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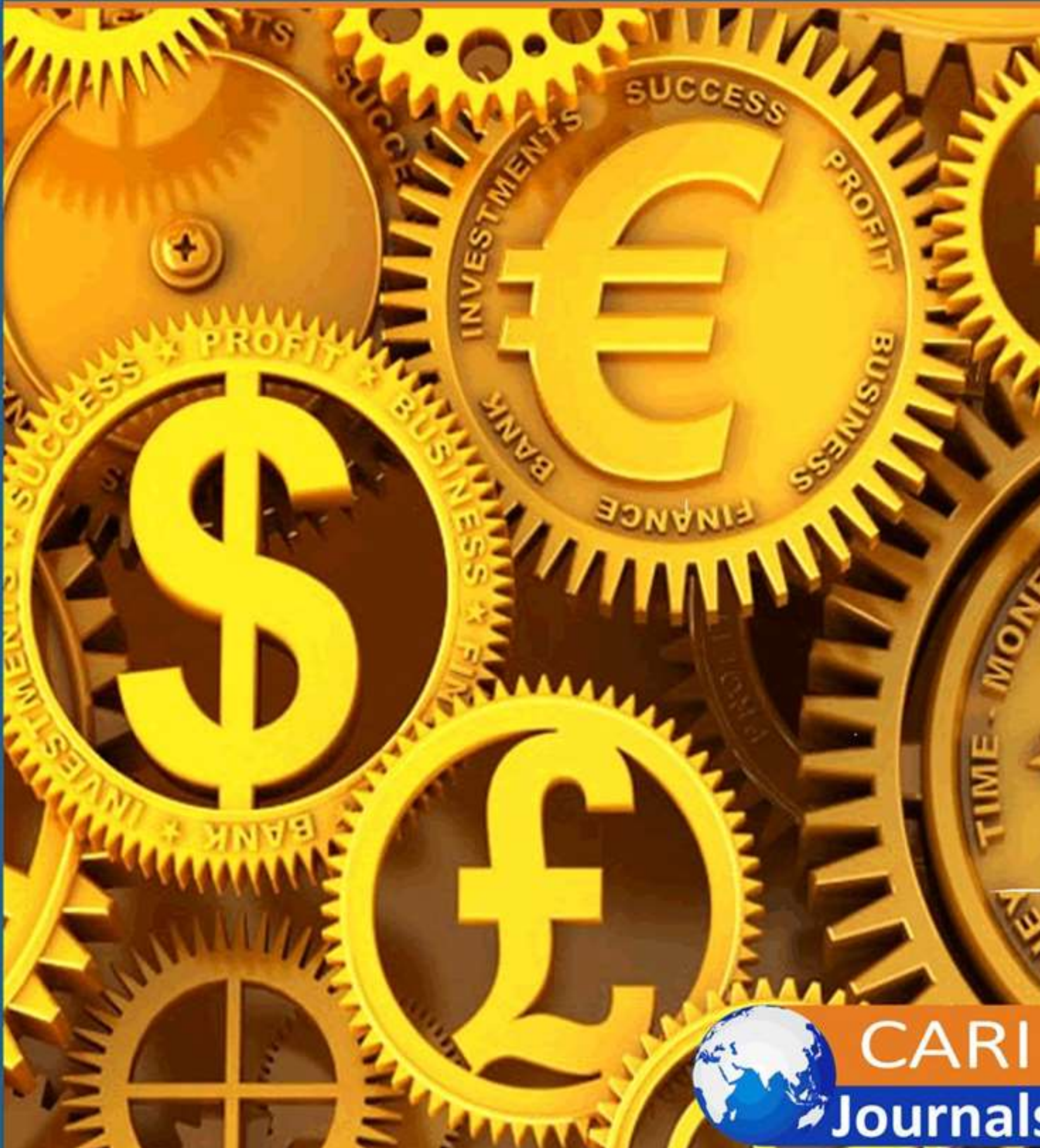

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Decoding Egypt's Exchange Rate Puzzle: Forecasting Official and Unofficial Market Trends with Advanced Models

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ABSTRACT

Purpose: This paper investigates, for the first time, the dynamics of Egypt's unofficial exchange rate alongside the official rate, a critical issue for investment decisions and macroeconomic stability. The study aims to model and compare the behavior, determinants, and volatility characteristics of both exchange rates.

Methodology: The study employs time series econometric techniques, including ARIMA, ARIMA-GARCH, ARIMAX, and ARIMAX-GARCH models. The Cairo Overnight Index Average (CONIA) and EGX 30 market returns are incorporated as exogenous variables. Volatility is modeled using several GARCH specifications (SGARCH, EGARCH, TGARCH, and GJR-GARCH) under alternative error distributions.

Findings: The results show that the official exchange rate is significantly influenced by EGX 30 returns, while its autoregressive and moving average components are insignificant. In contrast, the unofficial exchange rate exhibits strong autoregressive and moving average dynamics but is unaffected by the selected exogenous variables. Moreover, the unofficial exchange rate displays pronounced volatility clustering, best captured by an SGARCH model with a student's t-distribution.

Unique Contribution to Theory, Practice and Policy: This study fills a major gap in the exchange rate literature by explicitly modeling Egypt's unofficial exchange rate and its volatility. The findings provide investors and policymakers with a robust framework for understanding exchange rate risk in dual-market environments. Policymakers are encouraged to account for unofficial market dynamics when designing exchange rate and monetary policies, while investors can use the proposed modeling approach to improve risk assessment and forecasting accuracy.

Key Words: *Egypt, Currency Shortage, Exchange Rate, Time Series Analysis, ARIMA, GARCH, Black Market, Multifactor Model.*

JEL Code: E47, C53, F31.

