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M. R. Abonazel, N. Elnabawy

Using the ARDL bound testing approach to study the inflation rate in Egypt

KEYWORDS

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ABSTRACT

According to economic theory, the change in any economic variables may affect another economic variable through the time and these changes are not instantaneously, but also over future periods. The autoregressive distributed lag (ARDL) model has been used for decades to study the relationship between variables using a single equation time series. The ARDL model is one of the most general dynamic unrestricted models in econometric literature. In this model, the dependent variable is expressed by the lag and current values of independent variables and its own lag value.

This paper studies the dynamic causal relationships between inflation rate, foreign exchange rate, money supply, and gross domestic product (GDP) in Egypt during the period 2005: Q1 to 2018: Q2. Using the bounds testing approach to cointegration and error correction model, developed within an ARDL model, we investigate whether a long-run equilibrium relationship exists between the inflation rate and three determinants (foreign exchange rate, money supply, and GDP). The results indicate that the exchange rate and the growth in money supply have significant effects on the inflation rate in Egypt, while the real GDP has no significance effect on the inflation rate

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1. INTRODUCTION

The ARDL model is considered a standard least squares regression with lags of both independent and dependent variable as regressors, see Greene (2008). Although ARDL model have been used in econometrics for decades, they have gained popularity recently as a method of checking cointegration between economic variables proposed by Pesaran and Shin (1999) and extended by Pesaran et.al (2001). In economic literature, there are number of cointegration techniques, according to Emeka and Kelvin (2016), the econometric terminology of "cointegration" is used to reflect the existence of a long-run equilibrium among economic variables that converges over time and ARDL approach is considered as a latest of these cointegration technique used to examine dynamic and equilibrium relationships between dependent variables and independent variables. The examples of cointegration techniques such supposed by Engle-Granger (1987), Johansen (1988), Johansen-Juselius (1990), Saikkonen and Lutkepohl (2000) and Pesaran et.al (2001). ARDL is used, since they found that the variables in question are found non stationarity and they are integrated of the same order, then cointegrating relationship (i.e., the susceptibility of the variables to move together) between the variables in the long-run can be studied by the ARDL approach.

According to Pesaran and Shin (1999) and Pesaran et al. (2001), the ARDL test can be adopted for applying cointegration analysis to empirically determine the relationship among the economic variables that is regardless the regressors are stationary at its level, integrated of order one, or a mixture of both. The convenience of using ARDL model is that it is based on a single equation framework so that it takes sufficient numbers of lags and direct the data generating process in a general to specific modeling framework (Harvey, 1981). Besides, Haug (2002) mentioned that the ARDL approach is better with a small sample although Ghatak and Siddik (2001) argued that the Johansen cointegration test requires a large sample to find a valid result.

2. THEORETICAL BACKGROUND

As econometricians always suggest that there is an equilibrium relationship between economic variables depending on time under consideration as specified by theory, the dynamic models are more suitable to specify the relationship between those variables. Models are described to be dynamic since they monitoring the variation of economy and its responses over time. Hill et al. (2012) defined a dynamic relationship as it is the change in a variable in such point of time which may have an effect on the variable itself, or the other variables, in future time periods, these effects not only occur instantaneously but are spread over future time periods. There are different ways to express this dynamic relationship, one of these ways; when we have y as a dependent variable and it is a function of its lag as in lagged dependent variable model beside the current value of x (independent variable) as following:

$$y_t = f\,(y_{t-1}, x_t), \tag{1}$$

where y_t and x_t are the current value of both dependent and independent variables, respectively, y_{t-1} is the value of y in the previous one period, but if we have the dependent variable y as a function of current and past values of an independent variable x then it's called *distributed lag model* which is a dynamic model while we can say that the impact of an explanatory (x) on dependent (y) happens over time not only in the same level time. It is recognized as a variation in the level of a regressor variable may have behavioral implications on other levels of time which refers that the consequences of economic decisions in such time *(t)* have an impact on such economic variables and it can last a long time at time t, and at times $t + 1$, $t + 2$, and so on. For example; fiscal and monetary policy changes may take many months to have a remarkable impact through the economy and the policy makers are concerned with the time frame of changes and the time of bath through effect. To take a decision, they must know the magnitude of policy change that will happen at the such level of time, one future point of time after the change, two future time of point, and so on. The simplest case of DL model is when we have one explanatory variable, the model as described as:

$$y_t = f\,(x_t, x_{t-1}, x_{t-2}, \ldots), \tag{2}$$

where x_{t-1} and x_{t-2} are refer to the values of x two periods ago (two lags), whatever the function would be. The assumption of DL*(q)* are too close to the assumption of multiple regression with some modification for distributed lag which concluded in the following points:

1. $y_t = \vartheta + \alpha_0 + \beta_0 x_t + \beta_1 x_{t-1} + \ldots + \beta_{t-q} x_{t-q} + e_t$
2. y and x are stationary random variables, and e_t is independent of current, past and future values of x.
3. $E(e_t) = 0.$
4. $Var(e_t) = \sigma^2$
5. $Cov(e_t, e_s) = 0;\ t \neq s.$
6. $e_t \sim N(0, \sigma^2)$

If we combine the equation (1) and (2) of the two previous techniques, we will obtain a dynamic model with lagged dependent and explanatory variables, as following:

$$y_t = f\,(y_{t-1}, x_t, x_{t-1}, x_{t-2}).$$

This model is called autoregressive distributed lag (ARDL), it is a natural expansion that has lags of both x and y on the right-hand side. According to economic theory, change in any economic variables may affect another economic variable through the time and these changes are not instantaneously, but also over future periods. The ARDL has been used for decades to study the relationship between variables using a single equation time series. It is a parsimonious infinite lag distributed model, the autoregressive (AR) expresses a regression of y_t on its lags, the distributed lag (DL) component reflects the lag effect of x's. The form of ARDL(p,q) model is expressed as follow:

$$y_t = \vartheta + \alpha_1 \times y_{t-i} + \ldots + \alpha_p \times y_{t-p} + \beta_0 \times x_t + \beta_1 \times x_{t-1} + \ldots + \beta_q \times x_{t-q} + e_t, \tag{3}$$

where p is a number of lags of y (lag order of y) and q is a number of lags of x (lag order of x). We can rewrite (3) as following:

$$y_t = \vartheta + \Sigma_{i=1}{}^{p}\alpha_i \times y_{t-i} + \Sigma_{i=0}{}^{q}\beta_i \times x_{t-i} + e_t$$

