results of the SRI indices*

Significance Level: -3.431467(1%), -2.861918(5%) and -2.567014(10%)

SRI Index	ADF	P-Value	PP Test	P-Value	Remarks
DJSI US	-25.63541	0.0000	-1447.595	1.0000	Reject H_0 for presence of unit root
DJSI World	-20.81783	0.0000	-756.2363	0.0001	Reject H_0 for presence of unit root
DJSI World Ex All	-26.12968	0.0000	-1017.207	1.0000	Reject H_0 for presence of unit root
DJSI North America	-25.70356	0.0000	-1396.535	1.0000	Reject H_0 for presence of unit root

Graphical presentation of volatility clustering

Generally, the plotting of financial time series data exhibits that the large and small changes tend to occur volatility clustering that means good news is followed by more large returns and bad news is also followed by more small returns. This behaviour was first observed by Mandelbrot (1963) and Fama (1965), and further extended by Baillie et al. (1996), Chou (1988) and Schwert (1989). The volatility clustering or in other words the volatility shocks influence the expected volatility in many periods. Thus, to check this, the daily returns of the SRI indices are plotted in graphical way. It clearly emerges from the charts that the daily returns of all the SRI indices exhibit volatility clustering, in which there are some periods of high volatility follows by larger return and other periods of relative calm or tranquillity follows by smaller return for the sample period.

Chart 1. *Volatility clustering of daily SRI return of DJSI US*

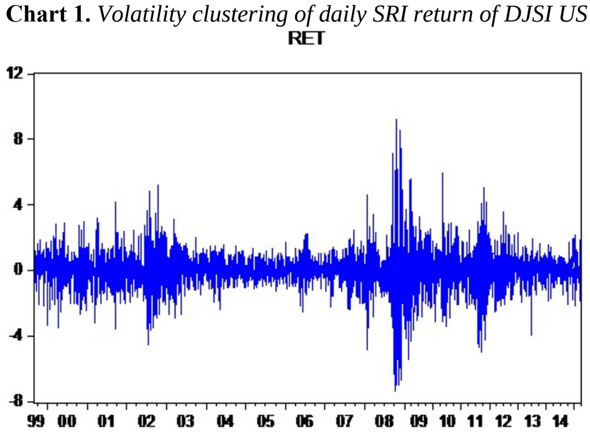


Chart 2 . *Volatility clustering of daily SRI return of DJSI World*

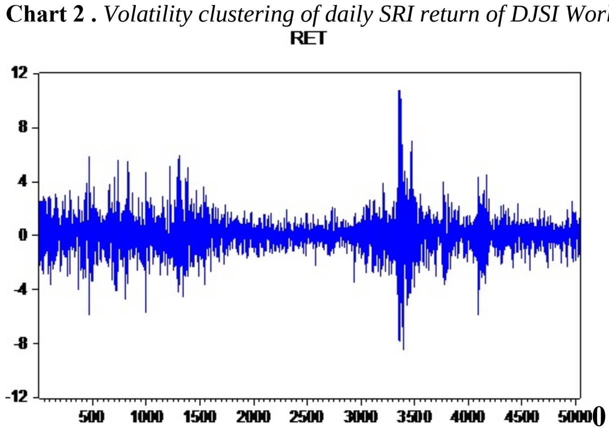


Chart 3. *Volatilityclustering of daily SRI return of DJSI World Ex All*

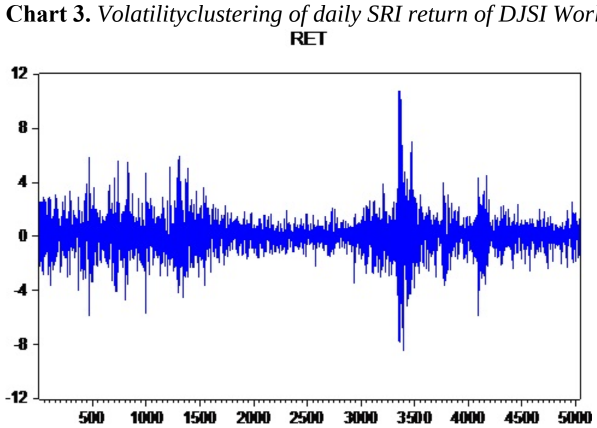
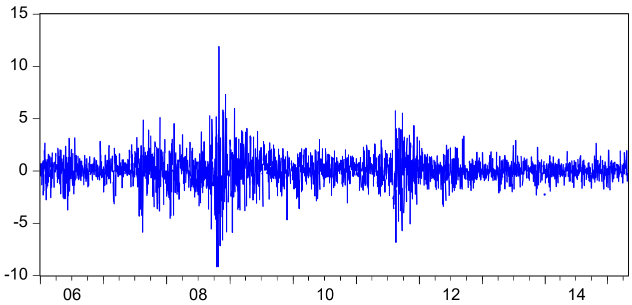


Chart 4. *Volatility clustering of daily SRI return of DJSI North America*



Estimation of ARCH effect

The presence of ARCH effect is tested through ARCH-LM test after taking into consideration the values of squared residuals which is derived from the AR(1) model. It is found (Table 3) that the F-statistics of all the SRI indices are highly significant with their p-values of 0.0000 with a confidence level of 1% that indicates ARCH effect exists in the residual series and the variances of the return series are not constant. Finally, this result is confirmed by Q-statistics that is highly significant for all cases indicate the existence of ARCH effect. Hence, the study proceeds to test the GARCH models.

Table 3. *ARCH-LM Test*

HETEROSKEDASTICITY TEST: ARCH						
SRI Index	F-Stat.	Prob.	Obs*R^2	Prob.	RESID^2(1)	Prob.
DJSI US	186.8566	F(1,5037):0.0000	180.2443	$\chi^2(1)$: 0.0000	0.186128 (13.66955)	0.0000
DJSI World	69.33634	F(1,5034):0.0000	68.42165	$\chi^2(1)$: 0.0000	0.116549 (8.326844)	0.0000
DJSI World Ex All	72.24276	F(1,5034):0.0000	71.24897	$\chi^2(1)$: 0.0000	0.118946	0.0000
DJSI North America	235.2960	F(1,5061):0.0000	224.9315	$\chi^2(1)$: 0.0000	0.211774 (15.33936)	0.0000

The necessary conditions for GARCH measure to be variance and covariance stationary are $\alpha_0 > 0$; $\alpha_i \geq 0$, i = 1,..., q; $\beta_i \geq 0$, i = 1,..., p; and $\sum\alpha_i + \beta_i < 1$. It is observed from the tables (Tables 4, 5, 6 and 7) that the above specified conditions ($\alpha_0 > 0$; $\alpha_i \geq 0$; $\beta_i \geq 0$; and $\sum\alpha_i + \beta_i < 1$) are satisfied by the SRI indices during the pre-recession, post-recession, recession and the whole periods. Here, the summation of ARCH and GARCH effect measures the shock persistence which is given in the last column of the tables. But, some of the SRI indices (DJSI World, DJSI World Ex All, DJSI World Enlarged, DJSI World Enlarged Ex All Ex AE& DJSI North America) have violated the last condition ($\sum\alpha_i + \beta_i < 1$) during the recession period regarding shock persistence. Generally, higher shock persistence indicates periods of high (low) volatility in the process will last longer. It is found that the coefficients of the terms C(4)*RESID(-1)^2 are significant (ARCH Effect) at 1% level that confirms about volatility of risk is affected significantly by the past squares residual terms of the indices during the four periods (pre-recession, post-recession, recession and whole periods). On the other hand, the coefficients of the terms C(5)*GARCH(-1) are also significant at 1% level of all the indices that means, past volatilities of all the SRI indices returns are significantly influence the current returns during the three periods and the whole period.