1. Introduction

Egypt's economy faces notable hurdles and prospects, notably concerning the disparity between its official and unofficial exchange rates for the Egyptian Pound. This variance stems from economic volatility, inflationary forces, and currency devaluations, giving rise to a secondary market where the Egyptian Pound is valued differently from the official rate. Parallel markets reflect underlying demand–supply imbalances and can influence inflation, investment decisions, and macroeconomic stability. Parallel foreign exchange systems have been analyzed in the literature as arising from currency controls, restricted official access, and excess demand for foreign exchange, where the parallel rate typically exceeds the official rate by a “parallel-market premium.” (Kiguel & O'Connell, 1995)

In Egypt, prolonged foreign currency shortages, compounded by external shocks such as the COVID-19 pandemic and the Russia–Ukraine conflict, weakened tourism, remittance flows, and import capacity, intensifying pressures on the pound and foreign exchange reserves. In response, the Central Bank of Egypt (CBE) implemented significant currency adjustments, including a ~40 % devaluation of the Egyptian Pound (EGP) in January 2023 as part of broader exchange rate reforms (ITA, 2023). Over time, official exchange rate flexibility led to a divergence between the official EGP/USD rate and the rate observed in informal markets, with reports indicating that the unofficial or black-market rate has been considerably higher than the official rate during periods of acute shortage.

This devaluation increased non-payment risks as many businesses and consumers were unable to honor their obligations in foreign currencies. The disparity between the EGP and EGPp has continued to increase to around 60 EGP to the dollar on the black market as compared to the official rate of 30.9 EGP to the dollar. This situation presents a challenge to investments in Egypt since it creates uncertainty and potential volatility, affecting the returns on investments and the value of the assets, hence making it difficult to determine the real value of the investments, and to hedge against risks.

One of the prominent methods for predicting future values is time series analysis. The foundational work (Box & Jenkins, 1970) introduced a systematic approach for time series forecasting, known as the Autoregressive Integrated Moving Average (ARIMA) method. It involves three steps: model identification, parameter estimation, and model checking. Several papers have tried to predict macroeconomic variables, starting with the most recent research, (Navarro, 2024) tested the appropriate ARIMA to predict the Philippines’ monthly CPI and found that ARIMA (13,1,12) was the most suitable. Similarly, (Dutta, 2023) used ARIMA (3,1,1) to predict the S&P BSE SENSEX returns. Another economic indicator that was modeled using ARIMA was the GDP (Polintan, Cabauatan, & Mabborang, 2023). In the context of COVID-19, a study focused on estimating the real GDP growth and the debt-to-GDP ratios for Germany and Portugal (Melo, Perestrello, Lhano, Gouveia, & Santa-Clara, 2021) . Likewise, (Corpin, Marbella, Kua, & Mabborang, 2023) predicted inflation with a different model from a previous study (Nyoni, 2019) by employing the SARIMA model.

In our context, ARIMA can be used in forecasting exchange rates. In their paper, (Yıldıran & Fettahoğlu, 2017), forecasted the USD/TRY exchange rate using the ARIMA approach based on 3,069 daily observations to find ARIMA (2,1,0) as the optimal model for short-term forecasts and ARIMA (0,1,1) for long-term. (Ngan, 2016) forecasted the VND/USD exchange rate in Vietnam over twelve months in 2016 confirming the suitability of ARIMA for short-term forecasting. Similarly, (Nwankwo, 2014) calculated the yearly average of the NGN/USD exchange rate from 1982 to 2011 and found that ARIMA (1,0,0) model is appropriate. (Maniatis, 2012) rate compared ARIMA with exponential smoothing and probabilistic models for EUR/USD prediction and noted that probabilistic models are superior.

Despite its widespread use, ARIMA models have limitations. (Zhang, 2003) and (Pai & & Lin, 2005) pointed out that ARIMA assumes a linear relationship within the data, which may not capture real-world complexities. To mitigate this limitation, hybrid models combining ARIMA with artificial neural networks (ANN) have been proposed to better handle non-linear data. (Hsu, Sung, & Johnson, 2016) reviewed 30 studies across various financial markets and concluded that machine learning methods generally outperform econometric methods, but some exceptions exist. For example, (Babu, 2015) found that ARIMA model outperformed ANN in predicting the Indian rupee against major currencies.

ARIMA models fall short in modeling volatility. This is where GARCH models come into play. Conventional econometric models imposed an assumption of constant volatility and neglected the possibility of autocorrelation in variance. (Engle, 1982) developed the ARCH model which assumes that the conditional variance of the error term changes with time due to past shocks. (Bollerslev, 1986) extended this with GARCH model, which has become widely used for volatility modeling. More improvements have been made. For instance, (Baillie & DeGennaro, 1990) presented an issue of excess kurtosis by using the student's t-distribution. Other adjustments target the asymmetric response of positive and negative shock. Among them are, EGARCH, GJR-GARCH, and TGARCH models, which were established by (Nelson, 1991), (Glosten, Jagannathan, & Runkle, 1993), and (Zakoian, 1994) respectively. They have been used for forecasting stock returns as in (Alberg, 2008) and (Hansen, 2005).

In this context, (Dol, 2021) compared the performance of many volatility models during the period of crisis using daily price indices of stock markets of several countries and found that the GARCH model is superior to the asymmetric models in crises. On the same note, (Mohnot, 2011) examined the volatility in the foreign exchange rates in thirteen countries to determine if such volatility is predictable by employing the GARCH model to show that volatility shocks occur more frequently during crisis periods. (Aries, Giromini, & G and Meissner, 2006) empirically examined the volatility of the Brazilian Real, the Russian Ruble, the Chinese Yuan, and the Australian Dollar, concluding that these currencies were undervalued against the USD.

Modeling the exchange rate using a multifactor model or using it as an underlying factor to explain the behavior of certain endogenous variables is popular. The question is simple: can exogenous variables enhance the prediction of exchange rates? In studying the returns at the Stockholm Stock Exchange, (Talla, 2013), found out that inflation, interest rates, and exchange rates negatively affected returns. In their paper (Osamwonyi & Evbayiro-Osagie, 2012), the correlation between stock market and economic variables was essential in forecasting trends since the stock market reflects economic fundamentals.

The application of ARIMAX is important because explanatory variables from outside the model are integrated. In ARIMA the forecast is only based on the past values and errors of the series itself, but there is an enhanced form in the ARIMAX which includes independent variables. Relevant research to our analysis in Egypt is (Barakat & Elgazzar, 2015) which looked at the Egyptian and Tunisian stock markets to assess the relationship between economic variables and stock market performance.