The previous model assumes that we have one explanatory variable, hence, if we have k explanatory variables, the general ARDL$(p, q_1, q_2, \ldots, q_k)$ model;

$$y_t = \vartheta + \Sigma_{i=1}{}^{p}\alpha_i \times y_{t-i} + \Sigma_{i=0}{}^{q1}\beta_i \times x_{1t-i} + \ldots + \Sigma_{i=0}{}^{qk}y_i \times x_{kt-i} + e_t, \quad (4)$$

The ARDL model is commonly used when there is a serial correlation problem to obtain a transformed model with uncorrelated errors. One of the least squares' assumption is $cov\ (e_t, e_s) = 0$, and if this assumption is violated, we conclude that the errors have a serial correlation. Suppose we have a dynamic model with one explanatory variable and the errors are serially correlated, correlation between e_t and e_{t-1} can be expressed as e_t regress on e_{t-1} as following:

$$y_t = \beta_0 + \beta_1 x_t + e_t, \quad (5)$$

$$e_t = \rho e_{t-1} + v_t, \quad (6)$$

where the error of the previous model (6) is expressed in AR (1). By substituting (6) into (5):

$$y_t = \beta_0 + \beta_1 x_t + \rho e_{t-1} + v_t, \quad (7)$$

From (5),

$$e_t = y_t - \beta_0 - \beta_1 x_t;\ e_{t-1} = y_{t-1} - \beta_0 - \beta_1 x_{t-1}. \quad (8)$$

By substituting (8) in to (7), then we consider the model:

$$y_t = \delta + \delta_0 x_t + \vartheta_1 y_{t-1} - \vartheta_1 x_{t-1} + v_t,$$

where $\delta = (1-\rho)\,\beta_0,\ \delta_0 = \beta_1,\ \vartheta_1 = \rho,\ \delta_1 = \rho\beta_1$.

Now, we obtain the resulting model with uncorrelated errors which is ARDL (1,1). Hill et al. (2012) noted that the estimation method of this model is a linear least squares as long as the v_t satisfy the usual assumptions required for least squares estimation which mean that their mean is equal to zero and their variance is constant furthermore, they are not correlated. The existence of the lagged dependent variable y_{t-1} indicates that a large sample is needed to obtain an eligible properties of the least squares estimator, but the least squares procedure is still valid as long as v_t is uncorrelated but If this assumption is violated, the least squares estimator will be biased, even if the sample is larger.

The assumption of ARDL $(p, q_1, q_2, \ldots, q_k)$ in (4), can be expressed as following:

1. Linear in parameter.
2. $E(e_t) = 0$.
3. $Var\ (e_t) = \sigma^2$.
4. $Cov\ (e_t, e_s) = 0;\ t \neq s$.
5. $Cov\ (e_t, x_{ti}) = 0;\ \forall\, t,\ i = 1, 2, \ldots, k$.
6. e_t is normally distributed.

Because the estimation is straightforward, least squares estimation is an appropriate estimation technique under the mentioned assumptions above, see Hill et al. (2012).

There are a lot of interests of using ARDLs; The key one is that it can be applied when the variables are integrated of different order (Pesaran and Pesaran, 1997) which consistence with the argued of using the ARDL technique averts the problem of non-stationary time series data (Laurenceson and Chai, 2003). Another advantage is included in its definition that it reflects a dynamic effect lagged x's and lagged y's, by including a sufficient number of lags of y and x that can treat with serial correlation problem (Laurenceson and Chai, 2003). Furthermore, this approach is relatively more robust in small or finite samples consisting of 30 to 80 observations (Pattichis, 1999; Mah, 2000). While the test is based on a single ARDL equation, the number of estimated parameters is reduced (Pesaran and Shin, 1995). On other hand, the other cointegration method estimates equilibrium relationships with multi-equations frame work; however, the ARDLs assume just a single reduced form equation (Pesaran and Shin, 1995) Moreover, a dynamic error correction model (ECM) can be derived from ARDL by using a simple linear transformation (Banerjee et al., 1993)*.

Following Pesaran et al. (2001) the error correction representation of the ARDL model is as follows:

$$\Delta y_t = \alpha_0 + \Sigma_{i=1}^{p}\alpha_{1i}\times\Delta y_{t-i} + \Sigma_{i=0}^{q1}\alpha_{2i}\times\Delta x_{1t-i} + \ldots + \Sigma_{i=0}^{qk}\alpha_{(k+1)i}\times\Delta x_{kt-i} + \beta_1 y_{t-1} + \beta_2 x_{1t-1} + \beta_{k+1} x_{kt-1} + \varepsilon_t,$$

where the parameter β_i (for $i = 1, 2, \ldots, k+1$) is the corresponding long-run relationship, while the parameter α_i (for $i = 1, 2, \ldots, k+1$) is the short-run dynamic coefficient of the underlying ARDL model. Thus, the ARDL bounds test allow to model both I(0) and I(1) variables together. In bound test the null hypotheses is formed to test β_i since; H_0: $\beta_1 = \beta_2 = \ldots = \beta_{k+1} = 0$. Thus, the null hypothesis means that there is no cointegration versus the alternative of there is cointegration or H_1: at least one parameter not equal to zero. F-statistics is calculated to compare with Pesaran et al. (2001)'s critical values, knowing that it is derived from Wald test. If calculated F-statistics is found below the lower critical values that mentioned before, we can't reject the null hypothesis that there is not relationship between time series. If calculated F-statistics is between lower and higher bounds of critical values, it is violated to take a certain decision and referred to other cointegration tests. If calculated F-statistics is greater than the upper bound of critical values, we can deduce that there is relationship between time series. In other words, the null hypothesis is rejected.