Table 4. *Output of GARCH (1,1) Model (pre-recession period)*

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)							
	C(3)	Prob.	C(4)	Prob.	C(5)	Prob.	C(4) + C(5)
DJSI US	4.83E-08 (5.90038)	0.0000	0.033137 (11.96989)	0.0000	0.964778 (349.6507)	0.0000	0.997915
DJSI World	1.79E-08 (3.36806)	0.0008	0.058050 (5.442077)	0.0000	0.915496 (55.59851)	0.0000	0.973546
DJSI World Ex All	8.16E-09 (4.77859)	0.0000	0.047683 (11.12901)	0.0000	0.946435 (197.6186)	0.0000	0.994118
DJSI North America	0.002423 (6.02158)	0.0000	0.034095 (12.09592)	0.0000	0.963889 (344.4249)	0.0000	0.997984

Table 5. *Output of GARCH (1,1) Model (during recession period)*

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)							
	C(3)	Prob.	C(4)	Prob.	C(5)	Prob.	C(4) + C(5)
DJSI US	9.01E-07 (1.30049)	0.1934	0.112646 (3.526099)	0.0004	0.884202 (28.32625)	0.0000	0.996848
DJSI World	4.61E-08 (2.14926)	0.0316	0.120036 (5.145085)	0.0000	0.889752 (45.42194)	0.0000	1.009788
DJSI World Ex All	2.51E-08 (1.45584)	0.1454	0.110952 (5.414030)	0.0000	0.901664 (51.18480)	0.0000	1.012616
DJSI North America	0.038404 (1.16914)	0.1154	0.120352 (3.403858)	0.0007	0.880009 (26.74607)	0.0000	1.000361

Table 6. *Output of GARCH (1,1) Model (post-recession period)*

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)							
	C(3)	Prob.	C(4)	Prob.	C(5)	Prob.	C(4) + C(5)
DJSI US	5.09E-07 (5.36544)	0.0000	0.115626 (8.459787)	0.0000	0.853964 (54.56882)	0.0000	0.969590
DJSI World	1.79E-08 (3.45995)	0.0005	0.057955 (8.635652)	0.0000	0.932907 (124.2224)	0.0000	0.990862
DJSI World Ex All	1.79E-08 (3.46178)	0.0005	0.057353 (8.555217)	0.0000	0.933308 (124.3179)	0.0000	0.990661
DJSI North America	0.022622 (5.06634)	0.0000	0.110681 (8.367791)	0.0000	0.863578 (59.33741)	0.0000	0.974259

Table 7. *Output of GARCH (1,1) Model (whole period)*

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)							
	C(3)	Prob.	C(4)	Prob.	C(5)	Prob.	C(4) + C(5)
DJSI US	1.24E-07 (8.65622)	0.0000	0.056048 (17.52998)	0.0000	0.938859 (291.0860)	0.0000	0.994907
DJSI World	9.81E-09 (5.00173)	0.0000	0.067471 (13.70300)	0.0000	0.929602 (181.7286)	0.0000	0.997073
DJSI World Ex All	9.80E-0 (5.92823)	0.0000	0.058327 (16.56120)	0.0000	0.937630 (246.6942)	0.0000	0.995957
DJSI North America	0.005783 (8.62688)	0.0000	0.056018 (17.32907)	0.0000	0.939506 (293.4534)	0.0000	0.995524

The constant terms of some SRI indices in variance equation are not statistically significant at 1% level during the recession period. The persistence of conditional volatility (volatility clustering) indicated by ARCH coefficient (C(5)) present in the SRI indices (significant at 1% level) during all the periods (Pre-recession Post-recession, recession and whole periods). It is also found (Tables 8, 9,10 and 11) that the GARCH coefficients (C(6)) are statistically significant at 1% level during all the periods that confirms past shocks persistence of all the SRI indices returns are significantly influence the current returns. Now, the study observes the presence of leverage effect of the SRI indices returns which is provided by the coefficient C(4). It is found that the gamma coefficients (Equation 14) of all the SRI indices are non zero during all the periods that means asymmetric effect present in the volatilities of the SRI returns except the index DJSI Korea (-0.040447) during the recession period. Here, the γ (EGARCH) coefficients (C(4)) almost all of the SRI indices are significant at 1% level during three periods (pre-recession, post-recession and whole periods) but they are not negative that means leverage effect does not exist in the returns of SRI indices, which indicates positive innovations are weaken than the negative innovations or in other words, negative shocks (bad news) generate more volatility than the positive shocks (good news). It is also observed that during the recession period the γ (EGARCH) coefficients (C(4)) of all the indices are not statistically significant but they are positive except the γ coefficient of DJSI Korea index which is found to be negative (-0.040447). Hence, it may said that the leverage effect exists in the returns of the DJSI Korea index that means positive innovations are stronger than the negative innovations (negative shocks generate less volatility than the positive shocks).

Table 8. *Output of EGARCH (1,1) Model (pre-recession period)*

LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)*RESID(-1)/@SQRT(GARCH(-1) + C(6)*LOG(GARCH(-1))								
	C(3)	Prob.	C(4)	Prob.	C(5)	Prob.	C(6)	Prob.
DJSI US	-0.099145 (-10.1091)	0.0000	0.056739 (10.92565)	0.0000	0.069887 (16.66305)	0.0000	0.994459 (1194.236)	0.0000
DJSI World	-0.617914 (-5.95080)	0.0000	0.091030 (4.392070)	0.0000	-0.126839 (-7.27505)	0.0000	0.961190 (142.1599)	0.0000
DJSI World Ex All	-0.186768 (-8.78227)	0.0000	0.072638 (8.710118)	0.0000	-0.059581 (-16.7519)	0.0000	0.990041 (722.8691)	0.0000
DJSI North America	-0.040856 (-10.4833)	0.0000	0.059856 (10.92783)	0.0000	-0.071423 (-17.4909)	0.0000	0.994283 (1133.520)	0.0000

Table 9. *Output of EGARCH (1,1) Model (during recession period)*

LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)*RESID(-1)/@SQRT(GARCH(-1) + C(6)*LOG(GARCH(-1))								
	C(3)	Prob.	C(4)	Prob.	C(5)	Prob.	C(6)	Prob.
DJSI US	-0.323389 (-3.52179)	0.0004	0.099922 (2.075044)	0.0380	0.172044 (3.645976)	0.0003	0.974281 (107.1923)	0.0000
DJSI World	-0.238559 (-4.89635)	0.0000	0.055392 (1.947335)	0.0515	-0.180568 (-8.78518)	0.0000	0.983474 (226.5600)	0.0000
DJSI World Ex All	-0.205462 (-4.86676)	0.0000	0.050948 (2.025140)	0.0427	-0.164678 (-10.8100)	0.0000	0.985891 (256.4735)	0.0000
DJSI North America	-0.088573 (-2.56209)	0.0104	0.116451 (2.368268)	0.0179	-0.150047 (-3.09853)	0.0019	0.986227 (147.9124)	0.0000

