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DOES LONG-MEMORY PREVAIL IN SAUDI STOCK MARKET?

Khalafalla Ahmed Mohamed Arabi, Dirar Abdulhameed Alotaibi

King Khalid University

Abstract

We intend to explore whether there is a long-memory of Tadawul All Shares Index (TASI) returns and realized volatility for the period 26/1/1994–31/12/2020 as an indication of market inefficiency. Motivated by lack of in-depth analysis of previous studies, we investigated the existence of the long-memory with four models that are the autoregressive fractionally integrated moving average for returns (ARFIMA_R), and for realized volatility (ARFIMA_RV), a heterogeneous autoregressive model (HAR), and a combination of HAR&GARCH, (RARFIMA) for the whole period and up-and-down –trend-subsamples. The estimated long-memory of both raw returns and the realized volatility was positive and observed in all models, while the division of the whole sample into six sup-samples revealed very near positive values, and less than the threshold long-memory values via ARFIMA, and the combination of ARFIMA-HAR models, thus suggesting the marginal effect of the sample size on d values. Moreover, the presence of a long-memory exposed market inefficiency.

Key words: *Long-memory, Realized volatility, Sup-samples, TASI returns.*

INTRODUCTION

Investigation of long-memory i.e. long-range dependence (LRD) has brought about a multitude of empirics applying various methods of estimation to many areas such as irrigation, climate, trade, statistics, and econometrics to assess behavior and forecasting processes (Graves et al., 2016). Historically, Hurst was the first to detect the irregular range development in the hydrological time series in 1951, using a modified range standardized by sample standard deviation R/S. Hurst spent 62 years in Egypt as a hydrologist in charge of many tasks, studying the properties of the Nile basin and working with his team on the method of water control. The cumulative flows of rivers labeled adjusted range R was analyzed as the difference between the maximum and the minimum sum of random flows normalized by the standard deviation called the Rescaled Adjusted Range R/S. Then examined 690 time series of geophysical phenomena. Hurst's (1951) study in hydrology motivated Mandelbrot’s awareness in long memory processes, to bring about the idea of an ideal dam, which entails uniform outflow, always full reservoir, no outflow, and the minimal match with these conditions to determine the optimal height of the dam using Fractional Gaussian Noise (Graves et al., 2016), then Hosking and Granger merged long-memory spectrum into auto-regressive fractionally integrated moving average ARFIMA(p,d,q).) The Fractionally Integrated Generalized Autoregressive Conditional Heteroscedastic (FIGARCH) method was introduced by Baillie et al., (1996). However, due to the heterogeneity among traders the Heterogeneous Autoregressive (HAR) model was developed by Corsi (2009), and to address realized volatility to address the shortcoming of fractional difference i.e. non- multivariate process, and mixing between long and short memory. Opschoora and Lucasa (2017) accounting for fat tails presented a covariance matrix dynamics model. Baillie et al., (2019) assessed the contribution of rival explanations through the use of fractional long memory models combined with extended HAR models, and also random coefficient extended HAR models. They established evidence that the statistical modeling of long-memory is generally important in addition to more structural model explanations. However, the existence of long-memory is an indication of an inefficient market, that is the inability of financial markets to represent data on the prices of securities of singular stocks and the stock market as a whole (Malkeil, 2003). Large numbers and rationality of participants are characteristics of an efficient market seeking to foresee future stock values with the current accessibility of information (Fama, 1970).

In 1980 the Saudi Arabian Monetary Authority (SAMA) formed the stock exchange, the real beginning of which was in 1994. A variety of internal and external factors influenced the TASI trend, including price manipulation, cheating in financial reports, technological development, amendment of legislation, reforms, the first and second Gulf Wars, East Asian economic crisis, volatile oil prices, and the September 11 event (Arabi, 2018). The establishment of the Saudi Stock Market (SSM) (Tadawul) was approved by the Council of Ministries on 19/3/2007. The SSM witnessed five phases of development in infrastructure:

Phase (1) the first integrated electronic system for trading, settlements, and clearing (ESIS) was implemented in 1990.

Phase (2) in which the period 1997–2000 witnessed the integration of settlement, de-ownership, and transfer systems into a single platform, and the switching from notices to accounts as a means of proving ownership.

Phase (3) the capital market authority (CMA) launched the Horizon automated trading system, and switched to day-to-day leveling (T+0) instead of (T+1) and replace documents with investment account applications, accompanied by banks systems development, and trading in banks through the Internet, telephone banking and ATMs.

Phase (4) saw comprehensive development of the technical structure, and of all trading systems, the addition of new investment tools as well as the market data dissemination platform and market monitoring platform labeled (SAXESS, TARGIN, and SMARTS) (Muhammad et al., 2017).

