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Testing for Long Memory in Stock Market Returns: Evidence from Sri Lanka: A Fractional Integration Approach

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Abstract

Long memory of stock price return has not received its due attention from researchers in Sri Lanka. This study employs fractional integration approach to explain the behavior of stock price return of All Share Price Index (ASPI) in Sri Lanka. The study covers the period from January 02, 1985 to September 28, 2018, consisting of 8803 observations. The return of the ASPI is defined as $r_t = [\ln(\text{ASPI}_t) - \ln(\text{ASPI}_{t-1})] * 100$. The Autoregressive Fractionally Integrated Moving Average model (ARFIMA) is used to examine the presence of fractional integration in the return series. The time domain exact maximum likelihood is used to estimate the ARFIMA model. The Volatility of ASPI return series are proxied by absolute return, squared return and conditional variance derived from fractionally integrated GARCH (FIGARCH) model. The

autocorrelation function of volatility decays hyperbolically for lags 1 through 200. The results show that return series does not have long memory, while the volatility series have long memory. The findings indicate that stock market in Sri Lanka is not efficient and, the results provide information to the investors, regulators, practitioners, derivative market participants, traders and government policy makers to incorporate some risk in their strategies.

Keywords: ARFIMA, exchange rate, fractional integration, Long memory, Sri Lanka

1. Introduction

A Basic understanding of the statistical properties of stochastic behavior of stock price return series is important for investors, policy makes and financial analysts. The study of long-range dependence in financial time series has remained an active topic of research in economics and finance. It will assist investors to make good investment decisions. Statistical characteristics are extremely helpful for researchers who seek to understand stock price changes statistically and simulate them efficiently. The question of whether stock markets are efficient or not, is directly related to the long memory (LM) in the stock price changes (Sadique, and Sivapulle, 2001) . Therefore, detecting long memory in a stock price dynamics is important to understand whether stock markets of an economy are efficient or not. Optimal savings, and portfolio decisions may become extremely sensitive to the investment horizon if stock returns exhibit LM. Traditional tests of the capital asset pricing model and the arbitrage pricing theory are no longer valid if the series exhibit LM. LM would suggest a very strong market inefficiency. It is extremely important to understand not only stock price return change but also the volatility of stock price return in a stock market. The term volatility represents a generic measure of the magnitude of market fluctuations. Understanding volatility of stock return has also become extremely important to understand stock price dynamics in depth. The volatility of stock price return process is concerned with the evolution of conditional variance of the return over time.

The ARIMA model examines the temporal dynamics of an economic variable as *integer* integration, under which time series are presumed to be integrated to order *zero* or *one*. In addition, Conventional unit root tests only account for integer values. The ARFIMA model

(ARFIMA (p,d,q)) is highly restrictive, being constrained to the integer domain. For example, in practice, some series do not possess a unit root, while they show signs of dependence. Recent advances in computing and econometric techniques have motivated researchers to consider the fractional values of integration of the time series. The concept of fractional integration reveals the hidden characteristics of the LM or long range dependence and the short memory (SM) of economic stationary time series. The fractional differencing parameter approach accounts for the fractional values so that it generalizes the ARIMA model and offers more flexibility in modeling to explain both the short term, long term correlation structure of a time series. However, there are scarce studies investigating the memory properties of Sri Lankan stock price return using the fractional integration technique. This is a new attempt to study the ASPI dynamics based on the fractional integration approach

There are few studies such as Amarasinghe (2015), Hemamala and Jameel (2016), Lakmali and Madhusanka (2015), Menike (2006) and Wickremasinghe (2011) that have attempted to examine the ASPI dynamics. However, their focus has been mainly on economic aspects, such as factors affecting ASPI, or impact of ASPI changes on the economy. There exists no in-depth scientific econometric analysis on the LM of volatility dynamics of the ASPI changes. LM in volatility may lead to some types of volatility persistence as observed in financial markets and affect volatility forecasts and derivative pricing formulas. This study intends to fill this gap in the finance literature and provide an in-depth analysis.

Results of the study may provide relevant implications that will be useful/beneficial for stock market investors and policy makers. A comprehensive understanding of time series and statistical properties of ASPI in Sri Lanka might provide useful implications that would crucially determine the direction of future research and facilitate the development of effective monetary, and trade policies. Therefore, this study would contribute significantly to the existing knowledge. This paper makes two main contributions: first, it provides evidence of LM in the stock prices of ASPI in Sri Lanka; second, it presents a comprehensive research on LM characteristics in the Sri Lankan stock market returns as well as volatilities.

The objective of this study is to examine the long memory property in the ASPI price dynamics using the fractional integration approach. The specific aim of the study is to estimate the LM

parameter (d - fractional integration parameter) for Sri Lankan stock market using ASPI return and volatility series.