Table 10. *Output of EGARCH (1,1) Model (post-recession period)*

LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)*RESID(-1)/@SQRT(GARCH(-1) + C(6)*LOG(GARCH(-1))								
	C(3)	Prob.	C(4)	Prob.	C(5)	Prob.	C(6)	Prob.
DJSI US	-0.469740 (-8.31149)	0.0000	0.154358 (6.741382)	0.0000	0.162199 (11.23143)	0.0000	0.968554 (231.8815)	0.0000
DJSI World	-0.123761 (-5.37771)	0.0000	0.061036 (5.872363)	0.0000	-0.084202 (-10.5502)	0.0000	0.994151 (651.1890)	0.0000
DJSI World Ex All	-0.122186 (-5.43680)	0.0000	0.058961 (5.76208)	0.0000	-0.084656 (-10.5451)	0.0000	0.994162 (664.1348)	0.0000
DJSI North America	-0.114925 (-7.00725)	0.0000	0.147040 (6.93333)	0.0000	-0.156830 (-12.0648)	0.0000	0.973594 (285.5773)	0.0000

Table 11. *Output of EGARCH (1,1) Model (whole period)*

LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)*RESID(-1)/@SQRT(GARCH(-1) + C(6)*LOG(GARCH(-1))								
	C(3)	Prob.	C(4)	Prob.	C(5)	Prob.	C(6)	Prob.
DJSI US	-0.166232 (-14.2606)	0.0000	0.074317 (13.61056)	0.0000	0.097350 (23.78844)	0.0000	0.989684 (1006.995)	0.0000
DJSI World	-0.162143 (-14.3605)	0.0000	0.06767 (21.95612)	0.0000	-0.075733 (-26.2495)	0.0000	0.991545 (1167.146)	0.0000
DJSI World Ex All	-0.186962 (-12.4018)	0.0000	0.08218 (13.19459)	0.0000	-0.07512 (-25.4466)	0.0000	0.990472 (995.0646)	0.0000
DJSI North America	-0.055901 (-13.4173)	0.0000	0.076112 (13.74305)	0.0000	-0.096334 (-24.5906)	0.0000	0.990601 (1033.660)	0.0000

It is observed that the constant terms of the SRI indices in variance equation (Tables 12, 14 and 15) are significant (1% and 5% level) during pre-, post- and the whole periods, but insignificant during the recession period (Table 13).

The GARCH coefficients (C(6)) of all the SRI indices are statistically significant at 1% level which confirms that previous volatilities of the SRI indices returns are significantly influence the current returns during all the sub periods.It isfound that good news has an impact on conditional volatility(α)at different magnitudes during three sub periods and the whole periods while the bad news has the positive impact on ($\alpha_i + \gamma_i$) during the pre-recession, post-recession and the whole periods (Except DJSI US). Moreover, the bad news has the negative impact on ($\alpha_i + \gamma_i$) during the recession period (Except DJSI World index). Therefore, it may be said that the bad news increases conditional volatilities of the SRI indices during pre-recession, post-recession and the whole periods. On the other hand, good news has larger impact on volatility during the recession period as compared to the other periods except DJSI World index (0.188659). Moreover, it is also found that the γ (Equation 15) coefficients (C(5)) of all the SRI indices are not equal to 0 that means asymmetric shocks present in the SRI indices returns during all the periods. Although, the volatility shock is positive for the SRI indices during four periods and observes negative for DJSI US index during all the periods. If a fall in returns is accompanied by an increase in volatility greater than the volatility induced by an increase in returns, one may say leverage effect exist. Here, leverage effect exists in the SRI indices during pre-recession, post-recession, recession and the whole periods as γ coefficient is greater than zero ($\gamma > 0$). On the other hand, leverage effect doesn't exist in DJSI US index as the gamma coefficient is less than zero ($\gamma < 0$) during the four periods. Finally, the persistence of shock to volatility ($\alpha + \beta + \gamma/2$) is present in the SRI indices during the four periods given in the last column of the tables.

Table 12. *Output of TARCH (1,1) Model (pre-recession period)*

GARCH= C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) + C(6)*GARCH(-1)										
SRI Indices	C(3)	Prob.	C(4)	Prob.	C(5)	Prob.	C(6)	Prob.	C(4) + C(5)	C(4)+C(5) +C(6)/2
DJSI US	5.70E-08 (7.59981)	0.0000	0.059248 (15.70918)	0.0000	-0.069627 (-16.6134)	0.0000	0.972469 (357.3310)	0.0000	-0.010379	0.481045
DJSI World	2.40E-08 (5.76876)	0.0000	-0.014234 (-1.58716)	0.1125	0.121968 (6.465014)	0.0000	0.917658 (68.66317)	0.0000	0.107734	0.512696
DJSI World Ex All	1.07E-08 (7.684574)	0.0000	-0.004102 (-1.09439)	0.2738	0.071396 (13.60531)	0.0000	0.958612 (230.0087)	0.0000	0.067294	0.512953
DJSI North America	0.002665 (7.282554)	0.0000	-0.009670 (-3.32128)	0.0009	0.069896 (16.86153)	0.0000	0.972474 (349.1703)	0.0000	0.060226	0.516350

Table 13. *Output of TARCH (1,1) Model (during recession period)*

GARCH= C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) + C(6)*GARCH(-1)										
SRI Indices	C(3)	Prob.	C(4)	Prob.	C(5)	Prob.	C(6)	Prob.	C(4) + C(5)	C(4)+C(5)+ C(6)/2
DJSI US	1.78E-06 (2.836236)	0.0046	0.174014 (4.195026)	0.0000	-0.239648 (-4.29396)	0.0000	0.918076 (42.02547)	0.0000	-0.065634	0.426221
DJSI World	5.70E-08 (2.972881)	0.0030	-0.015167 (-1.37656)	0.1686	0.203826 (5.671210)	0.0000	0.913318 (64.88237)	0.0000	0.188659	0.550988
DJSI World Ex All	3.30E-08 (2.090909)	0.0365	-0.020497 (-2.20115)	0.0277	0.202475 (6.086560)	0.0000	0.923063 (71.41891)	0.0000	-0.040994	0.4410345
DJSI North America	0.074071 (2.598357)	0.0094	-0.064451 (-2.29592)	0.0217	0.247216 (4.228612)	0.0000	0.919738 (45.26592)	0.0000	-0.128902	0.395418