Phase (5) CMA took regulatory actions and administrative reforms. The capital of all listed companies in Saudi Riyal (SAR) 622.72 million. Saudi stock exchange is the largest in the Gulf Cooperative Council. TASI's closing prices rose steadily from the beginning of 1994–2002, followed by a sharp upward trend ending in 2006, tracked by a sharp decline ending in 2010, trailed by oscillations. Despite the apparent consistency of the returns phase, a positive return is a benefit whereas a negative is a loss. Because returns are either trading gains or dividends to the shareholder, this motivates us to test for long-memory, which decides whether there is long-term dependency.

This paper aims to investigate the existence of long-memory in returns data, and its realized volatility, followed by forecast assessment. There are few investigating long-memory studies available on the Saudi stock market including Bin Ateeg (2018) measuring the efficiency of Saudi, Dubai, and Kuwait stock markets via the ARIMA model. Lamounchi (2020) recognized the occurrence of long-memory of TASI daily returns and their realized volatility through ARFIMA only, to test the efficient market hypothesis for the period 1999–2019. However, we were different from Lamounchi in the length of period covered, doing more investigation of six subsamples according to up and downtrends, and using more estimation tools. In addition to taking into account the realized volatility that she ignored. The evidence from these prior studies has shown that the Saudi Stock Market (SSM) is inefficient. The purpose of this paper is to confirm the inefficiency due to the presence of long-memory by extending the analysis through four estimation models spanning the entire period from the beginning of the stock market to the end of 2020, as well as studying the effect of sample size on the magnitude and sign of difference parameter, addressing the following questions does series length affect long-memory presence? Do upward and downward patterns have the same fractional difference in size?

This paper is divided into six sections, starting with the introduction, followed by a literature review, methodology, analytical findings, discussion, and ending with the conclusion.

The awareness of high autocorrelation and dependence of time series led to a plethora of papers scrutinizing the essence of long-memory in these series, dating back to (Hurst, 1951) to Marwan et al., (2019) and Baillie et al., (2019) who point to the importance of long-memory in tying together stationarity and nonstationarity, and its presence by realized volatility. Econometricians have lagged 30 years behind physicists in the use of long-memory models (Baille, 1996).

Al Zahrani et al., (2020) used monthly readings of patients with diabetes in the AlBaha region of Saudi Arabia to construct a plausible model of ARFIMA(1,0.44,0) as an effective for monthly diabetes data for the period 2006–2016. Their finding raises concerns about the growing number of diabetes patients and the challenge facing the health directorate to put this problem under control. Lamouchi (2020) applied the ARFIMA approach to TASI returns to reach the empirical evidence that the long-memory behavior of TASI returns and historical volatility of the Saudi Stock Exchange violates the efficient market hypothesis. The policy implication of her findings is that the situation encourages investors to make use of this advantage to make abnormal returns.

Marwan et al., (2019) ascertained the superiority of ARFIMA after splitting the sample into crisis and pre-crisis, while the HAR model was less affected by changes. Likewise, Hassler and Pohle (2019) identified the supremacy of ARFIMA when applied to inflation series. Bin Ateeq (2018) linked the efficient market hypothesis and behavior model to study the Saudi, Dubai, and Kuwait stock markets concluding that these markets are inefficient. The main tool of analysis was ARIMA. Moreover, he studied the role of liberalization, crisis, and reform in these markets. Whoever, the Saudi stock market has been strengthened only by reform and neither by liberalization nor by the crisis. The division of data into crisis and pre-crisis was carried out by Caporale et al., (2017) generated insightful financial bubbles and anti-bubblies.

Madouri and Mkidiche (2017) intended to match the results of ARFIMA and ANN applied to the relationship between the exchange rate series of Algerian dinar, the US dollar, the pound, and the euro. ANN outperformed ARFIMA in forecasting the relationship between the dinar and the dollar, while ARFIMA was strong in forecasting the euro and the pound. Then, they have established the role of long-memory in the conditional variance of exchange series using ARFIMA-FIGARCH and ARFIMA-FIAPARCH models. They also set up that long-memory models are strong compared to short-memory models in the sample forecast result.

Sahed and Mkidiche (2014) dealt with the model of oil prices with long-memory models (ARFIMA) to estimate oil prices for the next 12 months starting from January until December 2014. Mensi et al., (2014) study the Saudi exchange rate against major currencies discovering long-memory via ARFIMA and FIGARCH, the planned news does not influence the volatility contrary to unscheduled. Five structural breaks were found. Mohamed et al., (2013) tested the long-memory of precious metals to find them sufficiently explained by the ARFIMA-FIGARCH model, which provides better out-sample forecast accuracy than several volatility models. Fulvio (2009) suggested an additive falls model of volatility mechanisms found over diverse periods and effectively attained the goal of long-memory reactions, fat tails, and self-similarity. Transitional and permanent fluctuation in real output has been studied by Marinko and Saša (2013) for long memory in real output through ARFIMA indicating that macroeconomic shocks in real output are highly persistent in Croatia.