Integrating GARCH with ARIMAX provides a dual benefit: it builds on the ability of external variables to explain the system using ARIMAX and incorporates heteroskedasticity of the error terms by the GARCH process. (Ahoniemi, 2008) compared ARIMA and ARIMAX and incorporate GARCH to see which model is better for predicting the VIX index in the United States.

Despite extensive research on exchange rate dynamics, a significant gap exists in the literature where the focus has been on the EGP, largely overlooking the EGPp. This omission is critical in the context of Egypt, where the EGPp has emerged as a pivotal element in the country's exchange rate transactions. The unofficial rate holds substantial importance for informal economic transactions, and investment decisions, yet its dynamics remain underexplored. This raises a crucial research question: How can the unofficial exchange rate in Egypt be modeled to understand its volatility and behavior over time?

This research aims to fill the gap identified in the existing literature by modeling the EGPp and analyzing its volatility, providing a nuanced understanding of unofficial characteristics and the interactions between the unofficial and official rates. This comparative analysis is not only critical for academic purposes but also holds practical significance for investors and policymakers. Through this contribution, the research will enhance our comprehension of Egypt's economic dynamics, providing a more holistic view of exchange rate behavior and its implications for economic stability and growth.

2. Methodology and Model Setup

The methodology outlines the process for predicting Egypt's official and unofficial exchange rates using ARIMA, ARIMA-GARCH, ARIMAX (with EGX 30 and CONIA), and ARIMAX-GARCH models. Additionally, the return series is modeled using various GARCH extensions to capture volatility. This includes data preparation, model specification, estimation, and evaluation.

2.1 Data Preparation

Data Selection

The study examines daily USD/EGP exchange rates in both official and unofficial markets, selected for their central role in Egypt’s foreign exchange dynamics. EGX 30 returns and the Cairo Overnight Interbank Average (CONIA) are included as exogenous variables to capture market and monetary conditions, consistent with established evidence of causal links between

International Journal of Finance
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exchange rates, interest rates, and stock market returns(Barakat & Elgazzar, 2015). The unofficial exchange rate covers January 2023–May 14, 2024, while the official rate spans January 2012–mid-May 2023; all series are aligned at daily frequency, with missing values in EGX 30 and CONIA addressed via linear interpolation.

Descriptive Statistics of Unofficial Rate

Table 1 summarizes the behavior of four variables: unofficial rate, EGX growth, unofficial rate growth, and CONIA. The unofficial rate displays time variation and potential structural movement. EGX growth shows small average changes with fat tails and negative skewness. The unofficial rate growth also exhibits negative skewness and high kurtosis, indicating frequent extreme movements. CONIA shows moderate variability and visible trend behavior.

Table 1 : EGPp descriptive statistics

	Unofficial Rate	*Growth of EGX*	*Growth Rate*	*CONIA*
Mean	43.1492	0,011%	0. 09%	0.1971
Standard Error	0.3859	0. 06%	0.06%	0.0015
Median	39.9780	0.0012	0.0011	0.1930
Standard eviation	8.6207	1,24%	1,26%	0.0326
Kurtosis	0.2931	6.6617	13.5085	1.3173
Skewness	0.7968	-0.5831	-0.4998	1.4634
Range	40.0610	12,36%	16,86%	0.1405

Descriptive Statistics of Official Rate

The descriptive statistics in the Table 2 provide an understanding of the exchange rate, market index return, and overnight interbank rate during the official rate period. The growth of the exchange rate (0.11%) shows the average percentage change in the exchange rate during the period, while the growth of the market index (0.07%) represents the average return on the market index. CONIA has a mean of 0.133, indicates the average interest rate in the interbank lending market during this time.

International Journal of Finance
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Table 2 : EGP descriptive statistics

	Rate	Growth of EGX	Growth Rate	CONIA
Mean	21.933	0. 07%	0.11%	0.133
Standard Error	0.249	0. 05%	0. 06%	0.001
Median	16.153	0. 001	0.0001	0.113
Standard eviation	8.409	1,7%	1.97%	0,05
Kurtosis	1.348	89.406	785.697	0.650
Skewness	1.352	0.425	26.486	1.189
Range	34.049	0.500	0.623	0.194

Stationarity Test

Stationarity was evaluated using the Dickey–Fuller (DF) and Augmented Dickey–Fuller (ADF) unit root tests. When evidence of serial correlation was present, appropriate lagged differences were included in the ADF specification to ensure white-noise residuals. Series found to be non-stationary were transformed using first differences of logarithms prior to estimation.

As a quick reminder, the Augmented Dickey-Fuller test is the t-test for the null hypothesis $H_0: \beta = 0$ based on the regression.

$$\Delta Y_t = c_0 + c_1 \times t + \beta \times Y_{t-1} + \sum_{i=1}^{p} Y_i \times \Delta Y_{t-i} + e_t$$

Equation 1 : ADF Test

2.2 Model Set up and Fitting

Model Specification

Let the probability-filtered space $(\Omega, \mathcal{F}, \mathbb{F}, P)$ with the filtration $\mathbb{F} = \{\mathcal{F}_t : \mathrm{t} \geq 0\}$, where Ω is the sample set, $\mathcal{F}$ is the sigma-algebra on Ω, $\mathbb{F}$ is the filtration on the measurable space $(\Omega, \mathcal{F})$ and P is a probability measure on $(\Omega, \mathcal{F})$. $\mathbb{F}$ is the filtration such that $\mathbb{F} = \{\mathcal{F}_t : \mathrm{t} \in \mathrm{T}\}$ is the set of non-decreasing sigma-algebras on the measurable space $(\Omega, \mathcal{F})$ such that: $\forall\, t \in T, \mathcal{F}_t \subseteq \mathbb{F}$ and $\forall\, t \leq s \in T, \mathcal{F}_t \subseteq \mathcal{F}_s$

Filtration $\mathbb{F}$ is a filtration that captures the flow of information over time from different variables, and contains 3 stochastic processes:

- ✓ $EX = \{EX_t : \mathrm{t} \in \mathrm{T}\}$ with EX_t being the daily foreign exchange rate.
- ✓ $IR = \{IR_t : \mathrm{t} \in \mathrm{T}\}$ with IR_t being the daily Cairo Overnight Index Average.
- ✓ $MR = \{MR_t : \mathrm{t} \in \mathrm{T}\}$ with MR_t being the daily return of the Egyptian stock market index EGX30.

