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Long-Memory Models in Testing the Efficiency Market Hypothesis of the Algerian Exchange Market

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Abstract: The purpose of this study is to examine the Efficiency Market Hypothesis (EMH) from the perspective of the Algerian exchange rate market. We apply different tests of dependence, long memory, volatility clustering and unit root tests over the three main Algerian exchange rate returns series vis–à-vis the US Dollar, the Euro, and the British Pound. Empirical findings suggest that combined Autoregressive Moving Average (ARMA)-Fractionally Integrated Generalized Autoregressive Conditional Heteroskedastic (FIGARCH) models were the most appropriate to represent the behavior of exchange rate returns. We also compare the predictive qualities of the estimated models and the Random Walk (RW) in terms of out-of-sample forecasting. The results are held to imply the rejection of the EMH in the Algerian exchange rate market. Therefore, the exchange rates fluctuations can be predicted, which may help public authorities intervene in the exchange market and assess the consequences of different economic policies.

Keywords: Algerian exchange rate market; EMH, random walk; ARMA-FIGARCH; out-of-sample forecasting.

Introduction

Exchange rates have required special attention from the monetary authorities of governments, given their critical role in macroeconomic stability and international trade. One of the most important aspects is whether these monetary authorities can influence exchange rates' time path, especially under floating regimes. Such influence can only be noticed if these exchange rates are forecastable, which is in total contradiction with the EMH of the foreign exchange market. Originally developed by Fama (1965) and deepened by Jensen (1978), this hypothesis suggests that new information received in a market reaches all investors simultaneously, and therefore asset prices cannot be estimated based on historical prices.

The question of the foreign exchange market's efficiency or inefficiency has enormous economic implications. On the one hand, the weak form of the EMH, in the sense of Jenson (1987), excludes the possibility of gaining systematic exceptional profits beyond transaction costs and risk premiums, because prices are supposed to reflect all the information available in the market (historical prices for the weak form). Hence, the exchange market requires minimal government intervention. On the other hand, if a foreign exchange market is inefficient, one can develop a model that can predict future fluctuations in exchange rates. Therefore, public authorities can determine the best way to influence exchange rates, reduce their volatility, and assess the consequences of different economic policies (Cheung, 1993). Following the weak form of the EMH, the prices observed in a market follow a RW, since the steps of a random walk are unpredictable (Fama, 1965).

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The Random Walk Hypothesis (RWH) associates steps with returns (*logarithmic variations of prices*), so that returns cannot be predicted from past values. And when RWH is true, both the latest and past returns are irrelevant if we attempt to predict future returns using linear predictors (Hakkio, 1986). However, the presence of a short or long memory (*dependency*) in these exchange returns shed doubts on this weak form of EMH. Such dependence behavior would imply high predictability of these returns which can be used to generate substantial profits. In the same vein, Tan et al. (2020) pointed out that the existence of long memory in the return series implies potential predictability to returns, which contradicts the EMH.

The issue of exchange rates predictability initiated by Meese and Rogoff (1983) continues to fuel a controversial debate between academics and practitioners regarding the EMH puzzle in the foreign exchange market. This hypothesis is traditionally tested by regressing forward and spot exchange rates. Nevertheless, it remains poorly addressed in the context of developing countries where the forward exchange market is either underdeveloped or inexistent (Canales-Kriljenko, 2002).

Given the recurring failures of fundamentalist models of exchange rates in beating the naive forecasts of exchange rates and their returns (Rossi, 2013), associated with the development of econometrics models, the interest has shifted towards non-fundamentalist models of exchange rates. With this respect, this paper addresses whether the EMH holds in the Algerian exchange market. Thus, we develop the following hypothesis:

The Exchange control measures implemented by most developing countries, as well as the various often-direct interventions of central banks, produce rather abrupt movements in the series of exchange rates, which would cause high volatility in exchange rate returns.

This paper intends to investigate the dynamic of daily Algerian exchange rates returns vis-à-vis of three hegemonic currencies in the exchange market (see Bank of International Settlements triennial report) namely the US Dollar, Euro, and the British pound over the period from 05-04-1999 to 02-04-2019. The main interest of this research is to test the EMH in the Algerian foreign exchange market using short/long memory models for the conditional mean of the series (ARMA/Autoregressive Fractionally Integrated Moving Average ARFIMA), volatility clustering models, and Generalized Autoregressive Conditional Heteroskedasticity (GARCH)/FIGARCH for the conditional variance. We compare the predictive power of our estimated combined models with those of the random walk.

The remainder of this paper is structured as follows: in section 2, we present a brief literature review dealing with the EMH in the exchange market and exchange rates predictability. Section 3 displays the long and short-memory models and the volatility clustering models used to capture the dynamics of the exchange rates returns. Data, variables, and research methodology are presented in section 4. We discuss the empirical results in section 5. Finally, section 6 concludes.

Literature review

Notwithstanding a large number of studies published over the last decades, the efficiency of foreign exchange markets remains unsettled. There are two-fold econometric approaches to test the efficiency of foreign exchange markets in the literature. The first one is a time series analysis of the parity of exchange rates in models that include market

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variables like spot and forward exchange rates. The second approach includes time series examinations like unit root tests, co-integration, ARIMA and GARCH processes.