A new fractionally integrated model based on the long-memory behavior of daily realized kernels and daily return observations for covariance matrix dynamics was presented by Opschoora and Lucasa (2017) justified fat tails, and formulated a numerically efficient matrix recursion that ensures positive definiteness under simple parameter constraints. They built realized covariance kernels by the use of intraday stock data over the period 2001–2012, displaying that the current model beats recent options such as the Multivariate HEAVY model and the multivariate HAR model, explicitly during non-crisis periods of long-memory manner.

Teyssiere and Gilles (2000) concentrated on new semi-parametric tests and estimators, such as the Newey and West Heteroscedastic and autocorrelation consistent (HAC) estimator of variance, the R/S testing non-existence of long-memory, then the KPSS statistic, and the rescaled variance V/S, nonparametric tests.

This paper intersects with other papers in the use of the AFIRMA and HAR models with different variants, and the notion of splitting data for further investigation, but differs in the length of a database, number, and basis of data division, where six sup-samples were obtained based on trend behavior and not crisis and pre-crisis.

METHODOLOGY

The dataset comprises daily observations of the Trade All-Share Index of the Saudi Stock market, its returns, and the realized volatility across the period 26/1/1994–31/12/2020 that is since the launch of the market index until the end year of 2020. Returns are denoted as R is constructed as percentage change using the natural logarithm, while realized volatility RV is the square root of returns variance, the square of returns is denoted RSQ, then LRV indicates the log of realized volatility. Since the ARFIMA approach is primarily a univariate model the returns of the choice of the closing price is the appropriate measure of market efficiency.

ARFIMA

The autoregressive component of the autoregressive integrated moving average (ARIMA and ARFIMA) embodies the residual from the previous observation into the regression model for the current observation, while the moving average assumes that the current disturbance term is a weighted sum of the current and lagged innovations. Baum (2013) stated that autoregressive polynomial, and moving average polynomial are required by ARIMA (ARFIMA as well) to be estimated through (fractionally) differencing to attain stationarity and inevitability.

Granger and Joyeux (1980) defined an autoregressive fractionally differenced moving average (ARFIMA) process {y_t} as:

$$\Phi(B)(1-B)^d y_t = \Theta(B)\varepsilon_t \tag{1}$$

where $\Phi(B) = 1 + \varphi_1 B + \cdots + \varphi_p B^p$, and $\Theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q$ are

the autoregressive and moving average (ARMA) operators, respectively; The fractional difference term $(1-B)^d = \sum_{j=0}^{\infty} \binom{d}{j} B^j$ has a binomial expansion. The ARIMA process is stationary and invertible second-order assuming that the roots of the polynomials $\Phi(B)$and $\Theta(B)$ are outside the unit circle, and the absolute difference i.e. |d|=1/2. The variance in daily returns is estimated as follows:

$$r_t = log(P_t/P_{t-1}) \tag{2}$$

where P = TASI closing price, t = period, and the log is the natural logarithm. This approach assumes that the average should be set at zero, taking into account upside and downside trends in the stock price movements.

Realized Volatility

The benefits of realized volatility (RV) include calculation of stability, measurement of changes in time, risk, pricing option, and forecasting method. Its greatest drawback is not forward-looking. The first step in of realized volatility calculation is to estimate the realized variance as a sum of squared returns $\sum_{i=1}^{N} r_t^2$. Second, take the square roots of the realized variance.

HAR Model

Heterogeneous Autoregressive (HAR) model was recommended by Corsi (2009) as follows:

$$RV_t = c + \beta^{(w)} RV_{t-1}^{(d)} + \beta^{(w)} RV_t^{(w)} + \beta^{(m)} RV_t^{(m)} + \varepsilon_t \tag{3}$$

The response to the information varies, some investors have quick responses, others as insurance companies, commercial banks, and pension funds prefer to respond to a lower rate of recurrence of information, on a weekly or monthly basis, as long-lasting volatility is taken by immediate investors as a measure for future volatility, contrary to the irrelevance of transitory volatility by abiding investors (Dimitrios et al., 2012).

Corsi et al., (2008) estimated the weekly, and monthly averages of realized volatility as follows:

$$RV_t^{(w)} = \frac{1}{5}\left(RV_{t-1}^{(d)} + RV_{t-2}^{(d)} + \cdots + RV_{t-5}^{(d)}\right) \tag{4}$$

Monthly Realized Volatility

$$RV_t^{(m)} = \frac{1}{22}\left(RV_{t-1}^{(d)} + RV_{t-2}^{(d)} + \cdots + RV_{t-22}^{(d)}\right) \tag{5}$$

The HAR's weekly and monthly terms of the model are structured to accommodate market members with various investment opportunities.