Hill et al. (2012) mentioned that ARDL has two major usages which are forecasting and multiplier analysis. Both of them are useful policy tools as Forecasting the future values of economic variables is a key concern of policy makers and the accurate forecasts are important to take an accurate decision, and the multiplier analysis refers to the effect, and the time frame of this effect which happen on such variable by the change of one other variable. For example, when the central bank of Egypt controls the discount rate attempting to influence inflation and unemployment, and since the effects of a change in the rate are not immediate, the central bank would like to know the time and the magnitude of variables response.

In all of the previous models, we have to specify the lag length as a prior of estimation. While the theory rarely tells us information about the lag length, it should be determined empirically. There are several criteria available to obtain information about the appropriate lag length, though they do not always achieve the same result. There is no "right way" to identify the length of a lag, we just forced to choice after looking at the evidence from several

* The ECM integrates the short-run dynamics with the long-run equilibrium without losing long-run information.

methods. Having specified the model, the appropriate lag length of the ARDL model has to be decided. As the approach of Blanchard and Quah (1989), a large lag length can be chosen as a prior step and then check that the results are independent of this assumption. A large lag length relative to the number of observations, will lead to poor and inefficient estimates of the parameters "over-fitted model". On the other hand, a too short lag length, will lead to false significance of the parameters, because of unexplained information that captured in the error term "under-fitted model". Deciding the number of lags is usually determined by a statistical method, like the Akaike information criteria (AIC), that developed by Akaike (1973), which considered the way of making a balance between the two cases underfitting and overfitting. the AIC is not a traditional hypothesis test as its not based on acceptance or rejection of null hypothesis, it based on scoring system, the selection of the “best” model is determined by an AIC as following:

$$AIC = -2 \log (L) + 2m,$$

where m is denoted as the number of parameters in the model (degrees of freedom) and the value of the log of the likelihood function of the estimated model. The other common lag selection criteria such as the Bayesian Information criterion (BIC), and Hannan Quinn criterion (HQ) were used as bases for selection criteria:

$$BIC = -2 \log (L) + m \log (n); HQ = -2 \log (L) + 2m \log (\log (n)),$$

where n is the number of observations (sample size).

3. LITERATURE REVIEW

One of the most recent research using ARDL is conducted by Ghouse et al. (2018) explores an alternative treatment for spurious regression because of the unit root and cointegration analysis which are the commonly uses to treat with the spurious regression are not steady because of some specification as choice of the deterministic part, structural breaks, autoregressive lag length choice and innovation process distribution. This study mainly focused on Monte Carlo simulations, it found that it is the missing variable in lag values that are the main cause of spurious regression can be treated by the alternative way which takes us back to the missing variable which further leads to ARDL Model. Thus, conclusion is providing evidence, that ARDL can be used as an alternative tool to avoid the spurious regression problem.

Bond (2002) focused on single equation estimation of ARDL models from panel data. The study used a large N (number of cross section data), and a small T (number of time periods). This structure is representative of micro panel data on individuals or firms, the estimation methods do not require the time dimension to become large in order to obtain consistent parameter estimates. The paper focused on single equation models with dynamics autoregressive and explanatory variables that are endogenous (not strictly exogenous), and on the Generalized Method of Moments (GMM) estimators that are widely used in this case. Using firm-level panel data, two examples are discussed as a simple autoregressive model for investment rates; and a basic production function. The paper concludes that the GMM estimators can be used to obtain consistent parameter estimation a wide range of microeconomic application. However, they may be subject to large finite sample biases. The comparison of the consistent GMM estimator to simple estimator like OLS level can detecting and avoid these biases in empirical studies, see Abonazel (2017) for more details about the GMM estimation.

Most of research on ARDL is application on financial and economic indicators one of research undertaken by Ghavam et al. (2005), to examine the long-run relationship between the inflation rate and its factors in Iran using ARDL approach. The results obtained mentioned that the GDP, the imported inflation, liquidity and the exchange rate are the most significant factors affecting inflation in Iran. Tian and Ma (2010) implemented the cointegration ARDL technique to investigate the relationship between exchange rate and the Chinese share market. The paper concluded that exchange rate and money supply affect stock market positively. Chaudhry et al. (2011) used ARDL bounds testing approach for investigating the relation between foreign exchange reserves and inflation rates in Pakistan, over the period from 1960 to 2007. The empirical results found long-run cointegrating relationship between the two series. Chou and Tseng (2011) applied the ARDL bounds test using the time frame from 1982 to 2010 to investigate the effect of oil price volatility on inflation in Taiwan. The results found a long-run relationship, and confirmed that an increase in the global oil prices causes inflation only in the long-run.