It is now widely accepted that financial indices series such as exchange rates contain a unit root which indicates that any subsequent shock will have a permanent consequence over the time patch of the series (infinite memory). The unit root test is a common procedure to determine whether a financial variable follows a random walk. The null hypothesis implies that if the existence of a unit root for a particular series cannot be rejected, then the series meets the first criterion of the RWH (Azad, 2009). Nonetheless, unit root tests have very low power (Parikh & Wakerly, 2000), and are unable to distinguish between random walk behavior and very slow mean-reverting behavior (Booth et al., 1982; Lee & Chou, 2013; Lothian & Taylor, 1998; Varneskov & Perron, 2017). Therefore, the fractional approach enables us to extend the narrow definition of stationarity via long-memory and mean-reverting properties in time series, although the evidence of fractional differentiation is infrequent in the case of developing countries as mentioned by Gil-Alana and Sauci (2018).

On the other hand, the distinction between stationarity and unit root processes seems to be too restrictive. Indeed, the propagation of shocks in a stationary process occurs at an exponential rate of decay[1](only captures the short memory), while for a unit root process, the persistence of shocks is infinite (Floros, 2008). With this regard, ARFIMA models has have gained great interest for applications, given their ability to model short and long-term behaviors (defined as autocorrelations with long delays) of time series, which make them suitable to identify the long-term dynamic. In fact, the series resulting from a highly dependent process contain relevant information allowing to predict the evolution of future observations (Cheung, 1993; Liu & Lux, 2005).

Another stylized fact characterizing the series of exchange rate returns deals with the variability over time of the variance, therefore, a possible presence of an ARCH effect or volatility clustering where periods of low and high volatility mingle (Gao et al., 2020; Lillo & Farmer, 2004; Morana & Beltratti, 2004). Afzal and Sibbertsen (2022) argued that the exchange rate volatility may be a result of regional and international shocks effects on developing countries and it can be modeled as a long memory process.

The ARCH model introduced by Engle (1982), followed by a generalized version (GARCH model) introduced by Bollerslev (1986), paved the way for modeling and forecasting the volatility of exchange rate returns (Bollerslev et al., 1991). Another property of a double long memory in the exchange rate returns over the conditional mean and variance is perceived in the exchange rate returns series, where the ARFIMA model is most suitable to capture the long memory. Since the GARCH model does not account for long memory in volatility, FIGARCH is suitable for modeling long memory. Also, the presence of long memory in conditional variance implies that perfect arbitrage is not possible as indicated by Tripathy (2022).

To take into consideration, the different features of exchange rate returns (the double long memory and volatility clustering), many studies tested the EMH of the foreign exchange market through a combined ARFIMA-FIGARCH model in developed and emerging countries (Barkoulas et al., 2016; Beine & Laurent, 2003; Caporale & Gil-Alana, 2010, 2013; Floros, 2008; Kumar, 2014; Mensi et al., 2014; Ohanissian et al., 2008; Tschernig, 1994; Turkyilmaz & Balibey, 2014). However, the context of developing countries remains understudied.

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[1]At the empirical level, the modeling by ARFIMA processes introduced by the economist Granger in 1980 which was followed by Granger and Joyeux in 1980 and the hydrologist Hosking in 1981, provides a direct and practical framework for studying the behavior of the short and the long-term memory as pointed out by Graves et al. (2017).

Theoretical background

Dependence Models ARMA/ARFIMA

In the conditional mean, the ARFIMA specification has been proposed to fill the gap between short and complete shock persistence, so that the short-run behavior of the time series is captured by the ARMA parameters, while the fractional differencing parameter allows for modeling the long-run dependence. The basic ARMA(p,q) model is written as:

$$y_t = \phi_1 y_t + \cdots + \phi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}, t = 1, \dots, T \quad (1)$$

Assuming either$\varepsilon_t \sim NID(0, \sigma_\varepsilon^2$, or $E[\varepsilon_t] = 0$ and $E[\varepsilon_t^2] = \sigma_\varepsilon^2$ Using lag polynomials and introducing a mean μ, we write:

$$\Phi(L)(y_t - \mu) = \Theta(L)\varepsilon_t$$

With a fractional integration parameter d, the ARFIMA(p,d,q) model is written as:

$$\Phi(L)(1 - L)^d (y_t - \mu) = \Theta(L)\varepsilon_t \quad (2)$$

Where d is the fractional differentiation parameter.$d\epsilon R$, $(1 - L)^d$ is an operator of fractional differences, and $\{y_t\}_{t=1}^T$ is a set of observations of the process studied (in our case the exchange rates return).

Volatility Clustering Models GARCH/FIGARCH

GARCH Model

By allowing past conditional variances to appear in the conditional equation of the current variance, the conditional variance becomes:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_Q \varepsilon_{t-Q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_P \sigma_{t-P}^2$$
$$\sigma_t^2 = \omega + \sum_{i=1}^{Q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{P} \beta_j \sigma_{t-j}^2$$

Using lag polynomials, we get:
$$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2 \quad (3)$$
With: $\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \cdots + \alpha_Q L^Q et \beta(L) = \beta_1 L + \beta_2 L^2 + \cdots + \beta_P L^P$

This model is called generalized ARCH *(P,Q*) or GARCH *(P,Q),*where P represents the order of the GARCH part (σ^2) and Q represents the order of the ARCH part (ε^2). Some restrictions are necessary to ensure that σ_t^2 is positive for all t. Engel and Kroner (1995) suggest that the application of $\omega > 0, \alpha_i \geq 0$, $(for\ i = 1, \dots, q)$ and $\beta_i \geq 0$ $(for\ j = 1, \dots, p)$ is a sufficient condition for the conditional variance to be positive.