The natural logarithm of the sum of squared returns i.e. realized variance, was taken by Dimitrios et.al (2012) as a proxy for realized volatility $lrv_t = \log(r_t^2)$. Consequently, the HAR model is the following:

$$LRV_t = c + \beta^{(w)}LRV_{t-1}^{(d)} + \beta^{(w)}LRV_t^{(w)} + \beta^{(m)}LRV_t^{(m)} + \varepsilon_t \quad (6)$$

The squared returns are used by a third version of the HAR model as follows:

$$r_t^2 = c + \beta^{(w)}r_{t-1}^2 + \beta^{(w)}r_t^{(w)} + \beta^{(m)}r_t^{(m)} + \varepsilon_t \quad (7)$$

HAR-GARCH(p,q)

Corsi et al., (2008) used the standard HAR terminology to combine HAR and GARCH for realized volatility and provide conditional density and information available at time t-1(Ω_{t-1}) as follows:

$$RV_t = c + \beta^{(w)}RV_{t-1}^{(d)} + \beta^{(w)}RV_t^{(w)} + \beta^{(m)}RV_t^{(m)} + \sqrt{h_t\varepsilon_t}; \varepsilon_t|\Omega_{t-1} \quad (8)$$

$$RV_t = \omega + \sum_{j=1}^{q}\alpha_j\mu_{t-j}^2 + \sum_{j=1}^{p}\beta_j h_{t-j} \quad (9)$$

RARFIMA

Baillie et al., (2019) estimated a long memory model by combining the HAR model with the restricted ARFIMA model to produce RARFIMA.

$$(1-L)^d\lambda(L)RV_t = \varepsilon_t = \emptyset(L)(1-L)^dRV_t \quad (10)$$

$$\lambda(L) = 1 - \lambda_1L_1 - \lambda_2L_2^2 - \lambda_2L_2^3 - \lambda_2L_2^4 - \lambda_2L_2^5 - \lambda_3L^6 - \lambda_3L^7 \cdots - \lambda_3L^{22} \quad (11)$$

$$\emptyset_1 = \emptyset_2 = \emptyset_3 = \emptyset_4 = \emptyset_5 \equiv \lambda_2; \emptyset_6 = \emptyset_7 \cdots = \emptyset_{22} = \lambda_3 \quad (12)$$

The RARFIMA is a restricted ARFIMA model, that seems to be a reasonable approximation to the dynamic structure of several RV series, which is a HAR model augmented by the fractional difference and capable of reproducing autocorrelation function the hyperbolic decay (Baillie et al., 2019).

RESULTS AND DISCUSSION

The application of descriptive statistics is critical in describing the characteristics of dataset. They offer brief summaries of the sample and measures. They form the foundation of almost every quantitative data analysis, along with simple graphics analysis.

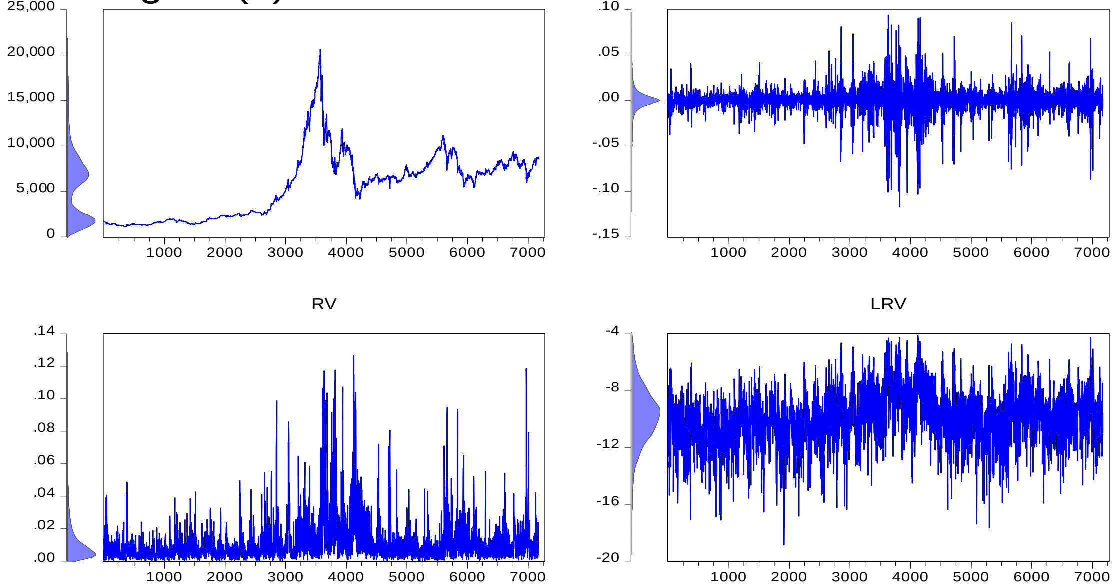
TABLE 1. DESCRIPTIVE STATISTICS

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
R	.0002	0.0007	0.093907	-0.11729	0.012909	-1.07405	16.9746
RV	0.012	0.0080	0.126416	8.04E-05	0.013641	3.311932	17.8990
LRV	-9.680	-9.6465	-4.13635	-18.8579	1.872419	-0.14909	3.52142
RSQ	0.0002	1.97e-5	0.01376	0.00000	0.00066	9.54509	119.255

The negative skewness of the returns series points to the long left tail. The realized volatility series are leptokurtic since their kurtosis statistic is greater than 3, pointing to fat tail resulting in a more possibility of major positive or negative events. This knowledge help investors measure the level of risk of an asset.