The research paper is organized as follows: Section 2 presents literature review. Section 3 describes the theoretical framework of fractional integration, Section 4 outlines methodology, section 5 explains results and discussions and the last section is the conclusion

2. Review of Literature

A lot of empirical studies have addressed the issue of the presence of long memory components in stock prices. Bachelier (1900) has originally examined the first complete model of stock return behavior over time. Osborne (1959) developed random walk model based on Bachelier's model. Fama (1965) performed the first rigorous testing of the random walk hypothesis with a statistical analysis equity return distributions.

Chow, et al. (1995) examined the issue of memory in common stock returns through an analysis of both short – and long-run dependencies in various equity time series using traditional rescaled range statistic-(R/S), and modified rescaled range statistic. They concluded that random walk hypothesis remains a valid description of stock market return performance.

Mandelbrot (1971) first studied the effects of long memory on financial markets using Hurst's R/S statistic to identify long memory behavior in asset return data. Since then, several empirical studies such as Greene and Fielitz (1977) have supported Mandelbrot's findings. They examine the daily returns of a plethora of securities listed on the New York Stock Exchange using the "R/S" statistic method and provide evidence in support of long memory in the daily stock return series.

Lo (1991) proposes a modified test of the R/S statistic which can distinguish between short term dependence and long term dependence and finds that daily stock returns do not show long range dependence properties. Cheung and Lai (1995) investigated long memory of stock markets of Austria, Italy, Japan and Spain and they detected long memory in these markets. In addition, this finding was invariant to the choice of estimation methods used in Several studies, Lo (1991), Ding *et al* (1993), Lee and Robinson (1996) and others have used various techniques for testing long memory in stock returns. The conclusions of these studies are mixed depending on the

testing techniques, such as sample periods, frequencies of the series, and composite stock returns. Vaga (1990) and Lux (1995) argue that an abnormal profit can be made if long memory is present in the stock return. Barkoulas *et al* (2000) report evidence of long memory in the Greek stock market for the period of ten years. They estimate the fractional differencing parameter through application of the spectral regression technique. In addition, they report that the ARFIMA model provides better out of sample forecasting accuracy in comparison to the benchmark linear (random walk) models. Sadique, and Sivapulle, (2001) have examined the presence of long memory in the stock returns of seven countries, namely Japan, Korea, New Zealand, Malaysia, Singapore, the USA and Australia. They applied nonparametric and semi-parametric methods to these returns to detect long memory properties.

A standard long memory model is ARFIMA (p, d, q) model introduced by Granger and Joyeux (1980) and Hosking (1981). These models provide an alternative to ARIMA (p, d, q) process by not restricting the parameter, d to an integer value (0 or 1) but allowing it to assume any real value.

Bhattacharya, and Bhattacharya, M (2012) investigated long memory property in ten emerging stock markets across the globe using Hurst-Mandelbrot's classical R/S statistic, and Lo's statistic and semiparametric GPH statistic (Geweke and Porter-Hudak, 1983). They found return series exhibit long memory and are not independent.

In the meantime, several studies investigated the presence of long memory in variance process. For example, Hiemstra and Jones (1997) found that the mean returns of a number of US common stocks do not possess long memory, whereas the squared returns do.

Bhattacharya, and Bhattacharya, (2012) studied the existence of long memory properties in ten emerging stock markets across the globe. Hurst-Mandelbrot's Classical R/S statistic, Lo's statistic and semi parametric GPH statistic were computed as well as modified GPH statistic of Robinson (1995). The findings suggest existence of long memory in volatility as well as in absolute returns and random walk for asset return series in general for all the selected stock market indices. Though LM in stock prices has been widely examined in developed countries as evident from the discussion above, there are scarce studies on LM in stock price return series in developing countries, particularly in Sri Lanka.

3. The Theoretical Model

This section describes the econometric models relevant to the paper. It covers the ARFIMA model that is employed to study mean dynamics. The FIGARCH model is employed to study the volatility dynamics.

3.1 Long Memory in Time Series

Long memory is also referred to as Long-range dependence. It basically refers to the level of statistical dependence between two points in the time series. More specifically, it relates to the rate of decay of statistical dependence between the two points as we increase the distance between them. Long memory describes the correlation structure of a series at long lags. In the time domain, long memory is characterized by a hyperbolically decaying auto covariance function. Long memory plays an important role in many fields by determining the behaviour and predictability of systems.

3.2 Autoregressive Fractionally Integrated Moving Average Model:

Granger and Joyeux (1980), Hosking (1981, 1982), Sowell (1990) and Geweke and Porter-Hudak (1983) have employed fractional integration approach to study long memory processes. Granger and Joyeux (1980) and Hosking (1981) introduced the ARFIMA model which is now widely used in practice to model long memory in equity returns.