4. DATA AND METHODOLOGY

According this background and literature review, this paper's objective is to examine the required conditions of ARDL application on inflation and its effective factors in Egypt and its interpretation. Inflation means the increase of general level of price for goods and services in an economy; and it is the major concern to all stakeholders. As central banks confirmed, the importance of inflation is premised on the distortions that high inflation can exert on domestic macroeconomic conditions, with the potential to derail the economy from the path of sustainable economic growth and development. Considering the impacts of inflation on the economy, there is a consensus among the world's central banks that price stability should be the prime objective of monetary policy. Consequently, the maintenance of price stability continues to be the overriding objective of monetary policy in Egypt. Thus, a good understanding of the factors driving inflation is required, (central bank of Nigeria). There is no dearth of literature on exploring what determines inflation and on forecasting inflation, thus numerous empirical studies have been conducted on the determinants of inflation and inflationary process in many countries, both developed and developing. The simple monetarist model is based on the quantity theory of money. We can say that there is a positive relationship between changes in money supply and the inflation in the long-run; while the money supply is defined as the whole stock of currency and other liquid substitutes revolving in the economy in a specific time. It can be cash, coins, and balances in savings accounts, and other near money instruments. Central bank of Nigeria presents many studies about the same context as follows; Durevall (1998) investigated the inflationary process in Brazil for the period 1968 to 1985. The author showed that an increase in money growth or oil-price inflation, increases overall inflation. Also, inflation increases when the rate of devaluation of the exchange rate increases, while it decreases when goes up. The exchange rate is the value of one nation's currency versus the currency of another nation or economic zone. Metin-Ozcan et al (2004) examined inflation in Turkey between 1988 and 2000. They found significant positive correlations between the prices of housing rents and the CPI, and both the US Dollar and German Mark exchange rates and the CPI. Cevik and Teksoz (2013), using Libyan annual data for the period 1964 – 2010, adopted the dynamic models to investigate inflation dynamics. The result indicated that government spending, money supply growth, global inflation, exchange rate pass-through played central roles in the Libyan inflation process. Laryea and Sumaila (2001) found that output and monetary factors were the main determinants of inflation in Tanzania in the short-run, while parallel exchange rate also played a key role, in addition to output and monetary factors, in the long-run. They remarked that inflation in Tanzania is engineered more by monetary factors than by real factors judging by the magnitudes of elasticities of price with respect to both money and output. Moriyama (2008) studied the inflation in Sudan during the period 1995:Q1 to 2007:Q2, the paper studies the effect of money supply growth, real GDP growth, nominal exchange rate, and foreign inflation in the same period. Noted that the GDP is the total monetary or market value of all the finished goods and services produced within a country's borders in a specific time period, and the GDP is a good indicator of an economy's size in a country, see Abonazel and Abd-Elftah (2019) and Abonazel and Rabie (2019). This paper found that the most variables that affect the inflation are the nominal exchange rate, the growth in money supply, and the foreign inflation which implies that some of the inflation in Sudan is imported.

According to the theoretical relationship among the economic and monetary indicators, the data used is Egypt's quarterly Inflation rate, real GDP, exchange rate and money supply collected from the Central Bank of Egypt's Statistical Bulletin from 2005:Q1 to 2018:Q2. We used E-views version ten to make our empirical study.

4.1. Descriptive statistics

In Egypt after revolution the 25th of Jan 2011, the exchange rate was moved from 5.84 in Jan 2011 to 6.02 in Jan 2012 (as shown in Figure 1), that push the black market to flourish and this was the peak of exchange rate market crisis in Egypt, So on the 3rd of November 2016, the CBE let EGP exchange rate completely to supply and demand forces. For a net importer country like Egypt where imports of goods and services constituted about 30% of the GDP, in real terms EGP devaluation had a great impact on prices due to the significant exchange rate to inflation. Thus, we can indicate that there is a positive relation between inflation and exchange rate, as increasing in Exchange rate leads the cost of goods and services to increase then the prices are raising up. Interest Rate has always been the most powerful tool to decline the inflation across managing money supply, CBE was increasing the interest rate after floating to encourage people to save instead of spending to decrease money supply which subsidy the value of EGP so as to contain inflation, so that the relation between money supply and inflation is Positive inflation, as it is considered a technique to decline the inflation by decreasing money supply using policy rate tool. On other hand, an increase happened in output or gross domestic products generates an increase in domestic incomes which leads to increase in money and product demand, and by applying an economic theory the increase in demand causes prices raising, so theoretically there is positive relation between GDP and inflation. The trend and main descriptive statistics of our data can be shown by the following:

Table 1

Main descriptive statistics

Variable	Abbreviation	Mean	Standard deviation	Maximum	Minimum
Inflation	INF	11.89756	6.33432	32.15	3.157089
Exchange Rate	FX	7.982743	3.991738	18.11333	5.3514
Real GDP	GDP	724728.8	109072.4	931306.6	466873.2
Money supply growth	M	4.3689	3.117622	13.3297	-1.7907