Figure 1 depicts the closing price (close), returns (R), realized volatility (RV), and log realized volatility (LVR).

Figure (1)



Stationarity may be the obvious feature of Figure 1 since the daily return, realized volatility, as well as log realized volatility oscillate around a constant means. The kernel density of closing prices is bimodal, daily returns and log realized volatility displays normal curves, while the realized volatility skewed to the left.

The presence of random walk renders the estimated process to be ARFIMA (0,d,0) and encounters four instances, first when the difference operator (d) equals 0.5 the process is non-stationary and invertible; second if (d) lies between zero and 0.5 the process has long memory; third if (d) lies between -0.5 and less than zero, the process has short memory; fourth when (d) is zero the process is white noise. Therefore the test for random walk is necessary. For consistency with previous studies, especially on Saudi subjects, we are checking the presence of unit root by KPSS. The null hypothesis rho (ϱ) is less than 1 against the alternative hypothesis ϱ = 1.

TABLE 2. UNIT ROOT TESTS

	Returns		Realized Volatility		Realized Variance	
Statistic	Level	Ist. Diff	Level	Ist. Diff	Level	Ist. Diff
KPSS	0.149944***		1.320810	0.017457***	2.270987	0.11966***

As the KPSS test statistic is less than all asymptotic critical values, the hypothesis, cannot be rejected, thus, TASI returns are stationary, while realized volatility and realized variance is integrated of order one I(1). On the other hand, tests in the annex dismiss the random walk hypothesis in both returns and realized series, except for period 2 of the realized volatility.

Estimation results are depicted in Table 3 showing the fractional difference, the autoregressive terms, and the moving average terms. The number of asterisks indicate the significance level, notably all estimates are highly significant at one percent (***).

TABLE 3. ARFIMA RESULTS

Coefficient	ARFIMA_R	ARFIMA_LRV	ARFIMA_RSQ	ARFIMA_RV
C		-9.76732***		
Difference	0.07706***	0.324107***	0.373808***	0.463685***
AR(1)	0.700299***	-0.27555***	-1.21369***	-0.72749***
AR(2)	-0.36882***		-0.97847***	-0.64195***
AR(3)	-0.29669***		-0.43338***	0.288462***
AR(4)	0.574738***			0.092194***
MA(1)	-0.68874***	0.629261***	0.928576***	1.193801***
MA(2)	0.28229***		0.679354***	0.712929***
MA(3)	0.377633***		0.207121***	-0.18709***
MA(4)	-0.62336***		-0.16311***	-0.45713***
MSE	0.017		7.65E-05	0.0094
Akaike	-5.876	3.332	-12.015	-6.601
R^2	0.019	0.533	0.199	0.684

Table 3 portrays the results of four ARFIMA models based on ARMA models selected by the automatic ARIMA forecasting. The first was estimated using raw returns, the second using a log of realized variance, the third fitted results obtained via the squared returns as a proxy for realized volatility, and the fourth using realized volatility calculated as the square root of realized variance. Estimates of the memory parameter and other estimated coefficients are all significant at a 1% level of significance as the stars advocate. The estimated d values range from 0.07 to 0.46 are all positive signifying long-memory. The choice between realized volatility models based on the coefficient of determination, mean square error, and Akaike information criterion, though the estimated ARFIMA favors the fourth model (ARFIMA_RV). Shocks take a longer time to disappear. Strong persistence means that the distant past of the process still strongly influences the present (Hassler & Pohle, 2019).

The TASI movement will be examined by dividing the entire periods according to periods of ups and downs, where the first and the second numbers brackets in Table 4 indicate the month and year of the spike or trough.