The most commonly used ARMA (p,q) model is not well suited to model the long-run behavior of a time series. The ARIMA model examines the temporal dynamics of an economic variable as *integer* integration, under which time series are presumed to be integrated to order *zero*, $I(0)$, or *one*, $I(1)$. This is highly restrictive, being constrained to the integer domain. Hence, we employ the fractional integration approach in the study. The ARFIMA model is not restricted to the integer domain and can assume real values. This is a parsimonious and flexible model to study long memory and short run dynamics simultaneously. Fractional integration is a more general way to describe long-range dependence than integer integration specification. This study employs the ARFIMA (p,d,q) frame work to test long memory in ASPI return dynamics. When $d=0$, the series is stationary, and shows SM and mean reversion with finite variance. In this case, the effects of a shock in a variable are transitory. When $d=0$, autocorrelation function (ACF) decays exponentially to zero. If $d=0.5$, the process is invertible but nonstationary. If $d= -0.5$, the

process is stationary but not invertible. When $d=1$, the series is integrated order one, having unit root, being non-stationary, with infinite variance, and is non-mean reverting. In this case, the effect of a shock in the series is permanent, having a long-term effect, forever persistent. If $d>1$, the series is non-stationary, non-mean reverting, with infinite memory. In this case, the effect of a shock is permanent divergence. For $d<1$, the series is mean-reverting. When $d \geq 0.5$, the series does not have stationary covariance, and consequently it has infinite covariance (Baillie *et al.* 1996). Therefore the process is non-stationary (Granger and Joyeux, 1980). However, long-range dependence is associated with all nonzero, $d>0$. Thus, the memory property of a process depends significantly on the value of d . For $-0.5 < d < 0$, the series is stationary, with intermediate memory and anti-persistent. If the parameter d is statistically significant, and lies $0 < d < 0.5$, it indicates the evidence of LM and behaves as if fractionally integrated, indicating strong dependence across past observations. The autocorrelations are positive and the ACF decay hyperbolically and monotonically towards zero as the lag length increases. The correlation between distant observations can be relatively high, implying that LM exists. The effects of a shock in real output last in the long run. When $0.5 < d < 1$, the process still has LM, but the series is no longer covariance stationary and mean reverting. The effect of a shock in the series is long-lasting and decays at an even slower rate. Thus, the memory property of a process depends significantly on the value of d .

Using the theoretical knowledge discussed above, we test whether the return of ASPI has LM. For return series, ARFIMA (p,d,q) process can be written as : $\phi(L)(1-L)^d r_t = \theta(L)\varepsilon_t$ where d is a fractional differencing parameter, L is the lag operator, $\phi(L)$, and $\theta(L)$ are lag polynomials of finite orders. $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \dots - \phi_p L^p$ represents the autoregressive polynomial of finite orders, $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \dots + \theta_q L^q$ represents the moving average polynomial of finite orders, the roots of $\phi(L)$, and $\theta(L)$ lie outside the unit circle, and $\varepsilon_t \sim iid(0, \sigma^2)$, and $(1-L)^d$ is the fractional differencing operator defined as an infinite binomial series expansion in powers of the lag operator as given below in [1].

$$[1] \quad (1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-L)^j = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)L^k}{\Gamma(k+1)\Gamma(-d)}$$

where $\Gamma(\cdot)$ is the gamma function, r_t is both stationary and invertible if the roots $\Phi(L)$ and $\Theta(L)$ are outside the unit circle, and $d < |0.5|$. The parameter d is allowed to assume any real value. This model permits the degree of differencing (d) to take fractional values. LM processes are stationary processes whose autocorrelation functions decay more slowly than SM processes. Hosking (1981) showed that the autocorrelation, $\rho(k) = \frac{\gamma(k)}{\gamma(0)}$ of an ARFIMA processes is proportional to k^{2d-1} as $k \rightarrow \infty$, i.e. $[\rho(k) \propto k^{2d-1}]$.

Note k =lags. It implies that the autocorrelations of ARFIMA processes decay hyperbolically to zero as $k \rightarrow \infty$. In the time domain, a hyperbolically decaying auto-correlation function characterizes the presence of LM. Thus, ARFIMA (p, d, q) processes are known to be capable of modeling long-run persistence. The d is the fractional integration parameter that measures long range dependence of the series. The power spectrum of the ARFIMA (p, d, q) process Y_t is given by [2]

$$[2] \quad f(\lambda) = \{4 \sin^2(\lambda/2)\}^{-\delta} f_e(\lambda), \quad \lambda \in [0, \pi]$$

where $f_e(\lambda)$ is the power spectrum of the ARMA (p, q) process that is positive and bounded. In case of long memory, $\delta > 0$, the spectrum of Y_t is unbounded for frequencies approaching 0;

$$\lim_{\lambda \rightarrow 0} f(\lambda) \lambda^{2\delta} = f_e(0).$$

The information criteria Akaike (AIC) and Schwarz (SBC) defined below in [3] and [4] are used to select a parsimonious model ARFIMA (p, d, q)

$$[3] \quad AIC = -2(\hat{l}/n) + (2(p+q+2))/2$$

$$[4] \quad SBC = -2(\hat{l}/n) + ((p+q+2)\ln(n))/2$$

where \hat{l} is the value of the maximized likelihood. The best model is selected for the smallest values of AIC or SBC. The selected ARFIMA model is a parsimonious and flexible model that can be used to study long memory.