Table 14. *Output of TARCH (1,1) Model (post-recession period)*

GARCH= C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) + C(6)*GARCH(-1)										
SRI Indices	C(3)	Prob.	C(4)	Prob.	C(5)	Prob.	C(6)	Prob.	C(4) + C(5)	C(4)+C(5)+C(6)/2
DJSI US	4.30E-07 (6.864020)	0.0000	0.192227 (8.556262)	0.0000	-0.212125 (-9.32878)	0.0000	0.887595 (62.86294)	0.0000	-0.019898	0.433848
DJSI World	1.12E-08 (3.922947)	0.0001	-0.008963 (-1.40881)	0.1589	0.090008 (10.05719)	0.0000	0.957178 (162.7413)	0.0000	0.081045	0.519111
DJSI World Ex All	1.11E-08 (3.965567)	0.0001	-0.010344 (-1.64729)	0.0995	0.091218 (10.07862)	0.0000	0.957782 (165.7289)	0.0000	0.080874	0.519328
DJSI North America	0.018328 (6.254477)	0.0000	-0.012349 (-1.11047)	0.2668	0.191213 (9.329366)	0.0000	0.895503 (66.63633)	0.0000	0.178864	0.537183

Table 15. *Output of TARCH (1,1) Model (whole period)*

GARCH= C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) + C(6)*GARCH(-1)										
SRI Indices	C(3)	Prob.	C(4)	Prob.	C(5)	Prob.	C(6)	Prob.	C(4)+C(5)	C(4)+C(5)+ C(6)/2
DJSI US	1.32E-07 (10.08145)	0.0000	0.089987 (18.98056)	0.0000	-0.100998 (-20.9788)	0.0000	0.953118 (292.7559)	0.0000	-0.011011	0.4710535
DJSI World	1.06E-08 (9.94507)	0.0000	-0.008167 (-3.21227)	0.0013	0.008167 (18.23472)	0.0000	0.958992 (493.8076)	0.0000	0.000000	0.479496
DJSI World Ex All	1.22E-08 (9.61745)	0.0000	-0.004589 (-1.61160)	0.1070	0.088960 (18.68901)	0.0000	0.952104 (304.5893)	0.0000	0.084371	0.5182375
DJSI North America	0.006016 (9.878996)	0.0000	-0.010106 (-3.66267)	0.0002	0.100247 (21.35689)	0.0000	0.953916 (299.8449)	0.0000	0.090141	0.5220285

To detect possible non-linear dependence in the return series of the SRI indices, TARCH (1,1) model is applied. BDS test is applied to check whether the standardised residuals are i.i.d. or not.

It is observed (Table 16) that the BDS test statistics almost all of the SRI indices are statistically insignificant at 1% level at the chosen distance (Here $\xi = 0.7$) and dimensions ($m = 2$ to 6) that means acceptance of null hypothesis or in other words, standardised residuals series of the SRI indices are independently identically distributed (i.i.d.).

Only the exception is DJSI Euro Zone index whose standardised residuals are not independently identically distributed up to the dimension 4 at a given level of distance and thereafter the standardised residuals are i.i.d.

Table 16. *BDS Independence Test (whole period)*

SRI Index	Dimension	2	3	4	5	6
DJSI US	BDS Statistic	-0.001660	-0.003219	-0.006055	-0.007419	-0.007877
	Std. Error	0.001281	0.002032	0.002415	0.002511	0.002417
	Z-Statistic	-1.295608	-1.584314	-2.507851	-2.954067	-3.258979
	Probability	0.1951	0.1131	0.0121	0.0031	0.0011
DJSI World	BDS Statistic	9.34E-05	-0.001505	-0.002956	-0.004233	-0.004474
	Std. Error	0.001281	0.002038	0.002430	0.002536	0.002448
	Z-Statistic	0.072881	-0.738652	-1.216676	-1.669305	-1.827355
	Probability	0.9419	0.4601	0.2237	0.0951	0.0676
DJSI World Ex All	BDS Statistic	-0.000693	-0.003745	-0.006299	-0.007846	-0.008013
	Std. Error	0.001274	0.002019	0.002398	0.002493	0.002399
	Z-Statistic	-0.544072	-1.854759	-2.626403	-3.146555	-3.340340
	Probability	0.5864	0.0636	0.0086	0.0017	0.0008
	Std. Error	0.001542	0.002440	0.002892	0.003000	0.002879
	Z-Statistic	-2.336027	-1.453895	-0.859110	-0.389675	0.131743
	Probability	0.0195	0.1460	0.3903	0.6968	0.8952
DJSI North America	BDS Statistic	-0.001230	-0.002090	-0.004798	-0.006240	-0.006663
	Std. Error	0.00123	0.002035	0.002418	0.002516	0.002422
	Z-Statistic	-0.958839	-1.027183	-1.984047	-2.480306	-2.751288
	Probability	0.3376	0.3043	0.0473	0.0131	0.0059
	Std. Error	0.002684	0.004265	0.005078	0.005291	0.005101
	Z-Statistic	-0.187240	0.263209	0.457150	0.618414	0.713789
	Probability	0.8515	0.7924	0.6476	0.5363	0.4754

A model will be good that depends in terms of their ability to predict the future returns. Numerous techniques are used to measure forecasting performance and selection of the best performing model among them is very difficult task. The most popular and common measure is root mean squared error (RMSE). There are also some less popular measures like mean absolute error (MAE), mean absolute percent error (MAPE) and Theil Inequality Coefficient (TIC) whose value ranges between 0 and 1. It is observed (Table 17) that the values of RMSE are lowest in DJSI US, DJSI World Ex All, DJSI North America, DJSI Europe and DJSI ASIA PACIFIC indices based on TARCH measure during pre-recession period. Similarly, the value of RMSE of the remaining indices is lowest based on EGARCH measure. Therefore, it may be concluded that TARCH and EGARCH measures are the best performing volatility forecasting model for the SRI indices. Whereas, if we adopt Theil Inequality Coefficient (TIC), then GARCH measure provides lowest TIC value for all the SRI indices (except DJSI World Enlarged) and hence GARCH measure is the best performing measure. As TIC is less popular measure therefore, we give importance first on the RMSE and then MAE and MAPE respectively.

Table 17. *Dynamic (Out of Sample) Forecast (pre-recession period)*

SRI Index	Model	RMSE	MAE	MAPE	TIC
DJSI US	GARCH	0.004450	0.002753	73.27400	0.981600
	EGARCH	0.004450	0.002738	71.986413	0.995413
	TARCH	0.004450	0.002733	71.80874	0.998787
DJSI World	GARCH	0.000842	0.000563	100.2221	0.92424
	EGARCH	0.000842	0.000555	85.86361	0.955856
	TARCH	0.000842	0.000556	86.98973	0.953108
DJSI World Ex All	GARCH	0.001181	0.000740	79.37831	0.962443
	EGARCH	0.001181	0.000734	74.63792	0.980476
	TARCH	0.001181	0.000732	72.81176	0.989322
DJSI North America	GARCH	1.009870	0.623915	343.8635	0.974224
	EGARCH	1.009860	0.618226	87.06904	0.999990
	TARCH	1.009821	0.618675	111.0804	0.996484

The study also examines the dynamic return forecast of the SRI indices during the recession period. It is found (Table 18) that the RMSE values of the DJSI World, DJSI Europe, DJSI Euro Zone and DJSI Asia Pacific are lowest based on TARCH measure and this measure is suitable for these indices for return forecasting. Similarly, the values of RMSE of the DJSI US, DJSI World Ex All, DJSI World Enlarged, DJSI World Enlarged Ex All Ex AE and DJSI North America indices are found to be lowest based on EGARCH measure and hence this measure is beneficial to predict future volatilities. Here, only the DJSI Korea index has the lowest RMSE based on GARCH measure. Therefore, it may be concluded that TARCH, EGARCH and GARCH measures are the best performing volatility forecasting model for the SRI indices during the recession period.