TABLE 4. SUP-SAMPLES

	Spike	Spike	Trough	Spike	Trough	Spike
ARFIMA	0.368	0.364	0.409	0.374	0.399	0.372
RARFIMA	0.494	0490	0.418	0.447	0.488	0.487
Observations	2616 (11/2002)	964 (2/2006)	656 (7/2009)	1382 (9/2014)	515 (9/2016)	1053 (9/2017)

The SSE witnessed rapid development in infrastructure and legislation. The steady upward trend was a response to the publishing of prices, corporate announcements, and financial reports, integration of settlement, clearance, and transfer system. Moreover, banks developed their systems and began trading online, banking telephone, and ATM. The sample period of realized volatility was divided into 6 sup-samples of varying sizes according to the trend pattern, where an upward trend was marked as a spike and downward as a trough. The number of observations, the month in which troughs and spikes occurred, as well as d values, revealed in Table 4 for ARFIMA & RARFIMA. It is clear that the length of the sample period has very little effect on the size of the fractional difference, and does not alter its sign. The first period lasted over 2000 days, from 1994 to the end of November 2002, followed by a slowdown from December 2002 to January 2006, then an upward trend for 964 days, then a downward trend for 656 days, an upward trend for 1,382 days, a slowdown for the next 515 days, and finally an upward trend for the remaining period, i.e. 1,053 days. It has been observed that days of upward trends outnumber days of downward trends. Despite this, the difference estimates are not significantly different from one another, with a slight increase in d values during downward trends. Caporale et al., (2017) used the idea of splitting the entire sample period into sub-periods to generate insightful financial bubbles and anti-bubblies. Similar insights are obtained by dividing the entire period into six sub periods based on the recognized ups and downs and their effect on the estimated fractional difference.

TABLE 5. ESTIMATION RESULTS OF HETEROGENEOUS MODELS

Coefficient	HAR_LRV	HAR_RSQ	HAR_RV	RARRIMA	HAR-GARCH
Constant	-1.07394***	0.000109***	0.003181***	0.005965***	0.002419***
RV(-1)	0.536064***	0.136908***	0.627148***	0.38953***	0.607815***
Weekly RV	0.06373***	0.266301***	2.062568***	2.565826***	3.040062***
MonthlyRV	0.2892***	0.394281**	6.011209***	5.200225***	7.802264***
Daily RV				0.248907***	
Constant					1.56E-06***
RESID(-1)^2					0.160515***
GARCH(-1)					0.83585***
MSE			0.0088	0.007	0.0030
AIC	3.227	-10.373	-5.961	-6.729	-5.86
R^2	0.56	0.191	0.531	0.625	0.613

Table 5 shows the significance levels of HAR, RARFIMA, and HAR-GARCH components estimates at 5% (**) and 1%(***). Except for the monthly RV of HAR RSQ at 5%, all estimates are highly significant at the 1% level.

Following Corsi (2009) OLS is enhanced by the option Bartlett kernel, Newey-West covariance correction to eliminate any potential autocorrelation (Feng et.al 2019). The stationarity of HAR residues points to the adequacy of the model. The estimated parameters are significant on the 1% significance level, including the positive d values of the RARFIMA model. The impact on current realized volatility in the standard HAR model is dominated by the lagged realized volatility, and monthly average, while the weakly average component has a low impact indicating a declining impact of the monthly component. The components therefore can be used as a proxy for market weights. Matching the results of the standard HAR model with HAR-GARCH similarity is noted for Corsi et al., (2008) when combing HAR and GARCH models together, the constant and weekly volatility parameters increased, the lagged realized volatility decreased. As well as an improvement in the goods of fit based on the Akaike information criterion. The output of HAR-GARCH is also similar to that of Dimitrios et al., (2012). The RARFIMA indicated the important role of monthly and weekly averages on realized volatility compared to ARMA terms.

The selection criteria are all in favor of RARFIMA models with significant estimated and positive parameters. The monthly average has a dominant impact on the realized volatility followed by the weekly average. The comparison between HAR-GARCH and RARFIMA shows similar results.

Starting with the closing price, the gradual increase in the curve over the first thirty two months was attributed to the improvement of the Saudi economy following the liberation of Kuwait, improved oil prices, and the decline in interest rates. Then the rapid rise in closing price was triggered by the increase in corporate capital, the merger of banks, the listing of companies in the Saudi Stock Market (SSM), and the development in technological infrastructure. The slowdown was triggered by the economic crisis that occurred in East Asia, which hurt petrochemical firms, a decline in oil prices, and a rise in interest rates. The decline in oil production has led to a major jump in oil prices, followed by opening the door to investment in the Saudi market for foreign investors through local equity funds. Besides, the EU accepted the accession of the Kingdom to the world trade organization, the big return of money invested abroad, the functioning of the Capital Market Authority and the executive management, the Cabinet allowed Gulf Cooperative Council GCC citizens to trade banking and insurance shares, the release of new rules: the listing of more companies, and licensed persons, as well as, oil prices continued to rise. In addition, news have played an obvious role in the price movement, as exemplified by the Minister's of Finance incorrect comment of on stock overvaluation at the beginning of the 1990s, which led to a sharp fall in the stock market, the rise of collective sales, bankruptcy of many senior and small shareholders, and the loss of market faith, which continued this decline until the beginning of June of 1995. In addition to the incorrect decisions, the capital market in the light of regulatory initiatives for the assessment of electricity fluctuations, stopping manipulations by examining the reasons for the substantial increase in stocks, contributed to a decline in their shares.