3.3 The FIGARCH Model

The FIGARCH (p,d,q); fractionally integrated GARCH model introduced by Baillie, Bollerslev, and Mikkelsen (1996), and was used to capture long memory in volatility. In the FIGARCH model, the persistent behavior of volatility is modelled using a fractional difference parameter (d), while short term volatility is modeled by conventional ARCH and GARCH parameters.

The standard generalized autoregressive conditional heteroscedasticity (GARCH) model is stated as

$$[5] \quad h_t = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)h_t$$

where h_t , ε_t^2 are conditional and unconditional variances of ε_t respectively.

$$\omega = \varepsilon^2[1 - \beta(1) - \alpha(1)]$$

$$\alpha(L) = 1 - \sum_{j=1}^q \alpha_j L^j$$

$$\beta(L) = 1 + \sum_{j=1}^p \beta_j L^j$$

The GARCH (p,q) process in equation [5] can be rewritten as an ARMA (m,p) process in ε_t^2 such that we have

$$[6] \quad [1 - \alpha(L) - \beta(L)]\varepsilon_t^2 = \omega + [1 - \beta(L)]v_t$$

where $v_t \equiv \varepsilon_t^2 - \sigma_t^2$.

To ensure covariance stationarity the roots $[1 - \alpha(L) - \beta(L)]$ and $[1 - \beta(L)]$ are constrained to lie outside the unit circle. When the autoregressive lag polynomial, $1 - \alpha(L) - \beta(L)$, contains a unit root, the model is referred to as an integrated GARCH process (Engle and Bollerslev 1986) and is specified by

$$[7] \quad \varphi(L)(1 - L)\varepsilon_t^2 = \omega + [1 - \beta(L)]v_t$$

From this model, the FIGARCH model is obtained by introducing the fractional differencing operator, $(1 - L)^d$, such that

$$[8] \quad \phi(L)(1-L)^d \varepsilon_t^2 = \omega + [1-\beta(L)]v_t$$

Like ARFIMA process for the mean, the fractional differencing operator, $(1-L)^d$, can also be given by the gamma function. In addition, $d \in (0,1)$ and all the roots of $\phi(L)$ and $[1-\beta(L)]$ lie outside the unit circle. The FIGARCH (p,d,q) model nests a variety of other GARCH models, and is equivalent to the standard GARCH model and the IGARCH process, when $d=0$ and $d=1$, respectively. The value of the fractional differencing parameter, d , captures long memory in the FIGARCH model and depends on the decay rate of a shock. The interpretation of the long memory parameter is not identical to that reflected by the ARFIMA because the FIGARCH process may not be covariance stationary but strictly stationary and ergodic for $0 \leq d \leq 1$, and hence the unconditional variance of ε_t does not exist (Baillie, et al, 1996)

4. Methods

4.1 Data

Data used in the study are the daily stock prices of Sri Lanka, indicated by ASPI. This is the longest and the broadest price measure of the Sri Lankan Stock market. The Colombo All Share Index is a major stock market index which tracks the performance of all companies listed on the Stock Exchange in Sri Lanka. It is a capitalization weighted index. The All Share Price Index (ASPI) has a base value of 100 as of 1985. The ASPI measures the movement of share prices of all listed companies in Sri Lanka.

The study covers the period from January 02, 1985 to September 28, 2018, consisting of 8803 observations. These data were collected from the Colombo Stock Exchange (CSE). The daily changes of the ASPI are measured by the return series defined as

$$[9] \quad r_t = [\ln(\text{ASPI}_t) - \ln(\text{ASPI}_{t-1})] * 100$$

where ASPI_t = All stock price indices, $\ln(\text{ASPI})$. The absolute return ($|r_t|$) and squared return (r_t^2) and conditional variance are used as proxies for the volatility of ASPI. Conditional variance is derived from the FIGARCH model. The LM parameter for ASPI return volatility

series is estimated by using the fractional integration GARCH (FIGARCH) model for variance equation.

4.2 Analytical tools

4.2.1 Unit root tests

Before estimating the LM parameter, we tested whether the ASPI return is non-stationary using standard unit root tests; the Augmented Dickey-Fuller (ADF) test, the Phillips and Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. Then, we tested for long memory of return of ASPI series using ARFIMA and FIGARCH models.

5. Results and Discussions

This section describes the empirical results of ARFIMA and FIGARCH models application for ASPI return series. In preliminary analysis, line graph, kernel density function, unit root tests are employed. The ARFIMA model is estimated to examine long memory of ASPI return series and the *FIGARCH* model is estimated to examine long memory of volatility of (second moment) ASPI return series.