FIGARCH Model

To mimic the presence of apparent long-memory in the autocorrelations of squared or absolute returns of various financial asset prices Baillie and al. (1996) introduced the Fractionally Integrated GARCH (FIGARCH) model by replacing the first difference operator of Equation (3). The conditional variance of the FIGARCH (p,d',q) is given by:

$$\sigma_t^2(\omega, \beta, \Phi, d') = \omega + \{1 - [1 - \beta(L)]^{-1} \Phi(L)(1 - L)^{d'}\}\varepsilon_t^2 \quad (4)$$

Chung (1999) emphasizes that there is a problem in Baillie, Bollerslev, Mikkelsen BBM model specification (1996) since the parallel with the ARFIMA framework of the conditional mean equation is not perfect, leading to misinterpretations of the estimated

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parameters. Indeed, the fractional differencing operator applies to the constant term in the mean equation (ARFIMA) while it does not apply in the variance equation (FIGARCH), and the author proposes a slightly different process:

$$\Phi(L)(1-L)^{d'}(\varepsilon_t^2-\sigma^2)=[1-\beta(L)](\varepsilon_t^2-\sigma_t^2) \tag{5}$$

Where σ^2 is the unconditional variance of ε_t .

The Combined Model ARFIMA-GARCH / FIGARCH

To capture the dependence behavior and the ARCH effect, we use the following combined model:

$$\Phi(L)(1-L)^d(y_t-\mu-b'x_{1t}-\delta\sigma_t)=\Theta(L)\varepsilon_t$$
$$\beta(L)\sigma_t^2=\omega+\alpha(L)\varepsilon_t^2+\gamma' x_{2t} \ / \ \ \beta(L)\sigma_t^2=\omega+\alpha(1-L)^{d'}\varepsilon_t^2+\gamma' x_{2t} \tag{6}$$

Where $x_1$andx_2 are predetermined variable vectors, and all the roots of $\Phi(L), \Theta(L), \beta\ (L)$and $\alpha\ (L)$ lie outside the zero circle.
With $\delta \neq 0$ the model makes it possible to integrate volatility in order to influence the mean.

Data, variables and research methodology

Data and variables

Data on exchange rates were collected from Thomson-Reuters via the DataStream Database. The study period ranges from 02/04/1999 to 02/04/2019 over a five-day week excluding weekends (5217 observations), covering a recent period which was characterized by a set of economic reforms and exchange rate devaluation policies. The graphs and the stationarity test of the observed exchange rate series suggest that the series are non-stationary (see Fig.1. in Annex 1). Therefore, we conduct our analysis based on the three exchange rate returns, formulated as follows:

$$RDZDXXX_t=100*[\log DZDXXX_t-\log DZDXXX_{t-1}], t=1,\dots,n$$

Where $RDZDXXX_t$ represents the exchange rate returns, $DZDXXX$ stands for spot exchange rates, XXX represents US dollar (USD), Euro (EUR) and the British Pound (GBP) respectively (see Fig.1. in Annex 1).

Research analysis

We apply the tests of stationarity, volatility clustering, auto-correlation and long memory over the series of exchange rates returns:

- ADF and KPSS tests (the stationarity)[2].
- ARCH-LM and the Ljung-Box test (Q^2-statistics) on squared series (volatility clustering).
- The Ljung-Box test (Q-statistics) on the series for autocorrelation.
- The R / S statistics of Hurst-Mandelbrot and the statistic of Lo, as well as the GPH test for the detection of the long memory.

To test the EMH in the Algerian exchange market we proceed as follows:

[2]Given that, the ADF and the KPSS tests have a contradictory nulls hypothesis. The possible rejection of the two tests suggests a possible presence of long memory.

Step 1: Estimation of a combined ARMA/ARFIMA – GARCH/FIGARCH models with different distribution for the residual (Normal, GED, Student and Skewed Student) due to the exhibited fat tails in the series displayed by the Density Function graphs.

Step 2: Conducting misspecification tests to ensure that the developed models capture the dynamics of exchange rate returns for both the first moment (Mean) and the second moment (Variance). So, we make sure there is no remaining information in the standardized residuals. These tests consist of Box Pierce on the standardized and squared standardized residuals (Q) and (Q^2), ARCH LM, Distributional Parameters: SK, KU and Jarque Berra. The information Criteria that should be minimized: Ackaike (AIC), Shwartz SIC, Hannan Quin, H/Q and Shibata S. (It is worth mentioning that SIC criteria favored parsimonious models). These information criteria complement the evaluation provided by the likelihood ratio. We also apply the test of Pearson CHI^2 (goodness of fit) to choose the corresponding distribution[3] and the Nyblom test to assess the constancy of the estimated parameters over time.