International Journal of Finance
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Let $Y = \{Y_t : \mathrm{t} \in \mathrm{T}\}$ the process defined as the daily foreign exchange rate value process (one for the official rate and the other for the unofficial rate).

This study aims to explain the Y_t process dynamics, so we define the conditional expectation of Y_t based on the information supplied by the filtration $\mathbb{F}$, as defined below. We assume that Y_t is a linear function of V_t where $\mathbb{F}$ the filtration generated by V_t such as:

$$E[Y_t|\mathcal{F}_t] = \pi + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=0}^{p} \delta_i \mathrm{X}_{\mathrm{t-i}}$$

Equation 2 : The conditional expectation

$$\mathrm{Y_t} = \mathrm{E}[\mathrm{Y_t}|\mathcal{F}_\mathrm{t}] + \varepsilon_\mathrm{t}$$

Where: $\mathrm{Y_t}$ is the exchange rate, π is a constant, $\mathrm{X_t}$ is a vector that groups all explanatory variables other than AR and MA components, ε_t represents the residual and φ_i, θ_i *and* δ_i are coefficients.

In addition, our model will be augmented using GARCH for conditional variance (volatility clustering). GARCH is parametrized as follows: $\varepsilon_\mathrm{t} = N(0, \sigma_t^2)$.

$$\sigma_t^2 = \omega + \sum_{j=1}^{m} \beta_i \sigma_{i-j}^2 + \sum_{j=1}^{n} \alpha_i \varepsilon_{i-j}^2$$

Equation 3 : Standard GARCH

Where: σ_{i-j}^2 is the expected volatility at time $t = i - j$, ε_{i-j}^2 is the error term at time $t = i - j$ and ω is a constant term. The long-term volatility for GARCH (1,1) for example, is defined as $\frac{\omega}{1-\alpha-\beta}$.

Parameters Estimation

Model parameters are estimated using maximum likelihood estimation (MLE) under the assumption of white-noise innovations, initially treated as normally distributed. While the unconditional likelihood can be derived analytically, its computation requires handling the joint distribution of initial observations; therefore, estimation is conducted using the conditional maximum likelihood function, which conditions on the first $\boldsymbol{p}$observations. Under normality, maximizing the conditional log-likelihood is equivalent to minimizing the sum of squared residuals, allowing parameters to be estimated using OLS-type procedures, with appropriate modifications for ARMA, ARIMAX, and GARCH extensions.

2.3 Model Performance

Model adequacy is assessed by testing residual autocorrelation using the Ljung–Box Q-test. The null hypothesis of no serial correlation is evaluated over a specified number of lags, with the test statistic asymptotically following a chi-square distribution adjusted for the number of estimated parameters. Failure to reject the null indicates that the model sufficiently captures the dynamic structure of the series.

International Journal of Finance
ISSN 2520-0852 (Online)
Vol. 11, Issue No. 1, pp. 36 - 55, 2026
www.carijournals.org

Residual normality is assessed using the Shapiro–Wilk test, which evaluates the null hypothesis that the residuals follow a normal distribution. The test is based on the correlation between the ordered residuals and their corresponding expected values under normality, providing a sensitive diagnostic for departures from Gaussian behavior.

Model performance is evaluated using both forecast accuracy and information criteria. Forecast errors are assessed using the Root Mean Squared Error (RMSE), which measures the average magnitude of prediction errors in the same units as the dependent variable. Model selection is guided by the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which balance goodness-of-fit against model complexity, with BIC imposing a stronger penalty on over-parameterization.

2.4 Modeling The Volatility of The Exchange Rate Using GARCH

To capture time-varying volatility in exchange rate returns, the study augments ARIMA and ARIMAX mean equations with GARCH-type conditional variance models when residual diagnostics indicate conditional heteroskedasticity. Let the exchange rate process be defined as: $Y_t = \mu_t + \epsilon_t$

With $Var(Y_t|\boldsymbol{\mathcal{F}}_t) = Var\,(\mu_t + \epsilon_t|\boldsymbol{\mathcal{F}}_t) = Var(\epsilon_t|\boldsymbol{\mathcal{F}}_t)$

Where μ_t denotes the conditional mean and ϵ_t is the innovation term.

Testing for ARCH Effects

The presence of conditional heteroskedasticity is assessed using the ARCH Lagrange Multiplier (LM) test, based on the auxiliary regression:

$$\epsilon_t{}^2 = \alpha_0 + \alpha_1\epsilon_{t-1}{}^2 + \alpha_2\epsilon_{t-2}{}^2 + \cdots + \alpha_k\epsilon_{t-k}{}^2 + e_t \; and \; t > k+1$$

With Hypotheses $H_0 : \alpha_1 = \cdots = \alpha_k = 0$ and the alternative hypothesis is $H_1 : \alpha_i \neq 0$

The test statistic is computed as:

$$F = \frac{(SSR_0 - SSR_1)/k}{SSR_1/(T-2K-1)}$$

Equation 4 : ARCH test

which follows an F distribution with k degrees of freedom and $T-2k-1$ under the null hypothesis. If T is large, kF can be used as the test statistic (a chi-squared distribution with K degrees of freedom).