5.1 Basic features of ASPI dynamics in Sri Lanka

Figure 1 exhibits a time series plot of ASPI. The ASPI series moves upward with slow increase till 2000 then increases remarkably with volatility. Visual inspection indicates that the series seems to be non-stationary. The second moment of the ASPI distribution vary over time.



Figure 1: ASPI behavior, January 02, 1985 to September 28, 2018

5.1.1 Stylized facts of ASPI return

The returns have very little correlation, close to zero. However, conditional mean remains roughly constant. The standard deviation of returns completely dominates the mean of the returns.

Figure 2 shows that the return series appears to be random fluctuations around zero and with time varying variance. However, the return series behave differently. It displays erratic behavior. The return series shows that the first moment seems to be constant, close to zero over time, but the second moment of the return, variance varies over time. There exists a volatility clustering salient feature in the ASPI return dynamics. These facts imply the necessity of considering nonlinear models to describe the observed patterns.

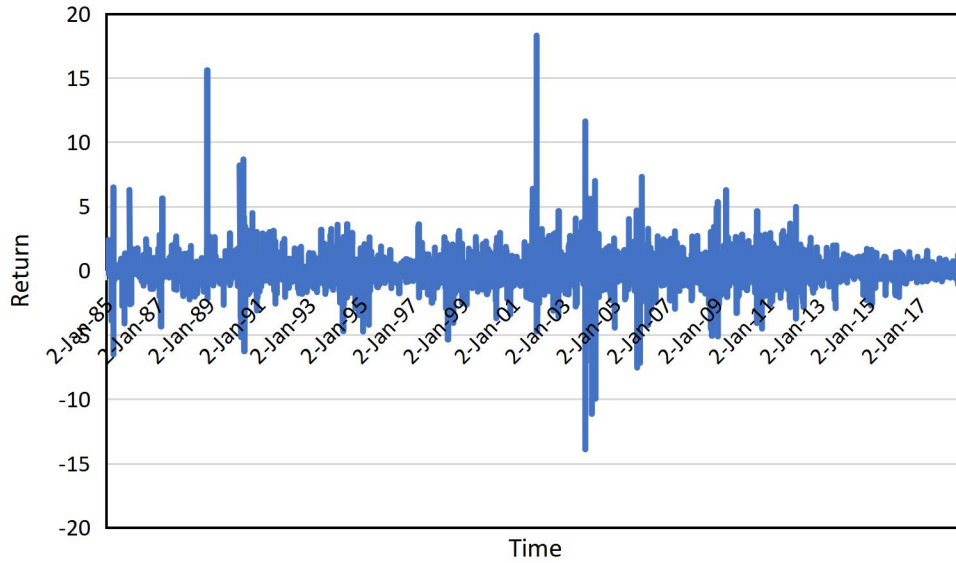


Figure 2: The Return of ASPI behavior, January 1, 1985 to September 28, 2018

Summary statistics for the ASPI stock returns for daily frequencies are given in Table 1. One of the features which stands out prominently ($K=36.79$) is that the kurtosis of the return series is much larger than the normal distribution value ($k=3$). This reflects the fact that the tails of the distribution of the return series are fatter than the tails of the normal distribution.

Table 1 : Summary statistics for stock returns

	Mean	Median	Minimum	Maximum	Std. Dev	Skewness	Kurtosis
ASPI return	0.05	0.01	-13.89	18.28	1.03	0.90	36.79

5.1.2 The Kernel Density Plot

The curve in Figure 3 shows the density plot which is essentially a smooth version of the histogram for the ASPI return distribution with the normal distribution imposed. It gives more weight to data that are closest to the point of evaluation. This shows that return distribution is symmetric and more peaked and have fatter tail than the corresponding normal distribution. Both very small and very large observations occur more often compared to a normally distributed return. The return density function shows leptokurtic behavior. This reflects the fact that the tails of the return distributions is fatter than the tails of the normal distribution. The significant values of Jarque-Bera and Shapiro statistics strongly confirm the non-normality of the returns.