The construction of returns and realized volatility of the closing price and the application of ARFIMA, HAR, and RARFIMA models have revealed the long term nature to emphasize past dependence, thus refuting the efficiency of the stock market. Lamounchi (2020) obtained this result with the application of ARFIRMA solely for returns. Our results support Bin Ateeq (2018) findings of market inefficiency. Kumar (2014) reached a conclusion that the Saudi stock market is not weakly inefficient which coincides with our results since we obtained a difference operator greater than zero, while the market weak efficiency requires a fractional difference to be set to zero. Many reasons can be attributed the inefficiency of the market, including the domination of the board of directors, poor corporate management, speculation, and manipulation of movement of prices. Gains were made to segment of investors from the rather large difference between the first offer and the first order, where they benefited from this ratio by making small gains only by buying from the nearest order and selling on the first offer. However, results indicate that the monthly average's effect on the realized volatility is twice the role of the weekly average's position, highlighting that large investors prefer slow investment actions. Results obtained by dividing the whole period into six samples according to surges, and downturns showed that the magnitude of the difference fraction values varies but in a very narrow range, which means that the sample size has a marginal effect on the d value.

CONCLUSION

The paper examined the occurrence of long-memory in the return series, and its realized volatility for the period 1994–2020 using 7,182 observations estimated by ARFIMA, HAR, a combination of both, and a combination of HAR-GARCH models. In the first step, we explored the existence of long memory in returns and realized volatility through the ARFIMA model. The return series unveiled a long-memory of 0.07, while realized volatility long-memory ranged between 0.32–0.46. In the second stage, we confined our analysis to realized volatility. Three types of the realized series as dependent variables that is a log of the realized variance, the square root of the realized variance, and the squared returns. Selection criteria preferred the combination of ARFIMA and HAR referred to as RARFIMA. To answer the questions posed above, further inspection by dividing the entire sample into six sup-samples, suggesting that sample length and upward and downward patterns have little influence on changing the magnitude of fractional difference. The ultimate result is that the SSM is marked as inefficient due to many internal and factors that require rigorous measures to be taken. This result is confirmed by the run test with zero test value of returns, 1,533 cases less than the test value, 1736 greater than the test value, and the asymptotic significance rejects the hypothesis of randomness. Many internal and external factors were behind the inefficiency. Since we reached the same conclusion of market inefficiency as Lamounchi (2020), we confirm her policy implication that this situation encourages investors to make abnormal returns. Moreover, the presence of a long-memory exposed market inefficiency. More effort should be made to increase the proportion of investors, to increase influence over the work of boards and executives, to introduce more governance, to eliminate market manipulations in the movement of prices, and easing requirements for international investors.

REFERENCES

Al Zahrani, S., AlRahman Al Sameeh, F., Musa, A.C.M. & Shokeralla, A.A.A. (2020). Forecasting Diabetes Patients Attendance at Al-Baha Hospitals Using Autoregressive Fractional Integrated Moving Average (ARFIMA) models. Journal of Data Analysis and Information Processing, 8, 183–194.

Arabi, Khalafalla Ahmed Mohamed. (2018). What drives Tadawul All Stock Index of the Saudi Stock Market? Archives of Business Research, 6(4), 176–190.

Baillie, Richard T., Fabio Calonaci, Dooyeon Cho & Seunghwa Rho. (2019). How Important is Modeling Long Memory in Realized Volatility? School of Economics and Finance, Working Paper 881.

Baum, Christopher F. (2013). ARIMA and ARFIMA models, Boston College.

Bin Ateeq & Yazeed Abdulaziz I. (2018). Assessing for the Volatility of the Saudi, Dubai and Kuwait Stock Markets: Time Series Analysis (2005–2016), Ph.D. Thesis Manchester Metropolitan University.

Caporale Guglielmo Maria, Luis Gil-Alana & Alex Plastun. (2017). Is market fear persistent? A long Memory Analysis, Working Paper.

Creal, D., S.J. Koopman & A. Lucas. (2011). A dynamic Multivariate Heavy-Tailed Model for Time-Varying Volatilities and Correlations. Journal of Business and Economic Statistics, 29, 552–563.

Corsi Fulvio. (2009). A Simple Approximate Long-Memory Model of Realized Volatility. Journal of Financial Econometrics, 7(2), 174–196.

Dimitrios P. Louzis, Spyros Xanthopoulos-Sisinis & Apostolos P. Refenes. (2012). Stock index realized volatility forecasting in the presence of heterogeneous leverage effects and long-range dependence in the volatility of realized volatility. Applied Economics.

FAMA, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. Journal of Finance, 25(2), Papers and Proceedings of the Twenty-Eighth Annual Meeting of the American Finance Association New York, N.Y. December, 28-30, 1969, 383–417.

Feng Ma, Xinjie Lu, Ke Yang & Yaojie Zhang. (2019). Volatility forecasting: long memory, regime-switching, and heteroscedasticity. Applied Economics.