Error Distribution and Maximum Likelihood Estimation

Volatility parameters are estimated using conditional maximum likelihood estimation (MLE). To accommodate deviations from Gaussianity commonly observed in financial returns, estimation is conducted under alternative distributional assumptions for ϵ_t

International Journal of Finance
ISSN 2520-0852 (Online)
Vol. 11, Issue No. 1, pp. 36 - 55, 2026 www.carijournals.org

The Normal Distribution

$$\epsilon_t \sim N(0, \sigma_t)$$

with conditional log-likelihood function:

$$L\big(\mathrm{f}\,(\epsilon_t, \ldots, \epsilon_{k+1}\,|\epsilon_1, \epsilon_2 \ldots\ldots, \epsilon_k, \mathrm{A})\big) = \sum_{i=k+1}^{T}\left(\frac{-ln(2\pi)}{2} - \frac{\ln(\sigma_t^2)}{2} - \frac{{\epsilon_t}^2}{2\sigma_t^2}\right)$$

Where: σ_t^2 is calculated recursively: $\sigma_t^2 = \alpha_0 + \alpha_1{\epsilon_{t-1}}^2 + \alpha_2{\epsilon_{t-2}}^2 + \cdots + \alpha_k{\epsilon_{t-k}}^2$

Student's t Distribution

To capture fat tails, innovations are assumed to follow a Student-t distribution with f degrees of freedom:

$$\mathrm{f}\,(\epsilon_t, \ldots, \epsilon_{k+1}\,|\epsilon_1, \epsilon_2 \ldots\ldots, \epsilon_k, \mathrm{A}, \mathrm{f}) = \prod_{k+1}^{T}\frac{\Gamma(\frac{\mathrm{f}+1}{2})}{\Gamma(\frac{f}{2})\sqrt{(f-2)\pi\sigma_t^2}}\left(1 + \frac{{\epsilon_t}^2}{(f-2)\sigma_t^2}\right)^{-\frac{\mathrm{f}+1}{2}}$$

Where: $\Gamma(x) = \int_0^\infty z^{x-1}e^{-z}\,dz$ a gamma function

Skew Generalized Error Distribution (SGED)

To jointly account for fat tails and skewness, the SGED is considered, with probability density: $f(\epsilon_t) = \frac{f\,exp(\frac{-1}{2}|\epsilon_t/\lambda|^f)}{\lambda 2^{\left(1+\frac{1}{f}\right)}\Gamma\left(\frac{1}{f}\right)}$

Where: $\lambda = \sqrt{(\Gamma\left(\frac{1}{f}\right)\Gamma\left(\frac{3}{f}\right)\frac{1}{2^{2/f}}}$, if $f = 2$; $\Gamma\left(\frac{1}{2}\right) = \sqrt{\pi}$ *and* $\Gamma\left(\frac{3}{2}\right) = \Gamma\left(\frac{1}{2}+1\right) = \frac{1}{2} * \Gamma\left(\frac{1}{2}\right)$

In this case, GED becomes a normal distribution with $\lambda = 1$, the likelihood function is:

$$L = \sum_{i=k+1}^{T}\left[\frac{-(\frac{\epsilon_t}{\lambda})^f}{2} ln\left(\frac{f}{\lambda}\right) - \left(1 + \frac{1}{v}\right)\ln(2) - (T-k)\ln(\Gamma(\frac{1}{\mathrm{f}})\right]$$

Conditional Variance Models

Standard GARCH

The baseline symmetric volatility model is the GARCH(m,n) specification:

$$\sigma_t^2 = \omega + \sum_{j=1}^{m}\beta_i\sigma_{i-j}^2 + \sum_{j=1}^{n}\alpha_i\varepsilon_{i-j}^2$$

Where α_i: captures short − run shock persistence and β_i captures long-run volatility persistence.

To allow for differential volatility responses to positive and negative shocks, the following asymmetric specifications are estimated:

EGARCH

International Journal of Finance
ISSN 2520-0852 (Online)
Vol. 11, Issue No. 1, pp. 36 - 55, 2026
www.carijournals.org

$$ln(\sigma_t^2) = \omega + \sum_{i=1}^{m} \alpha_i \frac{|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{s} \beta_j \, ln(\sigma_{t-j}^2)$$

If $\varepsilon_{t-i} < 0$, then this shock change $ln(\sigma_t^2)$ by $\alpha_i(1-\gamma_i)\frac{\varepsilon_{t-i}}{\sigma_{t-i}}$, if this shock is positive then $ln(\sigma_t^2)$ change by $\alpha_i(1+\gamma_i)\frac{\varepsilon_{t-i}}{\sigma_{t-i}}$, the exact effect of this leverage depends on γ_i . If it is negative, then negative shock increases more the volatility and if it is positive then the reverse is true.

TGARCH

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} (\alpha_i + \gamma_i \mathbb{I}_{t-i}) \, |\varepsilon_{t-i}| + \sum_{j=1}^{s} \beta_j |\sigma_{t-j}|$$

$\mathbb{I}_{t-i}$ is an indicator function of a ε_{t-i} such that, $\mathbb{I}_{t-i} = \begin{Bmatrix} 1 \; if \; \varepsilon_{t-i} < 0 \\ 0 \; if \; \varepsilon_{t-i} \geq 0 \end{Bmatrix}$

TGARCH focuses on threshold to capture volatility regime changes based on the sign of past returns. EGARCH focuses on the leverage effect parameter, capturing asymmetry in volatility response to positive and negative returns in terms of magnitude.

GJR-GARCH

The GJR-GARCH model is quite like the **TGARCH** model but uses squared residuals instead of absolute residuals. The conditional variance equation is:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} (\alpha_i + \gamma_i \mathbb{I}_{t-i}) \, \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2$$

Here, if $\mathbb{I}_{t-i} = 1$, then σ_t^2 changes by $(\alpha_i + \gamma_i)$, else it only varies by α_i. In case $\mathbb{I}_{t-i} = 1$. If gamma is positive, negative shocks will have a bigger impact on σ_t^2 than positive shocks. If gamma is negative the inverse is true. If γ_i is 0, the model will become a standard GARCH.

The empirical procedure evaluates the four GARCH extensions using three alternative error distributions (Normal, Student's t, and Skew Generalized Error (SGED)) yielding three candidate models for each extension. For each combination, model orders are selected through an iterative process in which multiple specifications are estimated and compared while holding the distribution and GARCH form fixed. The optimal specification within each distribution–extension pair is selected based on Bayesian Information Criterion (BIC) and parameter significance. This process results in twelve candidate models, from which the best-performing distribution is first identified for each GARCH extension, followed by selection of the overall optimal volatility model across extensions.