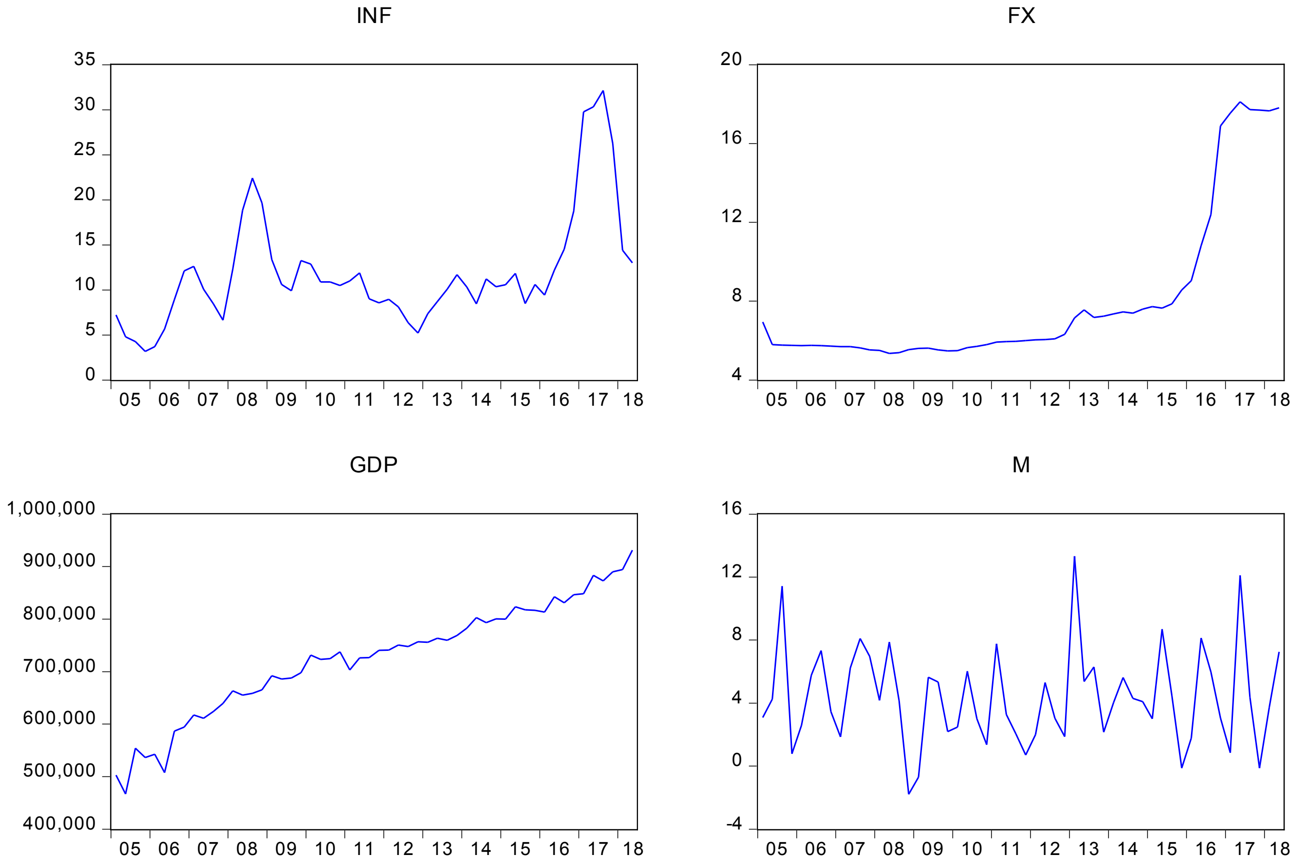

Figure 1 Time series plots of the variables from 2005:Q1 to 2018:Q2

The descriptive statistics for the four time series (as in Table 1) show that the Egypt inflation rate was varied between less than 5% and 10% (except the first floatation in 2003) just before 2016 and since then has been on the increase with about 200%. The exchange rate was stable before 2011 and since then has been on the small increase with about 150%. The real GDP also reveals a level of seasonality with the data exhibiting a large increase and it is replaced by GDP seasonally adjusted using the moving average method. Also, money supply has an increasing growth trend across the period. So according to the previous relations we can modeling the inflation (INF) followed by foreign exchange rate (FX), money supply (M) and real GDP seasonally adjusted (GDP).

Table 2

Correlation matrix of independent variables

	FX	GDP	M
FX	1	0.4953284	0.6919544
GDP	0.4953284	1	0.7766177
M	0.6919544	0.7766177	1

Table 2 shows that there is positive correlation between every pair of independent variables; moderate correlation between GDP and foreign exchange rate, approximately high between GDP and money supply and the same between the foreign exchange rate and money supply. The previous results of correlation indicate that there isn't a multicollinearity problem across independent variable as all correlation coefficient less than 0.8.

4.2. Stationarity

Engle and Granger (1987) showed that cointegration analysis is not applicable in cases of variables that are integrated of different orders (i.e, some series is I(1) and others series is I(0)), but by Johansen and Juselius (1990), ARDL cointegration procedure it is applicable and although ARDL cointegration technique does not require pre-testing for unit roots, stationary condition has to be checked for all series as an initial step of model estimation to avoid ARDL model crash in the presence of integrated stochastic trend of I(2), A series is said to be stationary if its mean, variance and structure don't change over time. In terms of unit root concept, a non-stationary time series is a stochastic process with unit roots or structural breaks. However, unit roots are major sources of non-stationarity. The presence of a unit root implies that a time series under consideration is non-stationary while the absence of it entails that a time series is stationary. Testing of stationarity is pioneered by Dickey and Fuller (Dickey and Fuller 1979, Fuller 1976) based on the unit root in time series. A logic behind the unit root test is that if a non-stationary series (X) has to be differenced d times to be stationary then this series have d unit roots at its level and must be integrated of order d, it can be written as (X) ~ I (d). The null hypothesis (H_0) of the Dickey-Fuller (DF) test is "series has a unit root" versus the alternative hypothesis (H_1) which is "the series is stationary". The DF test assumes the white noise of disturbance term, so if there is autocorrelation in the dependent variable it leads to autocorrelation in error term which causes the invalidity of DF test. In 1981, Dickey and Fuller had developed the DF test to augmented Dickey–Fuller test (ADF) by taking p lag values into consideration. The same null hypothesis and critical values table are used as DF test.

Table 3

Augmented Dickey–Fuller Test Results

Series	Integrated Order
INF	I (1)
GDP	I (0)
M	I (0)
FX	I (1)

Table 3 indicates that the ADF test confirmed that the included variables are stationary at I (0) (stationary at their level) and I (1) (integrated of order 1).

5. Estimation and specification

According to Pesaran et al. (2001), the error correction representation of the ARDL model is:

$$\Delta INF_t = \alpha_0 + \Sigma_{i=1}{}^{p}\alpha_{1i}\,\Delta INF_{t-i} + \Sigma_{i=1}{}^{q1}\alpha_{2i}\,\Delta FX_{t-i} + \Sigma_{i=0}{}^{q2}\alpha_{3i}\,\Delta M_{t-i} + \Sigma_{i=0}{}^{q3}\alpha_{4i}\,\Delta GDP_{t-i} + \beta_1 INF_{t-1} + + \beta_2 FX_{t-1} + \beta_3 M_{t-1} + \beta_4 GDP_{t-1} + \varepsilon_t$$