Table 18. *Dynamic (Out of Sample) Forecast (during period)*

SRI Index	Model	RMSE	MAE	MAPE	TIC
DJSI US	GARCH	0.010221	0.006941	1.52E+11	0.943776
	EGARCH	0.010212	0.006966	2.22E+11	0.920817
	TARCH	0.010214	0.006959	2.03E+11	0.927175
DJSI World	GARCH	0.002831	0.001659	121.8560	0.956388
	EGARCH	0.002825	0.001692	176.5398	0.910763
	TARCH	0.002825	0.001685	163.1839	0.919830
DJSI World Ex All	GARCH	0.002813	0.001638	103.2760	0.951325
	EGARCH	0.002808	0.001669	136.5300	0.909267
	TARCH	0.002810	0.001654	120.2580	0.928908
DJSI North America	GARCH	2.335990	1.567948	1.15E+09	0.950901
	EGARCH	2.333533	1.577840	2.17E+09	0.912516
	TARCH	2.334302	1.572022	1.63E+09	0.932142

The study also analyses the dynamic return forecast of the SRI indices during the post-recession period. It is found (Table 19) that the RMSE values of all the SRI indices are lowest based on GARCH measure during post-recession period. Therefore, it may be concluded that GARCH measure is the best performing measure as compared to the TARCH and EGARCH measures for volatility forecasting during the post-recession period.

Table 19. *Dynamic (Out of Sample) Forecast (post-recession period)*

SRI Index	Model	RMSE	MAE	MAPE	TIC
DJSI US	GARCH	0.004385	0.003018	3.60E+10	0.933163
	EGARCH	0.004387	0.003018	1.74E+10	0.966050
	TARCH	0.004387	0.003019	1.49E+10	0.970570
DJSI World	GARCH	0.001593	0.001109	3.16E+09	0.958971
	EGARCH	0.001594	0.001111	3.93E+08	0.993925
	TARCH	0.001594	0.001110	1.06E+09	0.985619
DJSI World Ex All	GARCH	0.001589	0.001108	127.7723	0.957590
	EGARCH	0.001591	0.001110	101.3169	0.994218
	TARCH	0.001590	0.001109	107.1825	0.984638
DJSI North America	GARCH	1.007800	0.692174	2.16E+10	0.933727
	EGARCH	1.008242	0.693275	1.06E+10	0.965864
	TARCH	1.008423	0.693594	8.92E+09	0.970942

Finally, the study examines the dynamic return forecast of the SRI indices when the study considers the whole period. It is found (Table 20) that the RMSE values of the DJSI US, DJSI World, DJSI World Ex All, DJSI World Enlarged, DJSI Europe, DJSI Euro Zone, DJSI Asia Pacific and DJSI Emerging Market are lowest based on TARCH measure and this measure is suitable for these indices for volatility forecasting. Similarly, the values of RMSE of the DJSI North America and DJSI Korea are found to be lowest based on EGARCH measure and hence this measure is helpful to predict future volatilities. Here, only the DJSI World Enlarged Ex All Ex AE index has the lowest RMSE based on GARCH measure. Therefore, it may be concluded that TARCH, EGARCH and GARCH measures are the best performing volatility forecasting model for the SRI indices during the whole period.

Table 20. *Dynamic (Out of Sample) Forecast (whole period)*

SRI Index	Model	RMSE	MAE	MAPE	TIC
DJSI US	GARCH	0.004977	0.003094	71.61256	0.973768
	EGARCH	0.004976	0.003077	68.42356	0.995201
	TARCH	0.004973	0.003075	68.32156	0.997498
DJSI World	GARCH	0.001516	0.000930	72.08215	0.972590
	EGARCH	0.001514	0.000926	71.07125	0.986537
	TARCH	0.001511	0.000924	68.12262	0.996765
DJSI World Ex All	GARCH	0.001512	0.000928	91.29290	0.970935
	EGARCH	0.001513	0.000924	84.81698	0.985491
	TARCH	0.001511	0.000921	81.02021	0.996626
DJSI North America	GARCH	1.134262	0.703628	3.61E+09	0.968967
	EGARCH	1.134067	0.700576	1.36E+09	0.987770
	TARCH	1.134099	0.699772	6.65E+08	0.994055

From chart 5 to chart 16 plots the dynamic forecast of the conditional variances of the SRI indices based on GARCH, EGARCH and TARCH measures of the daily returns. It is observed that the volatility shocks are slightly increased during the years 2002 and 2003 for all the indices (Except DJSI Emerging Market) based on all measures during the pre-recession period and after that relatively stable up to the year of 2007. But during the year 2008 and 2009 the volatility shocks are highly persistent of all the SRI indices (Except DJSI Emerging Market) based on all the measures because of global recession that adversely affect to the SRI indices and there after the volatility shocks are quite small up to the year 2012 and after that the shocks converge to a pretty stable state of all the indices.

Chart 5. *Dynamic Forecast of the Conditional Volatility of DJSI US Index based on GARCH*

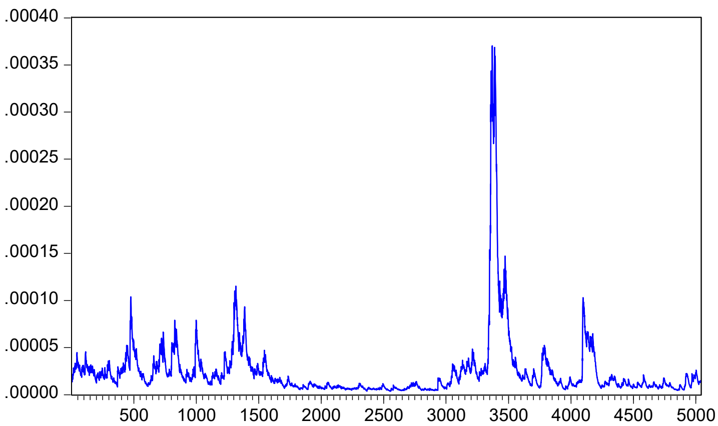


Chart 6. *Dynamic Forecast of the Conditional Volatility of DJSI US Index based on EGARCH*

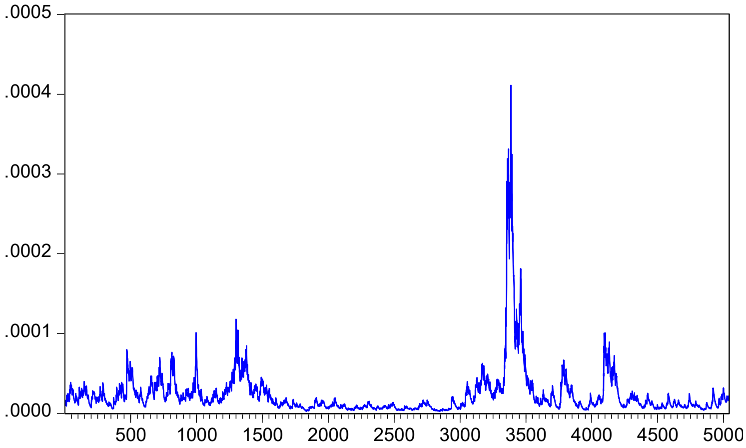


Chart 7. *Dynamic Forecast of the Conditional Volatility of DJSI US Index based on TARCH*