3. Empirical Findings

3.1 Unofficial Rate

This section presents the empirical analysis of the unofficial exchange rate EGPp. It covers stationarity testing, model estimation and comparison, model selection, and diagnostic evaluation, culminating in the identification of the most appropriate specification for forecasting and volatility analysis.

Stationarity Testing

Unit root tests indicate that all variables are stationary at the 5% significance level, with the exception of the level of the unofficial exchange rate EGPp. Stationarity is achieved after applying the first difference of the natural logarithm, yielding the growth rate defined as $ln\left(\frac{Y_{t+1}}{Y_t}\right)$.

The transformed EGPp growth series, along with EGX 30 growth and CONIA, is stationary and suitable for time-series modeling. Table 3 summarizes the stationarity test results.

Table 3: Stationarity of EGPp

	Unofficial Rate	Unofficial Rate Growth	EGX 30 Growth	CONIA
Statistic	-1,85	- 6,99	- 8,04	- 3,44
P-Value	64%	< 1%	< 1%	4,98%

Model Fitting and Comparison

The objective of this stage is to identify the most appropriate model for forecasting the unofficial exchange rate EGPp. Four model classes are considered: ARIMA, ARIMA–GARCH, ARIMAX, and ARIMAX–GARCH. Within each class, candidate specifications are estimated and evaluated using the Bayesian Information Criterion (BIC), Root Mean Squared Error (RMSE), and the statistical significance of estimated parameters. This procedure yields one optimal model per class, allowing for a systematic comparison across modeling frameworks.

The comparison reveals a clear trade-off between model parsimony and volatility representation. The ARIMA (2,1,3) specification achieves the lowest AIC value (770.12), indicating strong in-sample fit with minimal complexity. The ARIMAX (2,1,3) model performs similarly in terms of fit; however, its AIC and BIC values are marginally higher. More importantly, the coefficients on the exogenous variables (EGX 30 growth and CONIA) are statistically insignificant, suggesting that these variables do not provide additional explanatory power beyond the autoregressive and moving-average structure. Consequently, the inclusion of exogenous variables does not materially improve the predictive performance for EGPp.

Introducing GARCH components substantially improves the modeling of second-moment dynamics. Both the ARIMA–GARCH and ARIMAX–GARCH specifications exhibit significant ARCH and GARCH parameters (α and β), indicating that past shocks and past conditional variances exert a persistent influence on current volatility. Although the inclusion

International Journal of Finance
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Vol. 11, Issue No. 1, pp. 36 - 55, 2026
www.carijournals.org

of GARCH terms increases BIC values—reflecting higher model complexity—it successfully captures volatility clustering present in the series, as confirmed by the ARCH test results.

Overall, while ARIMA (2,1,3) is adequate for modeling the conditional mean of the unofficial exchange rate, augmenting it with a GARCH (1,1) structure provides a superior representation of the volatility process. Accordingly, the ARIMA (2,1,3)–GARCH (1,1) model is selected as the preferred specification.

Table 4: EGPp model results

	ARIMA (2,1,3)		ARIMA- GARCH (2,1,3) - (1,1)		ARIMAX (2,1,3)		ARIMAX-GARCH (2,1,3) - (1,1)	
BIC	795,38		812,43		804.87		824,05	
AIC	770,12		769,04		771.47		770,42	
RMSE	0,516		0,516		0,515		0,515	
φ_1	1,131	< 0,1%	1,131	< 0,1%	1,130	< 0,1%	1,130	< 0,1%
φ_2	-0,910	< 0,1%	-0,913	< 0,1%	-0,910	< 0,1%	-0,912	< 0,1%
θ_1	-0,493	< 0,1%	-0,495	< 0,1%	-0,488	< 0,1%	-0,485	< 0,1%
θ_2	0,364	< 0,1%	0,365	< 0,1%	0,362	< 0,1%	0,366	< 0,1%
θ_3	0,447	< 0,1%	0,447	< 0,1%	0,451	< 0,1%	0,452	< 0,1%
γ_1	-		-		-0,865	33,1%	-0,865	37,1%
γ_2					3,047	16,1%	3,043	17,8%
ω			0,0055	14,4%	-		0,0052	16,3%
α			0,212	0,2%			0,215	0,5%
β			0,775	< 0,1%			0,775	< 0,1%
ARCH test	< 0,1%		-		< 0,1%		-	

Residual diagnostic tests for the selected model are reported in Table 5. The residuals are stationary and exhibit no significant autocorrelation, indicating that the model adequately captures the dynamic structure of the series. However, the Shapiro–Wilk test rejects the null hypothesis of normality. The residual distribution displays near-zero skewness (−0.3) but extremely high kurtosis (11.2), pointing to pronounced heavy-tailed behavior.

Given this departure from Gaussianity, a student's t-distribution is more appropriate for modeling the error term. Consequently, statistical inference is conducted using robust standard errors, ensuring reliable hypothesis testing despite non-normal residuals.

Table 5: Tests of EGPp residuals

	Stationarity	**Autocorrelation**	**Normality**
Test result	<1%	11,06%	0,3%

Interpretations and Forecast

The estimated ARIMA (2,1,3) specification for the unofficial exchange rate (EGPp) indicates that its dynamics are driven by both past realizations and past shocks, reflecting strong persistence and short-term adjustments. Unlike the official exchange rate, the unofficial rate operates outside direct government intervention and therefore reflects underlying market conditions shaped by supply–demand imbalances. Periods of economic and political uncertainty, fluctuations in foreign currency availability, and shifts in investor sentiment contribute to pronounced movements in EGPp. Moreover, the relatively low liquidity of the unofficial market amplifies its sensitivity to large transactions and sudden information shocks, resulting in heightened volatility. The high kurtosis observed in the return distribution further confirms the prevalence of extreme movements, consistent with speculative behavior and elevated non-systematic risk.

Forecasting is conducted using the ARIMA(2,1,3)–GARCH(1,1) framework, which jointly models the conditional mean and conditional variance of the exchange rate. The ARIMA component generates forecasts of future exchange rate levels by capturing trend and serial dependence, while the GARCH component provides forecasts of time-varying volatility by modeling the persistence of past shocks. This integrated approach yields a comprehensive forecasting framework that accounts not only for expected future movements in the unofficial exchange rate but also for the uncertainty and risk surrounding those predictions.