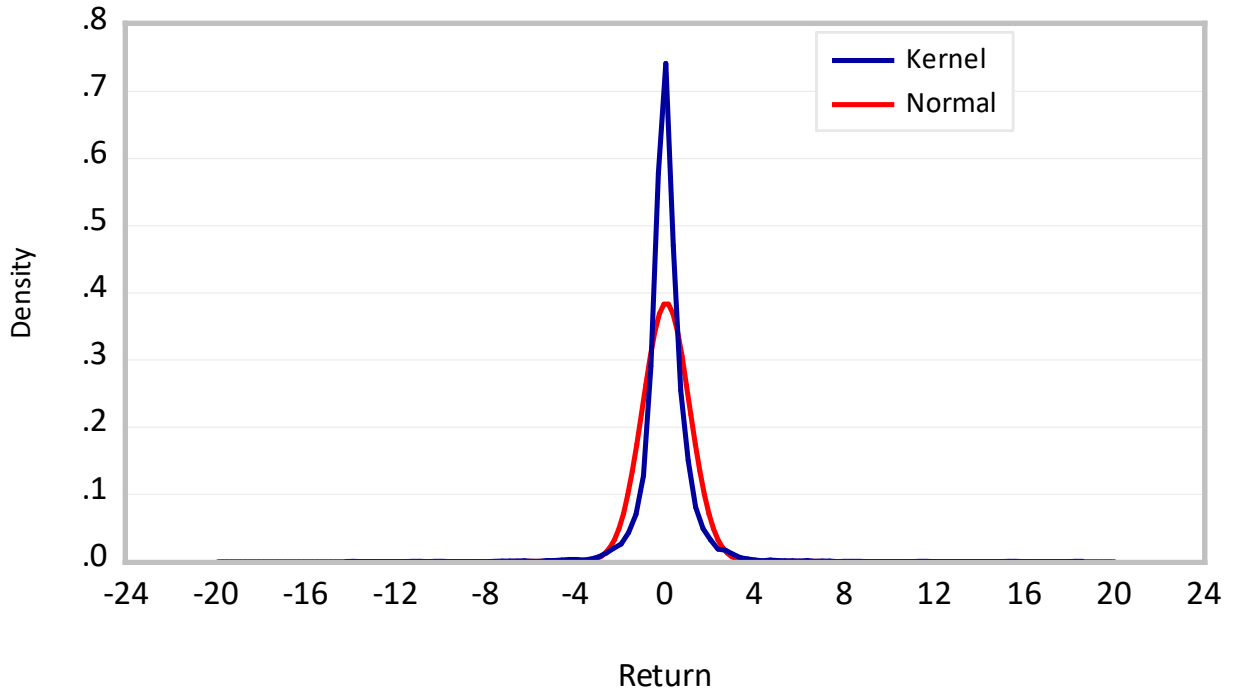


Figure 3: The Density function of Return of ASPI dynamics

It is also important to describe the second moment of a distribution and understand its dynamics. The volatility of the return series is given in Figure 4, Figure 5, and Figure 6 which show the dynamic pattern of the volatility proxies of ASPI return.