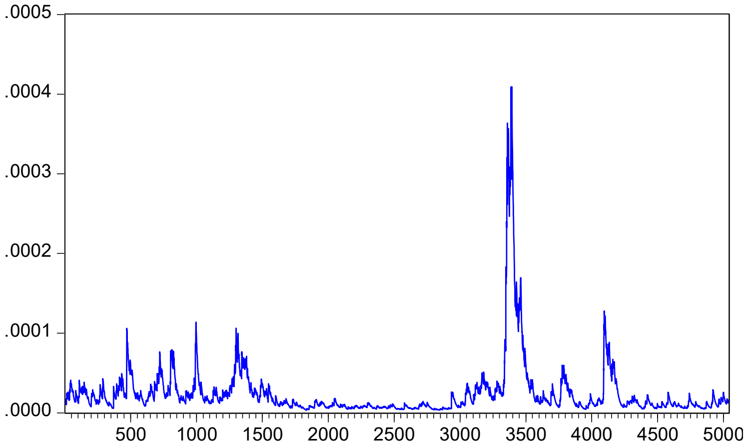


Chart 8. *Dynamic Forecast of the Conditional Variance of DJSI World Index based on GARCH*

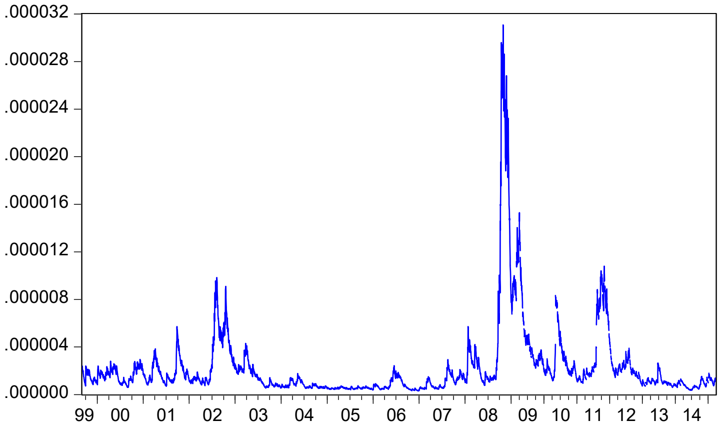


Chart 9. *Dynamic Forecast of the Conditional Variance of DJSI World Index based on EGARCH*

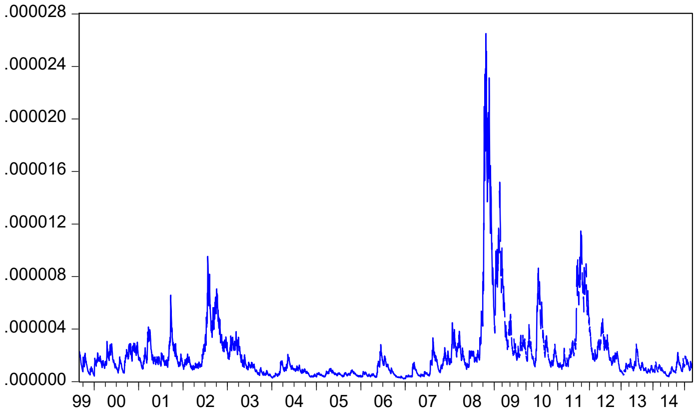


Chart 10. *Dynamic Forecast of the Conditional Variance of DJSI World Index based on TARCH*

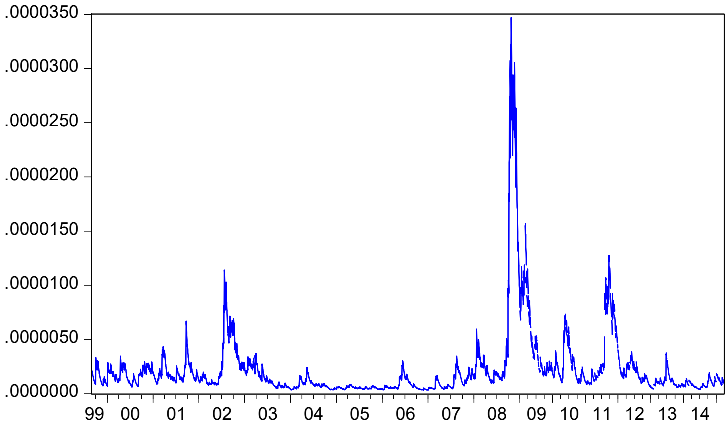


Chart 11. *Dynamic Forecast of the Conditional Variance of DJSI World Ex All Index based on* GARCH

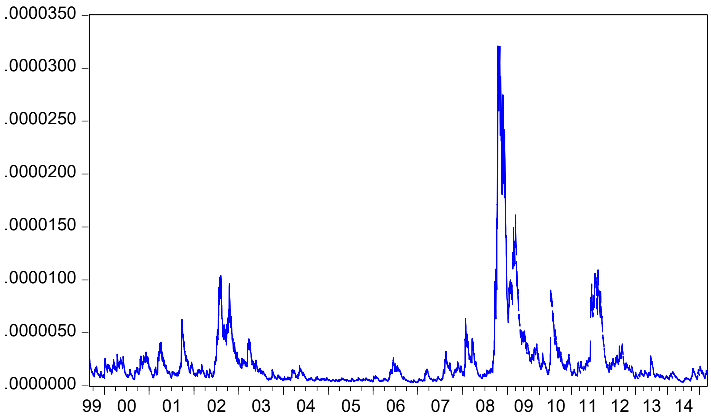


Chart 12. *Dynamic Forecast of the Conditional Variance of DJSI World Ex All Index based on* EGARCH

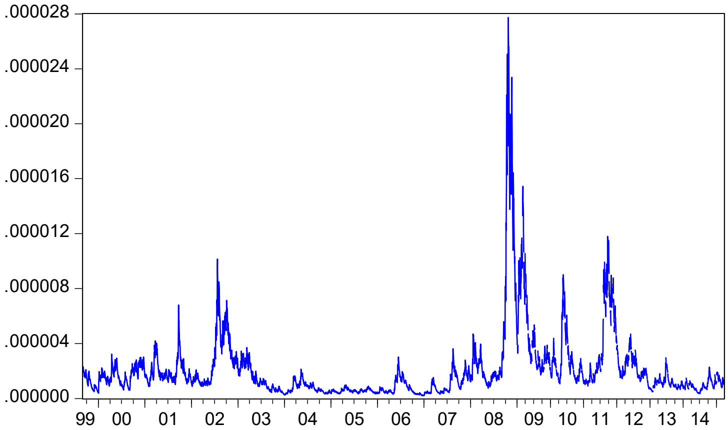


Chart 13. *Dynamic Forecast of the Conditional Variance of DJSI World Ex All Index based on* TARCH