3.2 Official Rate

This section analyzes the dynamics of Egypt's official exchange rate EGP, following the same empirical strategy applied to the unofficial rate. We examine stationarity properties, estimate and compare competing time-series models, assess residual diagnostics, and interpret the forecasting implications, with particular emphasis on the role of policy intervention and market conditions.

Stationarity Testing

Unit root test results indicate that the EGP growth rate and EGX 30 returns are stationary at the 1% significance level, while the level of the official exchange rate and CONIA are non-stationary. Stationarity of the exchange rate is achieved after applying the first difference of the natural logarithm, confirming that the growth rate of the EGP is suitable for time-series modeling. Table 6 reports the corresponding test statistics and p-values.

Table 6: Stationarity of EGP

	EGP rate	EGP growth rate	EGX 30 growth	CONIA
Statistic	-1,08	-10,7	-9,8	- 1,88
P-Value	92,5%	< 1%	< 1%	62,5%

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Model Fitting and Comparison

Model selection follows the same procedure adopted for the unofficial exchange rate. Four specifications are estimated (ARIMA, ARIMA–GARCH, ARIMAX, and ARIMAX–GARCH, all including a drift term) and compared using BIC, RMSE, and parameter significance. Table 7 summarizes the estimation results.

The ARIMA(0,1,0) model with drift provides the most parsimonious representation of the official exchange rate dynamics. Introducing GARCH components does not yield statistically significant ARCH effects, as confirmed by the ARCH test, indicating an absence of volatility clustering. Although ARIMAX specifications marginally reduce RMSE, the improvement is economically negligible and comes at the cost of increased model complexity.

Table 7: EGP model results

	ARIMA with drift (0,1,0)		ARIMA-GARCH with drift (0,1,0) - (1,1)		ARIMAX with drift (0,1,0)		ARIMAX-GARCH with drift (0,1,0) - (1,1)	
BIC	1999,68		2027,80		2001,08		2041,53	
AIC	1989,61		2004,12		1986,17		2012,04	
RMSE	0,579		0,579		0,577		0,577	
Drift	0,0273	10,2%	1,131	< 0,1%	0,027	11,1%	0,027	11,1%
φ_1	-		-		-		-	
θ_1								
γ_1					1,985	0,4%	1,988	0,55%
γ_2					0,239	91%	0,239	86%
ω			0,0005	99%	-		0,0005	98%
α			0,04	99%			0,04	99%
β			0,92	99%			0,93	99%
ARCH test	99,1%		-		99%		-	

Residual diagnostic tests for the selected ARIMAX (0,1,0) specification indicate that the residuals are stationary and free from serial correlation, confirming that the model adequately captures the conditional mean dynamics. However, the Shapiro–Wilk test strongly rejects normality, with extremely high skewness (26) and kurtosis (920), signaling severe departures from Gaussian behavior. Consequently, inference is conducted using robust standard errors to ensure valid statistical conclusions. Table 8 reports the diagnostic test results.

Table 8: Tests of EGP residuals

	Stationarity	Autocorrelation	Normality
Test result	<1%	98,3%	<1%

Interpretation and Forecast

The selected ARIMA (0,1,0) specification implies that future growth of the official exchange rate is not driven by its past realizations, reflecting the absence of intrinsic time-series dependence. The lack of ARCH effects is consistent with active government intervention in the foreign exchange market. Through mechanisms such as foreign reserve management, exchange rate controls, and coordinated monetary and fiscal policies, authorities dampen volatility and prevent persistent shock transmission. Moreover, controlled information flows and market microstructure features further contribute to the smooth behavior of the official rate.

In contrast to the unofficial exchange rate, the official rate is influenced by market returns, as captured by the ARIMAX specification. In this framework, exchange rate growth becomes a linear function of the EGX 30 return, with no internal dynamic structure. Forecasting the official exchange rate therefore hinges on predicting market returns rather than exploiting past exchange rate behavior.

To generate exchange rate forecasts, the EGX 30 growth rate is first modeled using an ARMA(2,2) specification. Diagnostic tests confirm the absence of residual autocorrelation, while volatility clustering is addressed using a GARCH(1,2) model with statistically significant parameters. The predicted market returns are then used as inputs in the ARIMAX model to obtain forecasts of the official exchange rate.

3.3 GARCH Comparison

Standard GARCH

Among the symmetric volatility models, the SGARCH(1,1) with Student's t-distributed errors emerges as the optimal specification, as it yields the lowest BIC while maintaining statistically significant parameters. Although the SGARCH model estimated with the Skew Generalized Error Distribution (SGED) also produces significant coefficients, its higher BIC suggests a weaker trade-off between fit and complexity. This result is consistent with the residual diagnostics, which indicate very low skewness and therefore limited gains from introducing an explicit skewness parameter. The estimated skew parameter is close to unity, confirming that the residual distribution is approximately symmetric (see Table 9)

Exponential GARCH

The EGARCH(1,1) specifications yield mixed and inconsistent results across distributions. In both the Gaussian and Student's t versions, the long-run variance (ω) and short-run volatility (α) parameters are statistically insignificant, while the persistence (β) and leverage (γ) parameters remain significant. Under the SGED specification, only the α parameter is insignificant. Although the Student's t EGARCH model exhibits a relatively low BIC, the instability and lack of significance of key parameters reduce its reliability. Nevertheless, the consistently significant γ coefficients across EGARCH models suggest that negative shocks exert a stronger effect on volatility than positive shocks of similar magnitude (Table 9).

International Journal of Finance
ISSN 2520-0852 (Online)
Vol. 11, Issue No. 1, pp. 36 - 55, 2026

Glosten-Jagannathan-Runkle GARCH

For the GJR-GARCH(1,1) class, the Student's t specification achieves the lowest AIC and BIC values. Most parameters are statistically significant, although the asymmetry parameter (γ) is not, indicating limited evidence of differential volatility responses to positive versus negative shocks. Similar to SGARCH and EGARCH results, the skewness parameter confirms that the residual distribution is close to symmetric. Overall, while the Student's t GJR-GARCH performs reasonably well in terms of fit, the absence of a significant leverage effect weakens its economic appeal. (Table 9).

