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The importance of foreign direct investment and energy consumption and their effects on economic growth in the case of MENA

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Abstract

The main purpose of this paper is to investigate relationship between foreign direct investment and economic growth for MENA countries from 1990 to 2014. We firstly tested heterogeneity and cross sectional dependence and found that all series have homogeneity and cross sectional dependence. For that reason, Hadri Kruzomi and Pesaran et al. Multifactor Error Structure panel unit root tests were used. For obtaining long-run relationship, we used Weterlund's panel and group cointegration tests. The results supported the long-run relationship, therefore, we used Common Correlated Effect Model, thanks to this method, and coefficients for each cross-section unit could be calculated individually.

Keywords: Economic growth; Energy; Renewable energy; MENA; FDI; IDE

1. Introduction

Since the early 1990s, the world has been experiencing globalization, liberalization, regulation and technological progress, major changes that affect various economic sectors in different countries of the world, including Most of them have chosen an economic policy issued by a pop-up in order to be able to improve its economic growth and development and meet the challenges associated with this opening up while providing an appropriate ground for global competition to attract more foreign investment. Therefore, attracting FDI is always a matter of continuing interest for home countries as host countries where there is an almost complete consensus on the benefits that can be made and be attracted by FDI, they will create jobs that will promote economic growth and development, as they allow the transfer of knowledge and technology and encourage reforms, especially for host countries.

In the context of development, we can also talk about the importance of energy, as this sector has seen growing interest in recent years. Realizing the need to develop this sector, in terms of its economic and environmental benefits, a number of researchers have in fact documented the benign effects of alternative energies (nuclear and renewable energy) in reducing carbon dioxide emissions and reducing the impacts of climate change (AlFarra and Abu-Hijleh, 2012; Apergis et al. 2010; Lee, 2014; Monia and Weld Raphael, 2010bAnother important characteristic of renewable energy resources is that they promote sustainable development. Glorioso et al (2007)

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Research on the relationship between foreign direct investment, energy consumption and economic growth is seen as a hierarchy of objectives and constraints that involve global, regional or local considerations and has attracted the interest of academic researchers and policy makers in the economic literature (Root and Ahmed, 1979; Dunning, 1981; Schneider and Frey, 1985) Mina (2020).

FDI and energy consumption were seen as the driving force of modern economies and societies. Therefore, as they were a top priority for economic growth, United Nations members would need to improve FDI and access to energy in order to achieve many economic growth objectives, including poverty reduction, industrialization, health and education.

Indeed, the growing interest of academics and scholars in the relationship between foreign direct investment, energy consumption and economic growth has made it a platform from which we are trying to seek to clarify their impact on economic growth by asking the following question: What is the importance of foreign direct investment and energy consumption and what are their effects on economic growth in the case of the countries of the Middle East and North Africa?.

2. Literature review and hypothesis

FDI uses foreign technology and management techniques to exploit local resources at low cost. There is a clear distinction between FDI and portfolio investment: in the FDI situation, the home company has direct and ultimate control over the scope and nature of day-to-day operations, and transfers not only capital to host countries, but also technology and management skills. On the other hand, portfolio investment is simply the provision of capital from a lender to a borrower; it is motivated by the per capita rate of return and obliges borrowers to repay the loan plus interest. The investment portfolio may involve the purchase of shares, bonds or other foreign securities and has no controlling interest in the investment. The main components of FDI are: equity, reinvested earnings (the investor's share of income retained in the form of dividends by subsidiaries in proportion to its share of equity) and intra-company loans (where the investor borrows funds from the subsidiary, usually without the intention of seeking repayment).

Hypothesis 1: Foreign direct investment (FDI) has a direct positive effect on economic growth.

In contrast, the subject of FDI has been studied by several economic disciplines both theoretically and empirically. The various existing theories on FDI evolve over time to adapt to new data in the international economic environment. It is first and foremost since the turn of the 2000s that the literature on FDI has experienced a strong acceleration, in line with the development of the phenomenon.

Indeed, the authors who have dealt with FDI have attempted to formalize its causes by developing or applying different theoretical approaches. The arguments put forward are inspired by several theories relating to economics, trade, investment or marketing.

Following a chronological order, the analysis will focus on the theories that have focused in particular on the impact of FDI on development and economic growth.

Blomston et al (1992) Khemici & Abdelmadjid, K. (2013), in studying the impact of FDI on growth, have shown that the magnitude of this impact depends on the stock of human capital in the host country. The authors highlight the positive effect of FDI on income growth. Moreover, (Ait Ken and Hanison, 1993), Idrissa & Abdou (2019), (Saggi, 2000) Acquah & Ibrahim (2019), have shown that FDI can generate negative, even mixed effects on the development of host countries.

In the same framework, Darrat et al (2005) carried out a comparative study (1979-2002) covering countries in two regions, namely those of MENA and those of Central and Eastern Europe. This study showed that FDI flows stimulate economic growth only in EU member countries. Whereas, the effect of FDI remains negative or even non-existent in the MENA countries.

Development economics argues that capital accumulation is a factor in long-term growth. However, this thesis has recently been challenged: the joint movement of investment (its GDP ratio) and the growth rate is largely driven by a third factor, technological innovation (Ben Habib and Jovanovic, 1991; King and Levine, 1994) Mtiraoui, A. (2020).

At this level, the OECD emphasizes the links between investment and growth, while conditioning them on the policy reforms that need to be put in place and on the need for co-operation between all countries, whether members or non-members of the organization.

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Hypothesis 2: Foreign direct investment has a negative effect on economic growth.