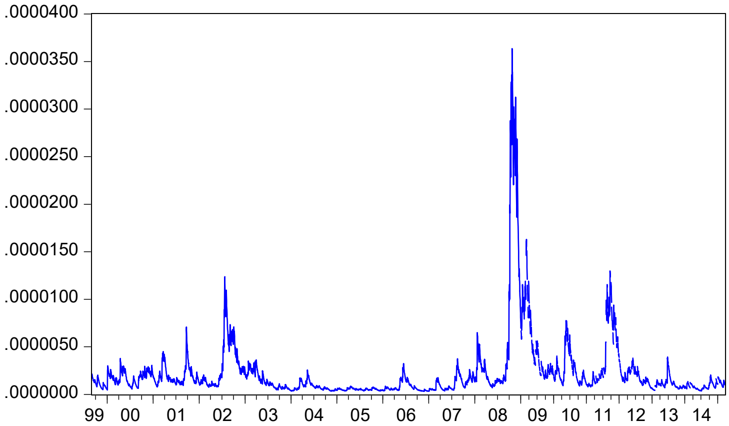


Chart 14. *Dynamic Forecast of the Conditional Variance of DJSI North America Index based on* GARCH

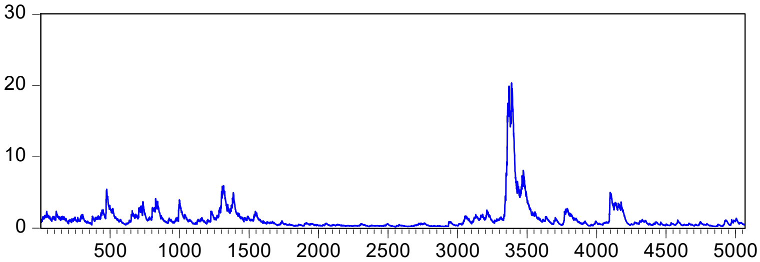


Chart 15. *Dynamic Forecast of the Conditional Variance of DJSI North America Index based on EGARCH*

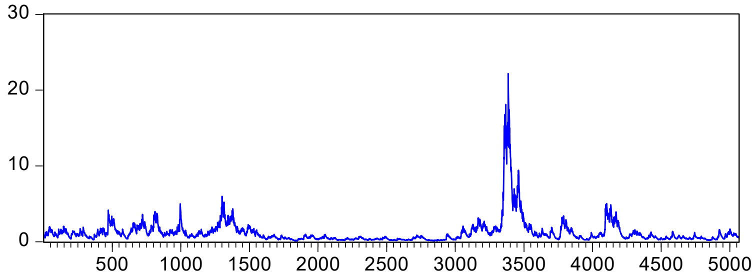
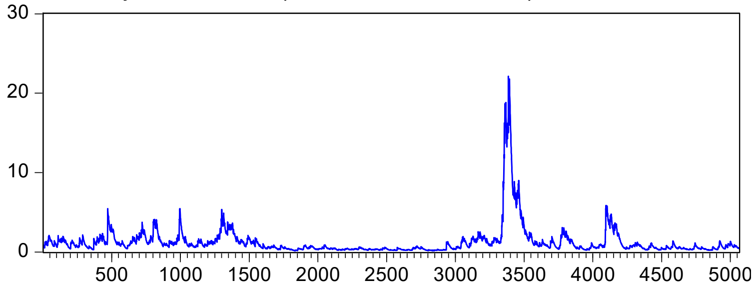


Chart 16. *Dynamic Forecast of the Conditional Variance of DJSI North America Index based on TARCH*



Conclusion

This study empirically examines various asymmetric effects of the SRI indices returns. It is found that the time series returns data of the SRI indices follow RWH and informationally efficient at their weak forms. Moreover, volatility shocks present in the indices returns where sometimes high volatility follows by a higher returns and vice-versa. GARCH coefficient shows that past volatility affects the current returns during the sub periods as well as the whole period which is also followed by the EGARCH measure. Based on EGARCH measure the returns of the SRI indices are free from leverage effects during sub periods and the whole period except DJSI Korea index. Asymmetric shocks and persistence to volatility shocks present in the indices during all the periods when TARCH measure is applied. The bad news enhances conditional volatilities during pre-, post- and the whole periods. On the other hand, good news has larger impact on volatility during the recession period. In TARCH measure leverage effects exist during all the periods except DJSI US index where leverage effect doesn’t exist. It is found that a particular measure is not appropriate to forecast volatility based on various criterions (RMSE, MAE and MAPE) during different sub periods. But GARCH measure is suitable during the post-recession period. In the pre-recession period TARCH and EGARCH measures is appropriate. Moreover, TARCH, EGARCH and GARCH measures are suitable during recession and the whole periods. It is also observed that the dynamic forecast of the conditional volatility of the SRI indices based on various measures increases during the recession period and after that quite small up to the year 2012 and thereafter the shocks converge to a pretty stable.

Note

(1)Alternativelythis model iscalled GJR (Glosten et al., 1993) or TGARCH model.

References

Akgiray, V., 1989. Conditional Heteroscedasticity in Time Series of Stock Returns, *Journal of Business*, Vol. 62, pp. 55-80.

Ameur, H.B. and Senanedsch, J., 2014. Socially Responsible Investments: An International Empirical Study of Time-Varying Risk Premiums, Vol. 30(5), pp. 1513-1524.

Black, F., 1976. Studies of Stock Price Volatility Changes, Proceedings of the American Statistical Association, Business and Economic Statistics Section, pp. 177-181.

Bollerslev, T., 1986. Generalized Autoregressive Conditional Heteroscedasticity, *Journal of Econometrics*, Vol. 31, pp. 307-327.

Bollerslev, T., 1986. A Conditional Heteroscedasticity Time Series Model for Speculative Prices and Rates of Returns, *Review of Economics and Statistics*, Vol. 69, pp. 542-547.

Bollerslev, T., Chou, R.Y. and Kroner, K.F., 1992. ARCH Modelling in Finance, *Journal of Econometrics*, Vol. 52, pp. 5-59.

Bollerslev, T., Engle, R.F. and Nelson, D.B., 1994., ARCH Models, in Handbook of Econometrics, Vol. 4, eds. R.F. Engle and D. McFadden, Amsterdam: North-Holland.

Baillie, R.T., 1997. Time Dependent Conditional Heteroscedasticity, Manuscript, Workshop of Time Series Analysis, Arrabida, Portugal.

Brandt, W.M. and Jones, S.C., 2006. Volatility Forecasting with Range-Based EGARCH Models, *Journal of Business and Economic Statistics*, Vol. 24(4), pp. 470-486.

Conrad, K. and Juttner, D.J., 1973. Recent Behaviour of Stock Market Prices in Germany and the Random Walk Hypothesis, Kyklos, Vol. 26, pp. 576-599.

Cooper, J.C.B., 1982. World Stock Markets: Some Random Walk Tests, Applied Economics, Vol. 14.

Christie, A.A., 1982. The Stochastic Behaviour of Common Stock Variances: Value, Leverage and Interest Rate Effect, *Journal of Financial Economics*, Vol. 10, pp. 407-432.