Step 3: The choice of the appropriate model amongst those that could capture the dynamic of exchange rate returns can be done either by minimizing information criteria or the log-likelihood parameter. As this study does not aim at modeling the exchange rate behavior, but rather tests whether the EMH holds in the Algerian exchange rate market. We will select the model that satisfies the Nyblom test which makes sure that estimated parameters are stable providing a *good forecast*.

Step 4: In line with many authors, we compare the predictive quality of the selected models (in terms of out of sample forecasting) with the predictive quality of a simple random walk process in which the first difference is independent within noise process D(RDZDXXX) = C(1). Thus, we use two major forecast error measures: Root Mean Square Error (RMSE) and Mean Square Error (MAE)[4].

Empirical results

Results about stationarity, volatility clustering, auto-correlation and long memory confirm that RDZDUSD, RDZDEUR, RDZDGBP series exhibit an ARCH-type effects (see the ARCH LM tests and the Q-Statistics on squared data in Table 5. Annex 1). Looking at the Q-Statistics on raw data, we conclude that an ARMA-type model seems justified. Moreover, following the results of the Hurst-Mandelbrot and Lo long-term dependence tests, we can exclude the presence of a long memory in the three exchange returns series. Finally, KPSS, ADF Statistics and the graphical visualization indicate that the series is likely to be I(0) (see Table 5 in Annex 1).

Table 1 presents the selected models according to the procedure explained supra. The results suggest that the model ARMA (*2,3*)-FIGARCH (*1,0.5,1*) manages to capture the dynamic of the DZDEUR returns. In fact, the estimated model satisfies all the Adequacy tests. The selected model is the one that minimizes the four information criteria (for the sake of brevity we report only SIC criteria). We notice that the SK parameter is not significantly different from zero confirming the result of the goodness of fit test concerning the choice of Student distribution for the standardized residuals (See Kernel Density.Fig.2. in Annex 2).

[3] For the goodness of fit test, the choice of g is far from being obvious. For T = 4221, B (Beine & Laurent, 2003) set g equal to 70. Given that the number of cells must increase at a rate equal to $T^{0.4}$, we use g = 70 for sample size of 5217. Actually, the asymptotic distribution of P(g) is bounded between a Chi^2 (g-1) and a Chi^2 (g - k -1) where k is the number of parameters. Since our conclusions hold for both critical values, we report the significance levels relative to the first one.

[4]The RMSE is the main criterion to compare the forecast accuracy, but the use of the MAE is more appropriate when exchange rates return follow a non-normal stable process with infinite variance or when the data distribution exhibits fat tails with finite variance (Grandolfo et al., 1990). Accordingly, we adopt the two criteria in this analysis.

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Table 1. Estimated model for the DZDEUR returns

ARMA(2,3)-FIGARCH(1,d'1) Specification			Tests on standardized errors "Adequacy"		Tests on standardized errors "Choice"	
Parameters	**Coef.**	**[P-value] (std.-E)**	**Parameters**	**Coef. [P-value]**	**Parameters**	**Coef. [P-value]**
Cst(M)	0.009622	[0.07]* (0.005)	Q(10)	8.93237 [0.11]**	SK	0.013729 [0.69]
AR(1)	-1.561036	[0.00]** (0.014)	Q(20)	14.6971 [0.47]**	KU	2.4433 [0.00]**
AR(2)	-0.951935	[0.00]** (0.0175)	Q(50)	33.083 [0.90]**	Shwartz	1.899031
MA(1)	1.33023	[0.00]** (0.0214)	Q(80)	59.0056 [0.91]**	Individual nyblom statistics	
MA(2)	0.586961	[0.00]** (0.0317)	$Q^2(10)$	13.9854 [0.08]**	Cst(M)	0.11161
MA(3)	-0.223134	[0.00]** (0.0154)	$Q^2(20)$	23.4824 [0.17]**	AR(1)	0.21227
Cst- Variance	1.270345	[0.05]** (0.6735)	$Q^2(50)$	50.8112 [0.36]**	AR(2)	0.09364
d'-FIGARCH	0.501866	[0.00]** (0.0569)	$Q^2(80)$	79.5010 [0.43]**	MA(1)	0.27847
ARCH(Φ1)	0.411720	[0.00]** (0.0678)	ARCH 1-5	2.1149 [0.06]**	MA(2)	0.08914
GARCH(β1)	0.714462	[0.00]** (0.0681)	ARCH 1-10	1.3516 [0.19]**	MA(3)	0.25731
Student(DF)*	4.945452	[0.00]** (0.3307)	ARCH 1-20	1.1708 [0.26]**	Cst-Variance	0.38227
Log-likelihood	-4735.82	-	P(60)	67.2168 [0.21]**	d'-FIGARCH	0.24315
Mean (RDZDEUR)	0.01299	-	P(70)	71.9994 [0.37]**	ARCH(Φ1)	0.26837
Variance (RDZDEUR)	0.58282	-	P(80)	94.6736 [0.11]**	GARCH(β1) Student (DF)	0.20679 0.36719

Note: - Student distribution, with 4.94545 degrees of freedom. FIGARCH (1,d',1) model was estimated with Chung's method. The models are estimated using a maximum likelihood (ML) approach. A quasi-Newton method of Broyden, Fletcher, Goldfarb and Shanno (BFGS).
Joint Statistic of the Nyblom test of stability: 4.22528 and Asymptotic 5% critical value for individual statistics = 0.47. The sample mean of squared residuals was used to start recursion. The symbols (***), (**) and (*) correspond to the significance of the parameters at 1%, 5% and 10% levels respectively if (p-value <0.01; 0.05.0.1), and the non-rejection of H0 for the tests. The estimation period is 04/05/199 to 07/24/2018.