The null hypothesis of no cointegration is that H_0: $\beta_1 = \ldots = \beta_4 = 0$, and the alternative hypothesis that cointegration exists is: H_1: at least one parameter not equal to zero, it's performed by Wald test using F-test. The null hypothesis can be rejected, when the value of F-statistic is greater than the upper bound critical value. Since there is a long-run relationship is exist, then the conditional autoregressive distributed lag model will be conducted that can be used to estimate the long-run coefficient:

$$\Delta INF_t = \alpha_0 + \Sigma_{i=1}{}^{p}\alpha_i\, INF_{t-i} + \Sigma_{i=1}{}^{q1}\beta_i\, FX_{t-i} + \Sigma_{i=0}{}^{q2}\theta_i\, M_{t-i} + \Sigma_{i=0}{}^{q3}\gamma_i\, GDP_{t-i} + u_t \quad (9)$$

The long run equation is:

$$INF_t = \alpha_0 + \beta_1\, FX_t + b_2 M_t + b_3 GDP_t + u_t \quad (10)$$

All variables defined in above and the lag lengths p and q are selected using AIC or SIC. The long-run parameters in (10) can easily be obtained from the OLS estimates of (9), thus:

$$\bar{a}_0 = \alpha_0 / (1 - \Sigma_{i=1}{}^{p}\bar{\alpha}_i);\ \bar{b}_1 = \Sigma_{i=0}{}^{q1}\bar{\beta}_i / (1 - \Sigma_{i=1}{}^{p}\bar{\alpha}_i);$$
$$\bar{b}_2 = \Sigma_{i=0}{}^{q2}\bar{\theta}_i / (1 - \Sigma_{i=1}{}^{p}\bar{\alpha}_i);\ \bar{b}_3 = \Sigma_{i=0}{}^{q3}\bar{\gamma}_i / (1 - \Sigma_{i=1}{}^{p}\bar{\alpha}_i).$$

The second step in the second stage of the bounds testing ARDL approach involves estimating a conditional ECM. "A principle feature of cointegrated variables is that their time paths are influenced by the extent of any deviation from long-run equilibrium. After all, if the system is to return to long-run equilibrium, the movements of at least some of the variables must respond to the magnitude of disequilibrium" (Enders, 2004). The following equation specifies the conditional ECM:

$$\Delta INF_t = \alpha_0 + \Sigma_{i=1}{}^{p}\alpha_{1i}\,\Delta INF_{t-1} + \Sigma_{i=0}{}^{q1}\alpha_{2i}\,\Delta FX_{t-1} + \Sigma_{i=0}{}^{q2}\alpha_{3i}\,\Delta M_{t-1} + \Sigma_{i=0}{}^{q3}\alpha_{4i}\,\Delta GDP_{t-1} + \upsilon ECT + \varepsilon_t,$$

where ECT is known as error correction term which indicate that the speed of adjustment parameter, the ECT shows how much of the disequilibrium is being corrected, that is, the extent to which any disequilibrium in the previous period is being adjusted in current point.

6. The Empirical Results

The estimating ARDL model with automatic lag selection using E-views version ten is ARDL (2,2,1,0) model, it was selected depending on the least AIC, as shown in figure 2.

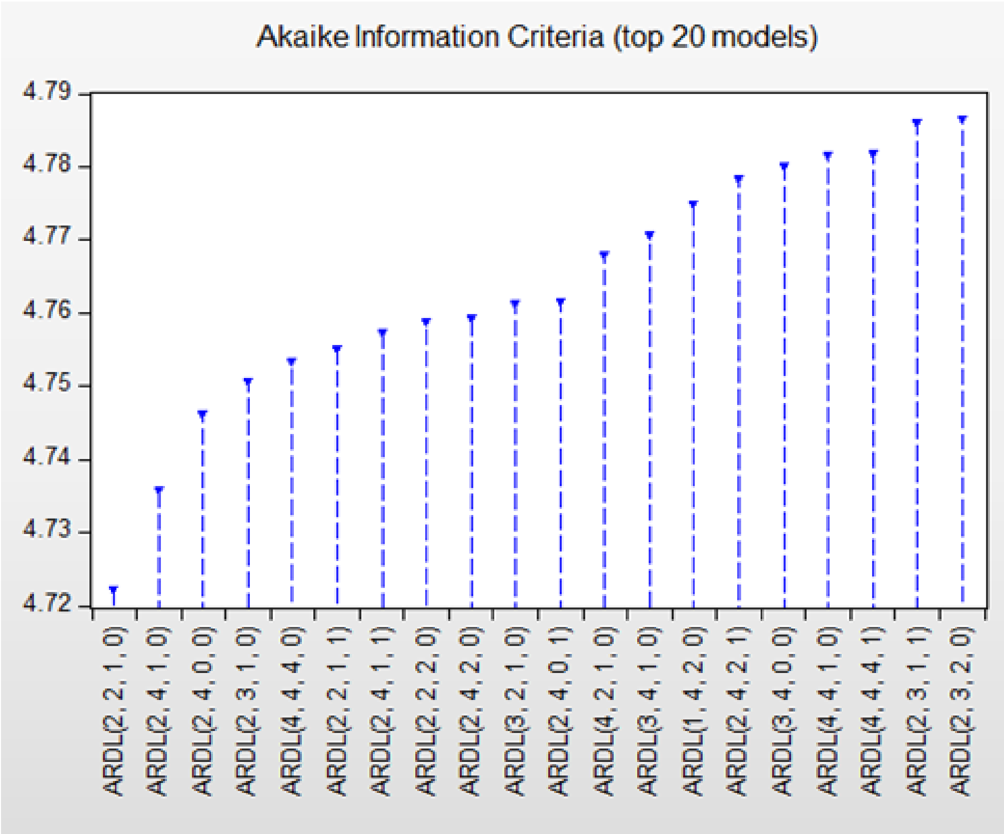

Figure 2 Model Selection Summary Graph

Table 4 shows that there are significant effects of the lags of some of the macroeconomic variables on Inflation. We have a highly significant effect of the first and second lag of foreign exchange rate, first lag of money supply growth have a significant effect at 10% level of confidence and also the first and second lags of inflation have a significant effect on the inflation rate and there is no lag of GDP is chosen for describe on inflation, in addition to the insignificance of GDP which consistence with the result of some neighbors countries like Sudan (see Moriyama, 2008).