Chou, R.Y., 1998. Volatility Persistence and Stock Valuations: Some Empirical Evidence using GARCH, *Journal of Applied Econometrics*, Vol. 3, pp. 279-294.

Chen, Y.W. and Lian, K.K., 2005. A Comparison of Forecasting Models for Asean Equity Markets, *Sunway Academic Journal*, Vol. 2, pp. 1-12.

Consolandi, C., Jaiswal-Dale, A., Poggiani E. and Vercelli, A., 2008. Global Standards and Ethical Stock Indexes: The Case of the Dow Jones Sustainability Stoxx Index, *Journal of Business Ethics*, Vol. 87(1), pp. 185-197.

Engle, R.F., 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation, *Econometrica*, Vol. 50, pp. 987-1008.

Engle, R.F. and Bollerslev, 1987. Modelling the Persistence of Conditional Variances, *Econometric Reviews*, Vol. 5, pp. 1-50.

Engle, R.F., Lilien, D.M. and Robins, R.P., 1987. Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model, *Econometrica*, Vol. 55, pp. 391-407.

Engle, R.F. and Ng, V.K., 1993. Measuring and Testing the Impact of News on Volatility, *Journal of Finance*, Vol. 48, pp. 1022-1082.

Engle, R.F., Focardi. and Fabozzi, F.J., 2007. ARCH/GARCH Models in Applied Financial Econometrics, JWPR026-Fabozzi c114-NP, pp. 1-14.

Fama, E.F., 1965a. The Bahaviour of Stock Market Prices, *Journal of Business*, Vol. 38, pp. 34-105.

Fama, E.F., 1965b. Tomorrow on the New York Stock Exchange, *Journal of Business*, Vol. 38, pp. 285-299.

Fama, E.F., 1970. Efficient Capital Markets: A Review of Theory and Empirical Work, *Journal of Finance*, Vol. 25(1), pp. 383-417.

Frennberg, P. and Hansson, B., 1993. Testing the Random Walk Hypothesis on Swedish Stock Prices 1919-1990, *Journal of Banking and Finance*, Vol. 17.

Granger, C.W.J. and Morgenstern, O., 1963. Spectral Analysis of New York Stock Market Prices, Kyklos, Vol. 16, pp. 1-27.

Godfrey, M., Granger, C.W.J. and Morgenstern, O., 1964. The Random Walk Hypothesis of Stock Market Behaviour, Kyklos, Vol. 17, pp. 1-30.

Glosten, L.R., Jagannathan, R. and Runkle, D.E., 1993. On the Relation between the Expected Value and the Volatility of the National Excess Return on Stocks, *Journal of Finance*, Vol. 48, pp. 1779-1801.

Garz, H., Volk, C. and Gilles, M., 2002. More Gain than Pain – SRI: Sustainability Pays Off, WestLBPanmure, <http://www.westlbpanmure.com/sri/pdf/sri_nov2002. pdf>

Gazda, V. and Vyrost, T., 2003. Application of GARCH Models in Forecasting the Volatility of the Slovak Share index (SAX), BIATEC, Vol. (XI), pp. 17-20.

Goudarzi, H. and Ramamarayanan, C.S., 2011. Modelling Asymmetric Volatility in the Indian Stock Market, *International Journal of Management*, Vol. 6(3), pp. 221-231.

Kendall, M.G., 1953. The Analysis of Economic Time Series, Part I: Prices, *Journal of the Royal Statistical Society*, Vol. 96, pp. 11-25.

Kurtz, L. and DiBartolomeo, D., 1996. Socially Screened Portfolios: An Attribution Analysis of Relative Performance, *Journal of Investing*, Fall, pp. 35-41.

Kurtz, L. and DiBartolomeo, D., 1999. Managing Risk Exposures of Socially Screened Portfolios, Northfield Information Services, Boston, <www.northinfo.com>

Lo, A.W. and MacKinlay, A.C., 1987. Stock Market Prices do not Follow Random Walks: Evidence from a Simple Specification Test, *Review of Financial Studies*, Vol. 1, pp. 41-66.

Longin, M.F., 1997. The Threshold Effect in Expected Volatility: A Model Based on Asymmetric Information, The Review of Financial Studies, Vol. 10(3), pp. 837-869.

Mandelbrot, B., 1963. The variation of Certain Speculative Prices, *Journal of Business*, Vol. 36, pp. 394-419.

Mackinnon, J.G., 1996. Numerical Distribution Functions for Unit Root and Cointegration Tests, *Journal of Applied Econometrics*, Vol. 11, pp. 601-618.

Mun, W.H., Long, S.B., Sundaram, L., Long, S.B. and Yin, S.O., 2008. Leverage Effect and Market Efficiency of Kuala Lumpur Composite Index, *International Journal of Business and Management*, Vol. 39, pp. 138-144.

Managi, S., Okimoto, T. and Matsuda, A., 2012. Do Socially Responsible Investment Indexes Outperform Conventional Indexes?, *Applied Financial Economics*, Vol. 22(18), pp. 1511-1527.

Newey, W. and West, K., 1987. A Simple Positive Semi-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, Vol. 55, pp. 700-708.

Nelson, D.B., 1990. Stationarity and Persistence in the GARCH(1,1) Model, *Econometric Theory*, Vol. 59, pp. 318-334.

Nelson, D.B., 1991. Conditional Heteroscedasticity in Asset Returns: A New Approach, *Econometrica*, Vol. 59, pp. 347-370.

Poterba, J.M. and Summers, L.H., 1988. Mean Reversion in Stock Prices: Evidence and Implications, *NBER Working Paper* No. 2343, Cambridge, Massachusetts.

Phillips, P.C.B. and Perron, P., 1988. Testing for a Unit Root in Time Series Regression, *Biometrika*, Vol. 75, pp. 335-346.

Panas, E., 1990. The Behaviour of Athens Stock Prices, *Applied Economics*, Vol. 22.

Poon, S.H. and Granger, C., 2003. Forecasting Volatility in Financial Markets: A Review, *Journal of Economic Literature*, Vol. 41(2), pp. 478-539.

Poon, S.H., 2005. *A Practical Guide to Forecasting Financial Market Volatility*, West Sussex, John Wiley and Sons.

Sharma, J.L. and Kennedy, R.E., 1977. A Comparative Analysis of Stock Price Behaviour on the Bombay, London and New York Stock Exchanges, *Journal of Quantitative Analysis*, Vol. 12, pp. 391-413.

Statman, M., 2000. Socially responsible mutual funds, *Financial Analysts Journal*, Vol. 56, pp. 73-82.

Schroeder, M., 2005. The Performance of Socially Responsible Investments: Investment Funds and Indexes, *Financial Markets and Portfolio Management*, Vol. 18, pp. 122-142.

Su, C., 2010. Application of EGARCH Model to Estimate Financial Volatility of Daily Returns: The Empirical case of China, Master Degree Project No. 2010: 142, pp. 1- 32.

Tse, Y.K. and Tung, S.H., 1992. Forecasting Volatility in the Singapore Stock Market, *Asia Pacific Journal of Management*, Vol. 9, pp. 1-13.

Zakoian, J.M., 1994. Threshold Heteroscedasticity Models, *Journal of Economic Dynamics and Control*, Vol. 18, pp. 931-944.