Source: authors' calculations

Turning to the estimated model for the DZDUSD returns. Table 2 shows that the ARMA (*2,3*)-FIGARCH (*0,0.29,1*) is more likely to capture the dynamic of the series. In fact, the estimated model does not satisfy all adequacy tests (Q(20), Q(50) and the goodness of fit test). The SK, KU and a statistically significant Jarque-Bera statistic of 1513.9 (not reported in Table 2) clearly rejects the normality assumption for the unconditional distribution. Indeed, SK and KU are significantly different from those of the normal distribution. Yet, we are aware of the inappropriate choice of distribution (see Fig.3. in Annex 2). However, we have obtained less satisfying results with Student, Skewed Student and G.E.D distributions. Accordingly, we accept this specification as it was the only one that satisfies the most considered criteria in this study (Nyblom test).

Table 2. Estimated model for the DZDUSD returns

ARMA (2,3) - FIGARCH (0, d', 1) Specification			**Tests on standardized Errors "adequacy"**		**Tests on standardized errors "Choice"**	
Parameters	**Coef.**	**[P-value] (std. error)**	**Parameters**	**Coef. [P-value]**	**Parameters**	**Coef. [P-value]**
Cst(M)	0.008594	[0.03]** (0.0041)	Q(10)	9.6774 [0.08]**	SK	0.61432 [0.00]**
AR(1)	-1.63705	[0.00]** (0.1120)	Q(20)	27.664 [0.02]***	KU	8.4039 [0.00]**
AR(2)	-0.84517	[0.00]** (0.085149)	Q(50)	62.696 [0.04]***	Shwarz	1.141007
MA(1)	1.405707	[0.00]** (0.1132)	Q(80)	94.973 [0.05] **	Individual nyblom statistics	
MA(2)	0.443367	[0.00]** (0.0801)	$Q^2(10)$	5.3916 [0.79]**	Cst(M)	0.39793
MA(3)	-0.20715	[0.00]** (0.0246)	$Q^2(20)$	12.218 [0.87]**	AR(1)	0.08294
Cst-Variance	0.020135	[0.05]** (0.0059)	$Q^2(50)$	47.153 [0.54]**	AR(2)	0.12447
d'-FIGARCH	0.292733	[0.00]** (0.0234)	$Q^2(80)$	57.360 [0.96]**	AR(1)	0.08294
ARCH(Φ1)	-0.13444	[0.00]** (0.0308)	ARCH 1-5	0.6823 [0.63]**	AR(2)	0.12447
Log-likelihood	-2835.26	-	ARCH 1-10	0.5288 [0.87]**	MA(1)	0.10395
Mean (RDZDUSD)	0.01138	-	ARCH 1-20	0.5125 [0.96]**	MA(2)	0.16939
Variance (RDZDUS)	0.30344	-	P(60)	969.53 [0.00]	MA(3)	0.07417
-			P(70)	999.27 [0.00]	Cst-Variance	0.15996
-			P(80)	1007.6 [0.00]	d'-FIGARCH ARCH(Φ1)	0.47002 0.29466

Note: Joint Statistic of the Nyblom test of stability: 4.22528 and Asymptotic 5% critical value for individual statistics = 0.47. The sample mean of squared residuals was used to start recursion. The symbols (***), (**) and (*) correspond to the significance of the parameters at 1%, 5% and 10% levels respectively if (p-value <0.01; 0.05.0.1), and the non-rejection of H0 for the tests. FIGARCH (0, d',1) model was estimated with BBM's method with 1000 truncation. The models are estimated using a maximum likelihood (ML) approach. A quasi-Newton method of Broyden, Fletcher, Goldfarb and Shanno (BFGS). The estimation period is 04/05/1999 to 07/24/2018.

Source: authors' calculations

Finally, Table 3 exhibits the estimated model for the DZDGBP returns**.** The results suggest that the ARMA (2,3)-FIGARCH (1,0.39,1) model manages to capture the dynamic of the DZDGBP returns. In fact, the estimated model satisfies all adequacy tests. The selected model is the one that minimizes the four information criteria. We notice that the SK parameter is not significantly different from zero confirming the result of the goodness of fit test about the choice of G.E.D distribution for the standardized residuals (See Kernel Density Fig.4 in Annex 2).