Threshold GARCH

The TGARCH (1,1) model with Student's t-distributed errors marginally outperforms alternative distributions based on BIC. However, the threshold parameter (γ) is statistically insignificant across all specifications, suggesting that volatility does not respond asymmetrically to positive and negative shocks. Moreover, the threshold structure in TGARCH and GJR-GARCH captures asymmetry only through the sign of shocks, without smoothly modeling differences in their magnitude. This limitation reduces their effectiveness in capturing more nuanced volatility dynamics (Table 9)

Table 3 : GARCH Model Output

	BIC	AIC	L	ARCH	α	β	ω	γ	Shape	Skewness
SGARCH										
Normal distribution	0,87	0,76	-185	47%	0,21 <1%	0,78 <1%	0,00546 15%			-
T distribution	0,64	0,61	-148	73%	0,23 <1%	0,76 <1%	0,00753 2%		3,55 <1%	-
GED	0,65	0,61	-146	69%	0,23 <1%	0,76 <1%	0,00635 1%		1,02 <1%	0,93 <1%
EGARCH										
Normal distribution	0,80	0,77	-188	47%	0,02 69%	0,95 <1%	-0,0652 49%	0,43 <1%		-
T distribution	0,66	0,62	-149	75%	0,02 66%	0,94 <1%	-0,1005 9%	0,61 <1%	3,16 <1%	-
GED	0,67	0,62	-148	72%	0,03 29%	0,94 <1%	-0,1179 3%	0,51 <1%	1,01 <1%	0,94 <1%
GJR-GARCH										
Normal distribution	0,79	0,76	-185	39%	0,22 36%	0,79 <1%	-0,0044 <1%	-0,06 46%		-
T distribution	0,66	0,61	-148	72%	0,30 <1%	0,73 <1%	-0,0070 6%	-0,06 6,6%	3,53 <1%	-
GED	0,67	0,61	-146	66%	0,28 <1%	0,74 <1%	0,0058 30%	-0,006 <1%	1,01 <1%	0,94 <1%
TGARCH										
Normal distribution	0,81	0,78	-189	8%	0,21 18%	0,8 <1%	0,0164 57%	-0,10 70%		-
T distribution	0,67	0,62	-149	40%	0,30 4%	0,75 <1%	0,0229 14%	-0,09 55%	3,12 <1%	-

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GED	0,67	0,62	-148	30%	0,26 <1%	0,76 <1%	0,0207 4%	-0,09 32%	1,01 <1%	0,94 <1%

Final Selection and Interpretations

Based on our analysis, the student's t distribution is consistently preferred across GARCH specifications, reflecting the high kurtosis and heavy-tailed nature of EGPp returns combined with near-zero skewness. This finding aligns with earlier residual diagnostics and confirms that extreme deviations from the mean are a defining feature of the unofficial exchange rate.

Among the four volatility extensions, the SGARCH (1,1) with Student's t-distributed errors is selected as the most appropriate model for EGPp volatility. All core parameters (α, β, and ω) are statistically significant, indicating a well-specified and stable variance process. In contrast, both GJR-GARCH and TGARCH models suffer from insignificant asymmetry parameters, implying either weak leverage effects in the data or inadequate modeling of asymmetry. Similarly, although EGARCH captures leverage effects, the lack of significance in key parameters undermines its reliability.

The high kurtosis and the Student's T distribution of the EGPp reveal that the USD/EGPp is characterized by extreme deviations from the mean. This indicates that the unofficial market is more sensitive to changes in supply and demand and political instabilities. The fact that there are periods of high volatility followed by periods of low volatility is a manifestation of volatility clustering, which is observed in the unofficial rate. This is due to investors' response to economic news and policy shifts that lead to waves of fluctuations. The absence of leverage effect in TGARCH and GJR-GARCH indicates that positive and negative news affect volatility in an equal manner. The SGARCH (1,1) model is the most appropriate. α (0.23) indicates a significant sensitivity to the most recent shocks, and β (0.76) indicates that the market also absorbs these shocks, showing a moderate level of impact of previously expected volatility. The ω (0.0075) is significant in maintaining the model's stability.

4. Conclusion and Limitations

This study examines the dynamics of Egypt's official and unofficial exchange rates using time-series and volatility modeling techniques. The results indicate that the official exchange rate exhibits relative stability and is primarily influenced by market returns, allowing for moderate forecasting accuracy using ARIMA-based models and showing no evidence of significant conditional variance. In contrast, the unofficial exchange rate is characterized by pronounced volatility, strong sensitivity to recent shocks, and significant conditional heteroskedasticity, as captured by GARCH models. The presence of high kurtosis and volatility clustering in the unofficial market underscores its exposure to speculative pressures and highlights the importance of robust risk management and monitoring frameworks.

Despite these contributions, the study faces several limitations. Exchange rate dynamics in Egypt appear to follow a regime-switching process, characterized by extended periods of stability punctuated by abrupt and substantial adjustments. While the exchange rate may be partially predictable during stable regimes, forecasting performance deteriorates during regime transitions. Models that explicitly allow for regime shifts, such as Markov-switching or threshold models, may therefore provide a more accurate representation of this non-linear behavior and constitute a natural extension of this research.

Moreover, recent advances in machine learning techniques, particularly Artificial Neural Networks (ANNs), offer promising alternatives for exchange rate modeling due to their ability to capture complex non-linear relationships that conventional econometric models may overlook. Future research could explore hybrid frameworks combining econometric and machine learning approaches to enhance predictive performance.

Another limitation concerns data availability for the unofficial exchange rate, which is only observed from 2023 onward. This restricted sample limits the ability to analyze long-term dynamics and structural changes in the parallel market. As additional observations become available, future studies will be better positioned to examine historical behavior and improve model robustness.

In summary, the findings highlight the fundamentally different behaviors of Egypt's official and unofficial exchange rates and emphasize the importance of accounting for these differences in empirical modeling. By incorporating these insights, private equity firms and other market participants can better navigate exchange rate uncertainty in Egypt and make more informed investment and risk management decisions.

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