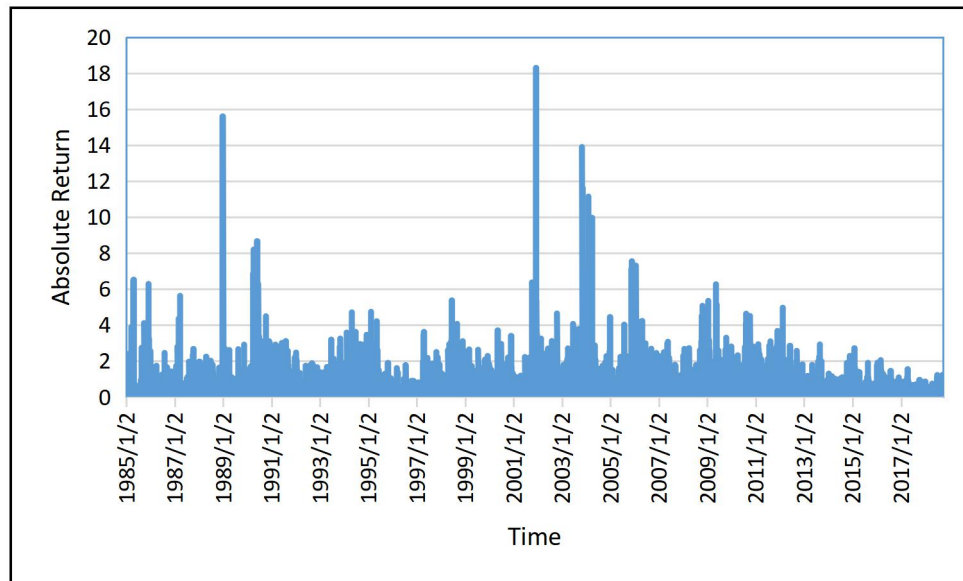


Figure 4 Absolute return dynamics

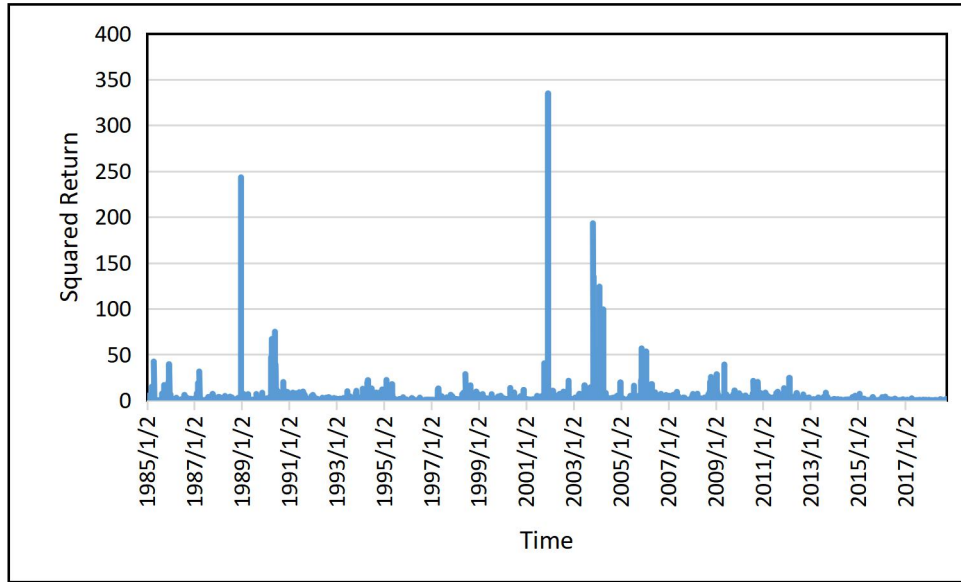


Figure 5 Squared return dynamics

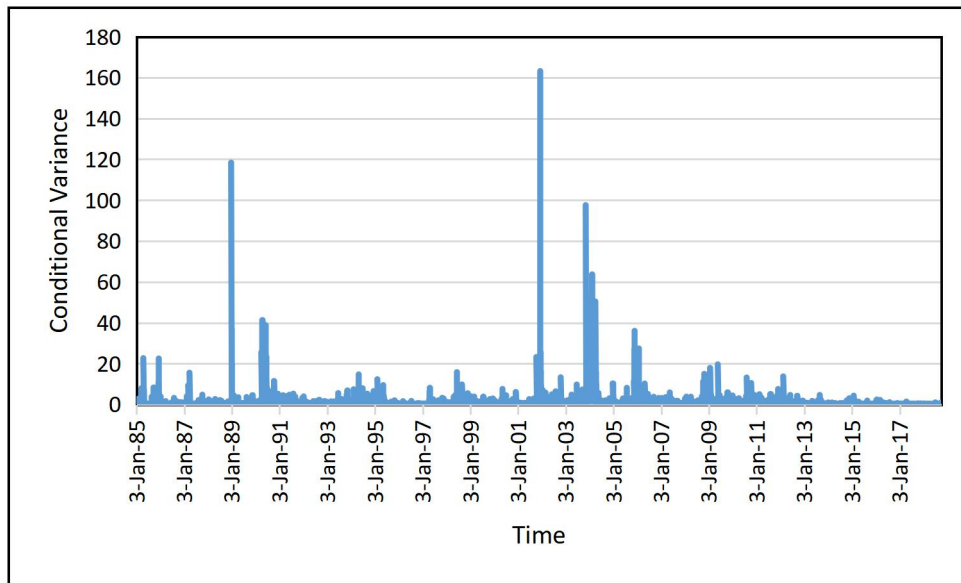


Figure 6 Conditional variance dynamics

5.1.3 The Autocorrelation function

The ACF of volatility proxies for the ASPI return decays slowly at hyperbolic rate. This figure provides strong evidence of long memory. The impact of shock ε_t on ASPI return does not diminish over time.

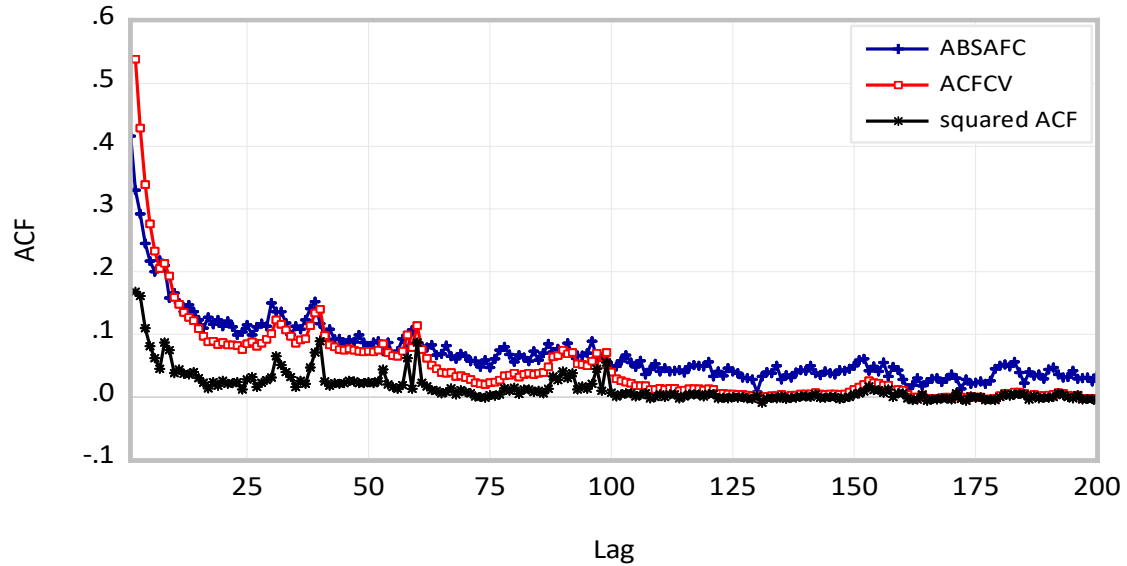


Figure 7 The ACF of squared return, absolute return and conditional variance of ASPI for lags 1-200.