Table 3. Estimated model for the DZDGBP returns

ARMA(2,3)-FIGARCH(1,d',1) specification			Tests on standardized errors " adequacy"		Tests on standardized errors "choice"	
Parameters	**Coef.**	**[P-value] (std-error)**	**Parameters**	**Coef. [P-value]**	**Parameters**	**Coef. [P-value]**
Cst(M)	0.012962	[0.01]** (0.00550)	Q(10)	10.9494 [0.05]***	SK	0.00250 [0.94]
AR(1)	-1.629221	[0.00]** (0.01482)	Q(20)	20.1812 [0.16]**	KU	2.4076 [0.00]**
AR(2)	-0.659010	[0.00]** (0.02374)	Q(50)	53.4506 [0.18]**	Shwarz	1.894249
MA(1)	1.517904	[0.00]** (0.02202)	Q(80)	89.8583 [0.11]**	Individual nyblom statistics	
MA(2)	0.444386	[0.00]** (0.03737)	$Q^2(10)$	6.46593 [0.59]**	Cst(M)	0.05246
MA(3)	-0.108018	[0.00]** (0.01309)	$Q^2(20)$	11.7220 [0.86]**	AR(1)	0.11959
Cst-Variance	0.015510	[0.00]** (0.00548)	$Q^2(50)$	34.7288 [092]**	AR(2)	0.15259
d'-FIGARCH	0.393823	[0.00]** (0.07457)	$Q^2(80)$	61.5929 [0.91]**	MA(1)	0.10406
ARCH(Φ1)	0.268670	[0.00]** (0.05476)	ARCH 1-5	0.78778 [0.55]**	MA(2)	0.13847
GARCH(β1)	0.570410	[0.00]** (0.07350)	ARCH 1-10	0.64782 [0.77]**	MA(3)	0.11532
G.E.D (DF)	1.285643	[0.00]** (0.04451)	ARCH 1-20	0.58757 [0.92]**	Cst-Variance	0.21811
Log-likelihood	-4723.78	-	P(60)	60.4032 [0.42]**	D'-FIGARCH	0.40406
Mean (RDZDGBP)	0.00744	-	P(70)	63.5777 [0.66]**	ARCH(Φ1)	0.18950
Variance (RDZDGBP)	0.51780	-	P(80)	74.3758 [0.62]**	GARCH(β1) G.E.D(DF)	0.28511 0.25816

Note: Joint Statistic of the Nyblom test of stability: 4.22528 and Asymptotic 5% critical value for individual statistics = 0.47. The sample mean of squared residuals was used to start recursion. The symbols (***), (**) and (*) correspond to the significance of the parameters at 1%, 5% and 10% levels respectively if (p-value <0.01; 0.05.0.1), and the non-rejection of H0 for the tests. FIGARCH (0, d',1) model was estimated with BBM's method with 1000 truncation. The models are estimated using a maximum likelihood (ML) approach. A quasi-Newton method of Broyden, Fletcher, Goldfarb and Shanno (BFGS). The estimation period is: 04/05/199 to 07/24/2018.

Source: authors' calculations

Given that all the three selected models' parameters satisfy completely the Nyblom test (<0.47 at 5 % level), ensuring the stability of those parameters over time. Accordingly, from these estimated models we can generate out of sample forecasts for the period 07/25/2018 to 04/02/2019 (it is worth remembering that the estimation period is 04/05/1999 to 07/24/2018) over different time horizons: short, medium, and long term). We have retained for this purpose the periods of 5, 30, 90, 180 days (D) to represent the three terms. Then, we compare their predictive qualities using two error measures: the RMSE and the MAE with those resulting from a simple random walk process.

According to the two criteria RMSE and MAE, the results of the out of sample forecasting show that the naive forecast based on the random walk does not beat the ARMA models for the three series of exchange rate returns and for the three-time horizons: short 5 days, medium 30-90 days, and the long run 180 days. Note that there is no conflicting result between the two criteria, thus, the latter result is often held to imply a rejection of the EMH in the Algerian exchange rate market for all terms.

We also notice that the exchange rate returns RDZDEUR barely beat the naïve forecast for the three-time horizons, which might be puzzling if we consider that, the only convertible currency in Algeria is the Euro (see Fig.2. Fig.3. and Fig.4. in Annex 2 for the Conditional Mean and the Conditional Variance Plot Forecast).

Table 4. Forecast Error measures: Estimated Models (ES) Vs Random Walk (RW)

	Horizon	ES Model 5 D	RW Model 5 D	ES Model 30 D	RW Model 30D	ES Model 90 D	RW Model 90 D	ES Model 180 D	RW Model 180 D
RDZDGBP	MAE	0.1098	0.2160	0.2447	0.3381	0.3159	0.3718	0.3554	0.4092
	RMSE	0.1359	0.2515	0.3439	0.4240	0.4402	0.4978	0.4792	0.5306
RDZDUSD	MAE	0.0743	0.4828	0.1434	0.4031	0.1314	0.3758	0.1229	0.3764
	RMSE	0.0840	0.5113	0.194	0.4769	0.1702	0.4544	0.163	0.4564
RDZDEUR	MAE	0.2782	0.2739	0.2532	0.2514	0.2502	0.2549	0.236	0.2427
	RMSE	0.3173	0.3219	0.3217	0.3267	0.3102	0.3181	0.301	0.3080

Source: authors' calculations

Conclusion

The present study explores the double-long memory of the Algerian exchange market over 20 years from April 1999 to April 2019 in line with the economic literature related to the exchange rate series. The study applied several tests of dependence: long memory, volatility clustering and stationarity, on the three Algerian exchange rate returns series vis–a-vis of the US Dollar, the Euro, and the British Pound, and thus to capture their statistical features. The estimated models were used to generate out-of-sample forecast within three time –horizons.