Table 4

The results of ARDL (2,2,1,0) model

Variable	Coefficient	Standard Error	T-Test	Significant
INF (-1)	1.0871	0.1099	9.8914	***
INF (-2)	-0.3402	0.1246	-2.7308	**
FX (-1)	2.3680	0.9159	2.5856	**
FX (-2)	-2.2376	0.6225	-3.5945	***
M (-1)	0.1901	0.1119	1.7000	*
GDP	-2.3E-06	5.1E-06	-0.4579	Not sig.
C	2.2632	3.2352	0.6996	Not sig.
$\bar{R}^2$ = 0.857 AIC = 4.745 SC = 5.082 HQC = 4.874				

Note: *** significant at 0.01, ** significant at 0.05, * significant at 0.1

6.1. Bound Test

As mentioned before the bound test is the test to determine if there is a long-run relationship as a null hypothesis says that; there is no long-run relationship, according to the value of F-statistics, first case; if this value lower than I(0) we don't reject the null hypothesis and there is no long rum relationship, second one; if this value greater than I(1) we reject the null hypothesis and we can indicate that there is long relationship, the last case; if this value lies between two bounds we cannot judge. Here, we are in second case as the value of F-statistic greater that upper bound which include that there is a long-run relationship at all level of significance 1%, 5%, and 10%.

Table 5

F-Bounds Test

Test Statistic	Value	Significant level	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	6.725238	10%	2.72	3.77
K	3	5%	3.23	4.35
		2.5%	3.69	4.89
		1%	4.29	5.61
Actual Sample Size	52		Finite Sample: n=55	
		10%	2.843	3.92
		5%	3.408	4.623
		1%	4.828	6.195
			Finite Sample: n=50	
		10%	2.873	3.973
		5%	3.5	4.7
		1%	4.865	6.36

Null Hypothesis: No levels relationship

6.2. Error Correction Model

Because there is cointegration, the error correction model is specified as follows:

Table 6

Error Correction Model Estimation

Variable	Coefficient	Std. Error	t-Statistic	Significant
C	2.2632	0.5879	3.8498	***
D (INF(-1))	0.3402	0.1004	3.3892	**
D (FX)	-0.0380	0.5153	-0.0738	Not sig
D (FX(-1))	2.2375	0.5181	4.3191	***
D (M)	0.1325	0.0783	1.6937	**
ECT	-0.2531	0.0472	-5.3645	***
$\bar{R}^2$ = 0.533117 AIC = 4.629173 SC = 4.854317 HQC = 4.715488				

Note: *** significant at 0.01, ** significant at 0.05, * significant at 0.1

The ECT shows how much of the disequilibrium is being corrected, that is, the extent to which any disequilibrium in the previous period is being adjusted in current point. A positive coefficient indicates a divergence, while a negative coefficient indicates convergence. If the estimate of ECT = 1, then 100% of the adjustment takes place within the period, or the adjustment is instantaneous and full, if the estimate of ECT = 0.5, then 50% of the adjustment takes place each period/year. ECT = 0, shows that there is no adjustment, and to claim that there is a long-run relationship does not make sense any. In our case the ECT is negative sign and highly significant which indicate convergence and we can conclude that 25% of adjustment from short run to long-run is take place each quarter, i.e, adjustment is taken place after 1 year (four quarters).

7. DIAGNOSTICS TESTS

7.1. Checking stability

A further step of estimating model is checking this model adequacy before making a forecast, these checking steps divided to checking model stability and diagnostic of residuals performance.

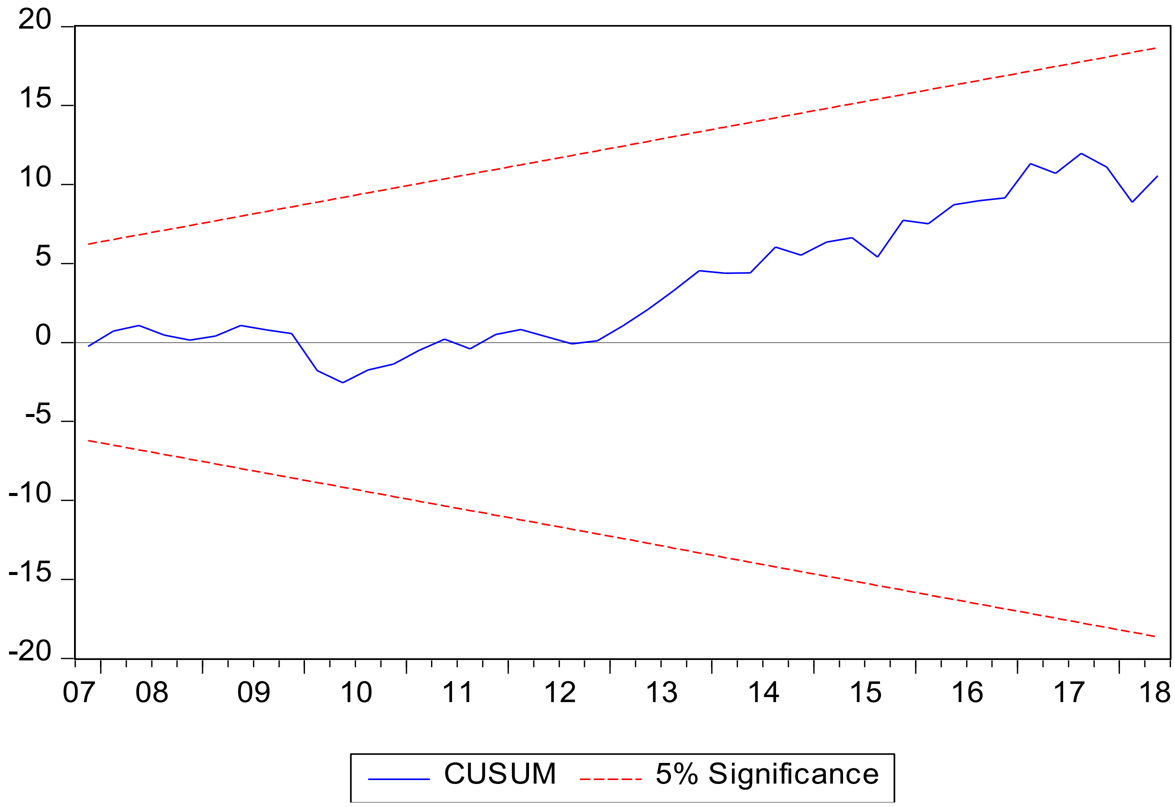

Figure 3 CUSUM Stability test of ARDL (2,2,1,0) model

For checking the stability and the accuracy of the estimated model CUSUM is used. Figure 3 confirms that the estimated model satisfies the stability condition as there is no root lying outside the significance level.