Fulvio Corsi, Stefan Mittnik, Christian Pigorsch & Uta Pigorsch. (2008). The Volatility of Realized Volatility. Econometric Reviews.

Granger, C. W. J., & Joyeux, R. (1980). An introduction to long-memory time series models and fractional differencing. Journal of Time Series Analysis, 1, 15–29.

Graves Timothy, Robert B. Gramacy, Nicholas W. Watkins‡ Christian L. E. Franzke. (2017). A brief history of long memory: Hurst, Mandelbrot, and the road to ARFIMA. Entropy, 437.

Hassler Uwe & Pohle Marc-Oliver. (2019). Forecasting under Long Memory and Non-stationarity. Cornell University.

Kasman, Adnan & Torun, Erdost. (2007). Long Memory in the Turkish Stock Market Return and Volatility. Central Bank Review, Central Bank of the Republic of Turkey.

Kumar, Anoop S. (2014). Testing Long Memory in Volatility in the Indian Foreign Exchange Market. Economic Analysis, LIX(203).

Lamouchi, Rim Ammar. (2020). Long Memory and Stock Market Efficiency: Case of Saudi Arabia. International Journal of Economics and Financial Issues, 10(3), 29–34.

Limam, I. (2003). Is long memory property of thin stock markets? International evidence using Arab countries. Review of Middle East Economics and Finance, 1(3), 251–266.

Madouri Hadda & Mkidiche Mohamed. (2017). A Comparative Study of ARFIMA and Artificial Neural Networks to Forecast Exchange Rate of Dinar. Algerian Journal of Economic and Financial Research.

Malkiel, Burton G. (2003). The Efficient Market Hypothesis and Its Critics.

Marinko Škare & Saša Stjepanović. (2013). A Fractionally Integrated Model for the Croatian Aggregate Output (GDP) Series. Economic Research-Ekonomska Istraživanja, 26(2).

Malkiel, Burton G. (2003). The Efficient Market Hypothesis and Its Critics.

Marwan Izzeldin, M. Kabir Hassan, Vasileios Pappas & Mike Tsionas. (2019). Forecasting realized volatility using ARFIMA and HAR models, Quantitative Finance, 19(10).

Mensi Walid, Shawkat Hammaoudah & Seong Min Yoon. (2014). Structural breaks and long memory in modeling and forecasting volatility of foreign exchange markets of oil exporters: The importance of scheduled and unscheduled news announcements, 30, 101–119.

Mohamed El Hedi Arouri, Shawkat Hammoudeh, Amine Lahiani & Duc Khuong Nguyen. (2013). Long memory, and structural breaks in modeling the return and volatility dynamics of precious metals.

Muhammad Mahboob Ali, Aviral Kumar Tiwari & Naveed Raza. (2017). Impact of return on long-memory data set of the volatility of Dhaka Stock Exchange market with the role of financial institutions: an empirical analysis. Banks and Bank Systems.

Onour Ibrahim. (2010). North Africa Stock Markets: Analysis of Unit Root and Long Memory Process API/WPS 0906.

Opschoora Anne & Andr´e Lucasa. (2017). Fractional Integration and Fat Tails for Realized Covariance Kernels and Returns.

Sahed Abdulghadir & Mkidiche Mohammad. (2014. Use of Long Memory for forecasting Oil Prices. Journal of Economic and Financial Research.

Tayefi Maryam & Ramanathan T. V. (2012). An Overview of FIGARCH and Related Time Series Models. Austrian Journal of Statistics, 41(3), 175–196.

Teyssiere G. (2000). Long-Memory Analysis. In: XploRe® — Application Guide. Springer, Berlin, Heidelberg.

ANNEX

Null Hypothesis: R is a martingale				
Date: 01/11/21 Time: 16:56				
Sample: 1 7282				
Included observations: 7180 (after adjustments)				
Heteroskedasticity robust standard error estimates				
User-specified lags: 2 4 8 16				
Joint Tests		Value	Df	Probability
Max |z| (at period 2)*		13.32935	7180	0.00
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.56166	0.032885	-13.3294	0.00
4	0.263749	0.05848	-12.5897	0.00
8	0.134912	0.086637	-9.98523	0.00
16	0.06676	0.119882	-7.78468	0.00

Null Hypothesis: RV is a martingale				
Date: 01/11/21 Time: 17:00				
Sample: 1 7282				
Included observations: 7180 (after adjustments)				
Heteroskedasticity robust standard error estimates				
User-specified lags: 2 4 8 16				
Joint Tests		Value	Df	Probability
Max |z| (at period 4)*		9.718701	7180	0.00000
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.971443	0.019899	-1.43509	0.15130
4	0.550888	0.046211	-9.7187	0.00000
8	0.306883	0.075476	-9.18321	0.00000
16	0.177995	0.110084	-7.46709	0.00000