Using a maximum likelihood estimator, the Empirical findings suggest that a combined ARMA (2,3)-FIGARCH (*p,d,q*) models captured the dynamic of the three exchange rate returns series with(*p≤1)* and (*q=1)* and a fractionally integrated parameter equal or less than 0.5 (*d≤0.5)* indicating a long memory in the volatility. And due to the exhibited fat tails of the series, the models were estimated with a non-gaussian distribution for the standard residuals' series.

From the analysis, it can be seen that long memory prevails in volatility series, offering potential evidence against EMH and suggesting that the Algerian Exchange Market involves the influence of news and shocks from the recent past. Accordingly, past prices can be used to forecast future exchange rates returns. The forecast outcomes suggest that we systematically beat the naïve forecast of a random walk model for the short, medium and long term with some concerns regarding the exchange rate returns Euro-Algerian dinar.

In terms of policy implications, the inefficiency of the Algerian exchange market implies that monetary authorities can predict the future fluctuations of the exchange rates and determine the best way to influence their trajectory and reduce volatility. Indeed, accurate forecasting of exchange rates volatility is required for asset pricing, allocation policies and hedging to exposure transactions, which can be helpful for financial and managerial decision-makers in managing risks associated with their different financial investment strategies. Furthermore, the ability to forecast exchange rates allows public authorities to adjust and assess the impact of the implemented exchange rates policies (currency devaluation/revaluation or sterilization) on different macroeconomic aggregates.

It is worth mentioning that, even though, beating the Random walk can provide insights into issues of market efficiency, however, it is not sufficient to reject the weak form of the efficient market hypothesis. In fact, economists have not yet reached a consensus about whether there is an explicit link between the random walk hypothesis and the market efficiency for three main reasons (Azad, 2009): the first reason deals with the inability of prices to quickly adjust to the new information. Second, because of distortions between capital pricing and risk valuation as prices are not set at the equilibrium level. Third, the existence of a parallel market due to the exchange rate controls and the divergence between the exchange parallel rate and the official rate. Finally, the EMH in the exchange market may be rejected when monetary authorities set restrictions under some exchange rates regimes and do not permit foreign banks to freely access to foreign exchange markets and products.

According to Hakkio (1986), if the theories of interest rate parity, the Fisher relationship and rational expectation do not hold in the exchange rates market, we cannot conclude for the rejection of the EMH even if one finds that the exchange rates increment, and their returns do not follow a random walk. This represents a limitation of our findings. Hence, we suggest testing these aforementioned theories in future research.

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Appendices

Annex 1

Table 5. Volatility Clustering, Dependence, Long Memory and Unit root Tests

	ARCH-LM 1-10	Q(50)	$Q^2(50)$	R/S de Hurst-Mand	R/S de Lo	*D*(GPH)	Test KPSS	Test ADF
RDZ/ DUSD	115.09 [0.00]	462.6 [0.00]	2653. [0.00]	1.32957	1.5257	-0.146 [0.00]	I(0)	I(0)
RDZD/ EUR	81.810 [0.00]	449.1 [0.00]	2396. [0.00]	0.60986	0.70918	-0.141 [0.00]	I(0)	I(0)
RDZD/ GBP	55.498 [0.00]	223.0 [0.00]	1405.3 [0.00]	0.840975	0.90427	-0.109 [0.00]	I(0)	I(0)

Note:
H0: Hurst-Mandelbrot = no long-term serial correlation and H0: Lo = no long-term dependence, the critical values of the Lo and Hurst-Mandelbrot tests are: 90%; [0.861, 1.747] - 95%: [0.809, 1.862] - 99%: [0.721, 2.098]. We cannot reject null hypotheses if the calculated value is within the ranges. The null hypotheses. H0 of the Q-statistics for the series and the squared series is the absence of serial correlations. The null hypothesis of the ARCH LM test is the homoscedasticity of the series, and we cannot reject the H0 hypothesis if the p-values shown in square brackets are greater than 0.01 and 0.05 for both confidence levels. The values in square brackets of the GPH test represent the p-values concerning the statistical significance of the differentiation parameter d (p-value <0.05, the parameter is significant).