7.2. Checking serial correlation and Heteroscedasticity

As widely used for checking serial correlation of the residuals, the LM test is used and it is confirmed that there is no longer serial correlation between residuals. As shown in Table 7; the null hypothesis that there is no serial correlation is not rejected at level 0.05 which mean that there is no evidence for serial correlation in the residuals term of the estimated model. Also, Table 7 shows that there is no heteroscedasticity (or the variance is constant) in the residuals, since we don't reject the null hypothesis of no heteroscedasticity at level 0.05.

Table 7

Serial Correlation and Heteroskedasticity tests

Test	Chi-squared value	P-value
Lagrange Multiplier (LM) for Serial Correlation	2.891407	0.2356
Breusch-Pagan-Godfrey for Heteroskedasticity	9.939242	0.2693

7.3. Checking Normality

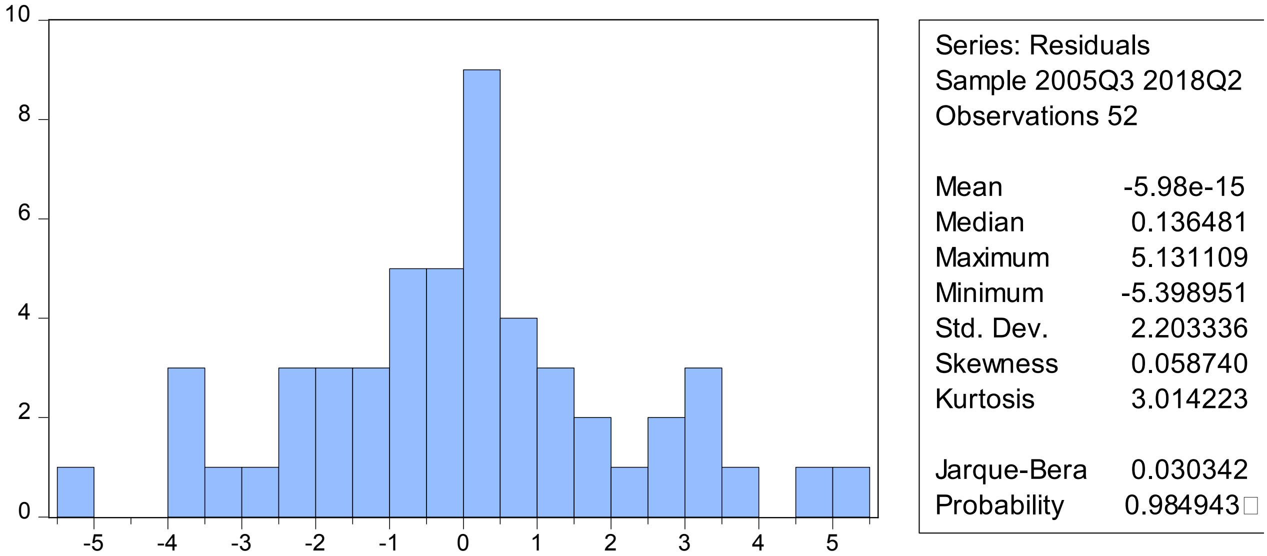

Figure 4 Normality Diagram and Jarque-Bera test

The Jarque-Bera (JB) test is used for checking normality of the residuals, the null hypothesis of JB test is the residuals are normally distributed, the probability (p-value) highly recommends the normality of residuals as we can't reject the null hypothesis event at the very high level of significance.

8. CONCLUSION

This study aimed to present one of the most effective dynamic models and recent as well, auto-regressive distributed lag, by applying it on the inflation rate in Egypt. The model overcomes the problem of mixed stationary and non-stationary series as it can treat with series which integrated from different orders, also it overcomes the serial correlation that happened in least square regression method. The inflation has a long-run equilibrium relationship with its determinants (foreign exchange rate, money supply and real GDP) and the best ARDL model describe this relation is ARDL (2,2,1,0). The current foreign exchange rate would still affect the rate of inflation in the next two quarters, the current money supply growth would affect the Inflation rate for the coming quarter and the current inflation rate would still have an influence on the inflation rate in the next two rates. According to our data, real GDP has no significant effect on inflation consistently with Sudan mentioned case. We also conclude that 25% of adjustment from short run to long-run is taken place each quarter.

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INFORMATION ABOUT THE AUTHORS

1. **Mohamed Reda Abonazel** (Egypt, Giza) – Associate Professor, PhD in Statistics and Econometrics. Associate Professor at Department of Applied Statistics and Econometrics, Faculty of Graduate Studies for Statistical Research. Cairo University. E-mail: mabonazel@cu.edu.eg; mabonazel@hotmail.com. ORCID ID: 0000-0001-6010-001X. Scopus Author ID: 57192680721. ResearcherID: R-7908-2018
2. **Nourhan Elnabawy** (Egypt, Cairo) – Researcher, Economic at research sector in Central bank of Egypt; Master student, Bachelor in statistics from faculty of economic and political science. Cairo University. E-mail: nourhanelnabawy@outlook.com. ORCID: 0000-0002-0625-594X.

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