5.2 Unit root test results

The results of unit root tests given in Table 2 indicate that ASPI at level is nonstationary, as the p value is greater than 0.05. The return series is stationary as the p value is less than 0.05 for ADF, PP and KPSS tests. However, in the case of volatility proxies, all proxies are stationary except the absolute return. The KPSS test is contradictory to ADF and PP test results show that Absolute return is not stationary series. This contradiction motivates for a fractional integration approach.

Table 2: Unit root test results

Exchange Rate	Level with intercept		
	ADF	PP	KPSS
LASPI (Level)	-3.902 (0.192)	-1.502 (0.532)	10.377 [0.463]
RETURN of ASPI	-37.529 (0.000)	-68.738 (0.000)	0.162 [0.463]
ABSOLUTE RETURN of ASPI	-5.222 (0.000)	-93.660 (0.000)	0.713 [0.463]
SQUARED RETURN of ASPI	-23.304 (0.000)	-95.394 (0.0001)	0.406 [0.463]
CONDITIONAL VARIANCE	-18.561 (0.000)	-74.009 (0.0001)	0.415 [0.463]

Note: p values are given in parentheses. Critical value (5%) is given in square brackets

5.3 Estimates of ARFIMA model

The estimated results of the ARFIMA model using STATA are presented in Table 3. Long memory parameter estimates of return series (d) is statistically significant and lie within the interval 0 to 0.5. This indicates that return series exhibits long memory. The autoregressive parameter estimates are given under AR (1), the parameter estimates of moving average term is given under MA (1). Log likelihood ratio values are given under LL, p values are given within parentheses, and d indicates fractional difference parameter. The MA parameter is significantly different from zero. The null hypothesis for the study is $H_0: d=0$ vs $H_1: d>0$. The findings show that the estimate of the fractional differencing parameter for return series is statistically significant.

Table 3: Results from ARFIMA (1,d,1) regression models for Return of ASPI series

ITEMS	Constant	AR(1)	MA(1)	d	LL	Wald- χ^2
Return of ASPI	0.050	-0.017	0.230	0.094	-11328.424	802.83
	(0,096)	(0.778)	(0.00)	(0.000)		(0.000)

Note: p values are in parenthesis

5.4 Evidence from the FIGARCH Volatility Model

Though the ADF and PP tests show that volatility proxies are stationary, the KPSS test indicates that absolute return is nonstationary that is contradictory with the results of other unit root tests. This contradiction motivates us to employ fractional integration technique. Fractional difference parameter estimates show that volatility proxies is stationary ($d < 0.5$) and have long memory. The absolute return is non-stationary and has long memory. The estimates of the *FIGARCH* model show that d is significantly different from zero. Long memory parameter estimates for volatility proxies are statistically significant and different from zero. It indicates that volatility series of ASPI return exhibits long memory. Long memory volatility series tends to change quite slowly over time. The effects of a shock take considerable time to decay.

Table 4: The FIGARCH (1,d,1) model of volatility proxies of ASPI

ITEMS	<i>constant</i>	d	ARCH	GARCH	LL
Squared-return	6.481	0.651	0.635	0.428	-24208.07
	(0.509)	(0.000)	(0.000)	(0.000)	-
Absolute-return	0.051	0.391	0.361	0.288	-9336.54
	(0.005)	(0.000)	(0.017)	(0.058)	-
Conditional variance	-	0.428	0.562	0.061	-16969.53
	-	(0.000)	(0.000)	(0.004)	-

(p values are in parentheses), LL=log likelihood

6. Conclusion

This study has examined the presence of the property of long memory in daily stock return of Sri Lanka for the period from January 02, 1985 to September 28, 2018. The *ARFIMA* models are estimated using maximum likelihood method. The estimates of long memory parameter (d) indicates that the return of ASPI series exhibits long memory. The estimated results suggest that the volatility of ASPI return exhibit long memory. The long memory of return and volatility of ASPI indicates that the impact of shocks on stock prices persists over a long period of time. This indicates that stock market in Sri Lanka is not efficient as well as unstable. The findings have important policy implications for government policy makers and participants of the stock market of Sri Lanka. Hence, the results provide information beneficial to the investors and traders to incorporate risk factors to their strategies. Hence, these findings are useful to the traders, investors in the stock markets in Sri Lanka.

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