Source: authors' calculations

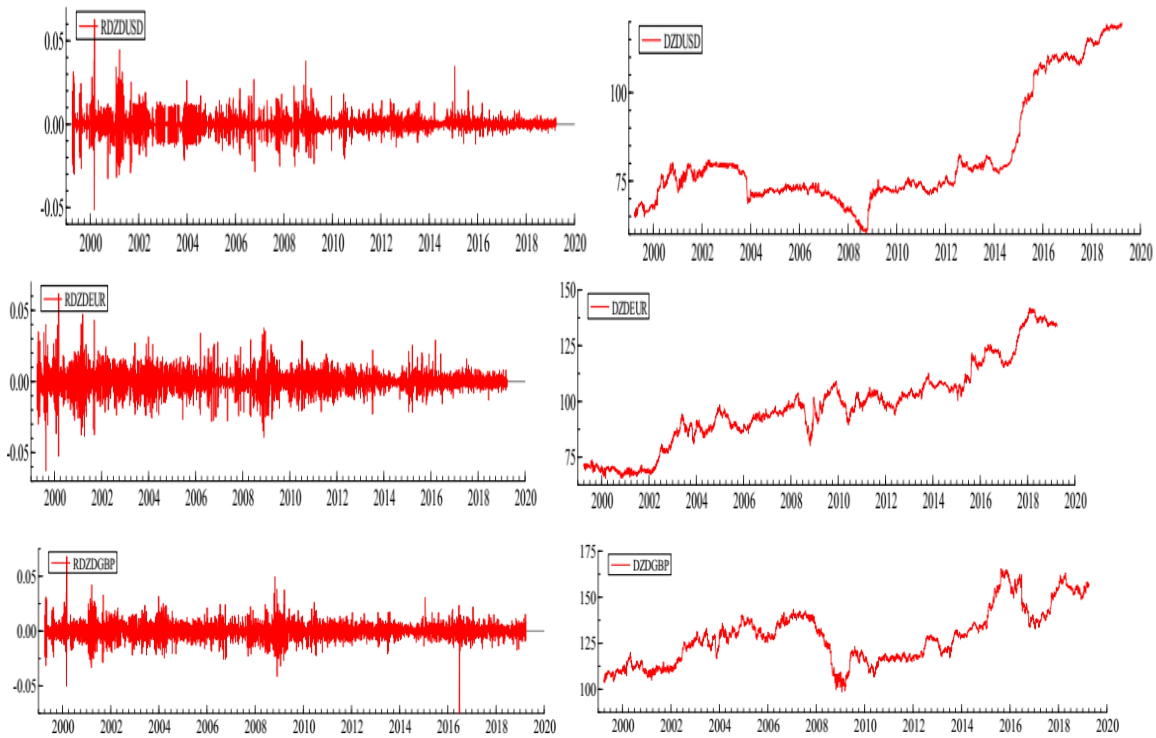

Figure 1. Evolution of Exchange rates and exchange rate returns
Source: authors' elaboration

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Annex 2

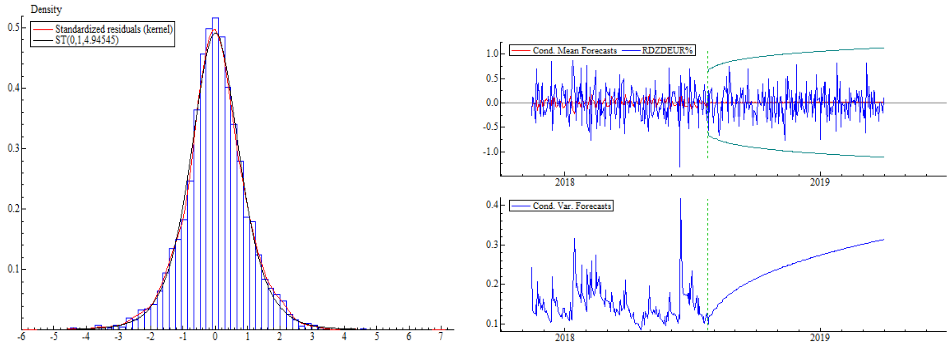

Figure 2. Standardized Residuals Density and Conditional Mean, Conditional Variance Forecasts of RDZDEUR
Source: authors' elaboration

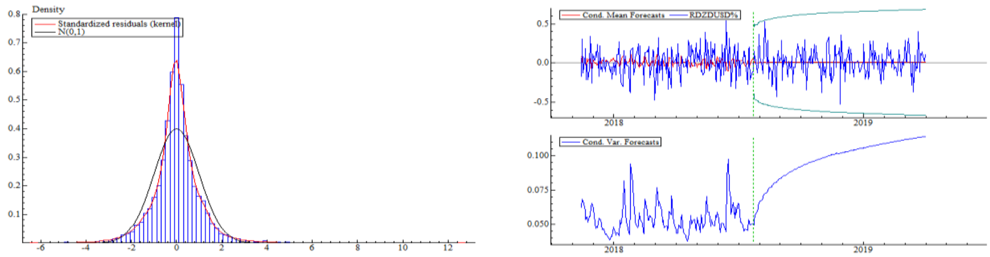

Figure 3. Standardized Residuals Density and Conditional Mean, Conditional Variance Forecasts of RDZDUSD
Source: authors' elaboration

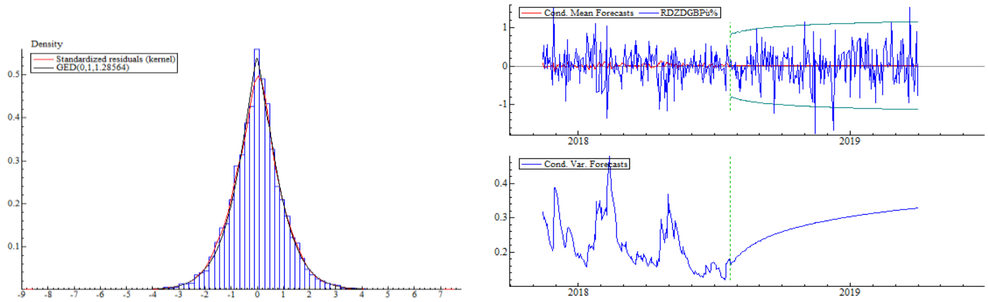

Figure 4. Standardized Residuals Density and Conditional Mean, Conditional Variance Forecasts of RDZDGBP
Source: authors' elaboration