In the energy literature, few studies have addressed the problem of intersectoral dependence and the degree of heterogeneity. Therefore, to address this problem, our study applied a heterogeneous panel technique with cross-sectional dependence. Moreover, energy policies developed at the global level can also affect individual nations. Moreover, it also manages exogenous shocks. This is one of the studies dealing with the problems mentioned by applying heterogeneous panel techniques for some countries.

Hypothesis 1: An increase in renewable energy consumption improves positive production, and if there is a decrease in renewable energy consumption, energy conservation policies will have a significant negative impact on economic growth. This means that renewable energy consumption leads to economic growth, which is called the growth hypothesis.

Hypothesis 2: The preservation hypothesis assumes a one-way causal relationship that links economic growth to renewable energy point-of-sale consumption; thus, a decrease or increase in energy consumption will not affect economic growth.

Hypothesis 3: The feedback hypothesis indicates a two-way causal relationship between renewable energy consumption and economic growth. Any increase in the use of renewable energy will play an important role in stimulating economic growth with the opposite effect.

Hypothesis 4: The neutrality hypothesis shows that these two variables are independent. Most of the existing energy literature has studied the links between renewable energy use and economic growth, but has given mixed empirical results from countries.

3. Methodology

All time series data below were collected from the database published by the World Bank. Our data include the following variables:

- **Economic growth**: measured by GDP per capita, an economic indicator of the wealth produced per year in a given country, in constant US dollars.
- **Foreign direct investment**: These investments play a major role in the internationalization of a firm. Highly appreciated by academics, they also help measure a country's economic attractiveness.
- **Energy consumption**: Energy consumption is variable according to various parameters. Among others, for a boiler it will depend on its efficiency, for an air conditioner on its COP and for a housing on its insulation.
- **Renewable energy**: Renewable energy is energy generated by natural processes that are continually replenished. It is measured by Renewable Energy Consumption (% of total final energy consumption).
- **Population**: In statistics, a population is a finite set of objects, units or individuals that are the subject of a study or observation and which is subject to statistical processing.

Details on the description of the variables used and their sources are presented in Table 1.

Table 1. Description of variables and data source

Variables	**Description**	**Source**
Growth economic	GDP growth (annual %)	World Bank
Foreign Direct Investment	Net foreign direct investment as % of GDP	World Bank

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Energy consumption	Total energy consumption	World Bank
Renewable Energy	Renewable energy consumption (% of total final energy consumption).	World Bank
Population	Total population	World Bank

Source: World Bank

3.1 Data source

The data used come from the World Bank database. These data will be annual and relate to Gross Domestic Product growth (annual GDP growth in %), Net Foreign Direct Investment as % of GDP, Renewable Energy Consumption (% of total final energy consumption), Total Population, Total Energy Consumption. There are 275 observations (1990-2015).

3.2 Empirical methodology

The paper uses a four-step empirical methodology. The first step is to examine the stationary properties of individual series in panel data. The second step is to test for the presence of cointegration. In the third step, we estimate our models using the estimator. The third step is to examine the short- and long-term causality between variables using the vector error correction model (VECM). In the third step, we estimate using individual effects models. In the last step one can be drawn from the ARDL which integrates the CT dynamics with the LT equilibrium without losing the LT information.

3.3 Unit root tests in panel data

The unit root test on time series data has become one of the most important tests for economists, particularly econometricians, although the unit root test on panel data is more recent. Unit root tests in panel data have become popular among economic researchers working on panel data structures because they are much more powerful than normal unit root tests for individual time series. Among the various unit root tests developed in the literature, Levin, Lin and Chu (LLC) (2002) and Im, Pesaran and Shin (IPS) (2003) are the most popular. Both tests are based on the ADF principle. However, LLC assumes homogeneity in the dynamics of the autoregressive coefficients for all panel members. In contrast, the SPI is more general in that it allows for heterogeneity in these dynamics. Therefore, it is described as a "heterogeneous panel unit root test". It is particularly reasonable to allow such heterogeneity in the choice of shift length in ADF tests, when the imposition of a uniform shift length is not appropriate. Furthermore, slope heterogeneity is more reasonable where cross-national data are used. In this case, heterogeneity is due to differences in the economic conditions and degree of development of each country.

Levin et al (2002) consider the following basic ADF specification:

$$\Delta X_{it} = \alpha_i + \beta_i X_{i,t-1} + \delta_i t + \sum_{j=1}^{k} \gamma_{ij} \Delta X_{i,t-1} + \upsilon_{it} \quad (1)$$

Where Δ is the first difference operator, X_{it} s the dependent variable i over the period t, is a white noise disturbance with a variance of σ^2. Both β_i and the order of shift

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$$\begin{cases} H_0 : \beta_i = 0 \\ H_1 : \beta_i \prec 0 \end{cases};$$

Where the alternative hypothesis corresponds to Xit being stationary. The test is based on the $t_{\beta_i} = \frac{\hat{\beta} i}{\sigma(\hat{\beta}_i)}$, or is the OLS estimate of β_i in equation (4) and $\sigma(\hat{\beta}_i)$ is his standard mistake.

According to the LLC test, the panel procedure significantly increases the efficiency of the finished samples. The proposed model is as follows:

$$\Delta X_{it} = \alpha_i + \beta X_{i,t-1} + \delta_i t + \sum_{j=1}^{k} \gamma_{ij} \Delta X_{i,t-1} + \upsilon_{it} \qquad (2)$$

At this level, Levin et al. (2002; LLC) also assumed:

$$\begin{cases} H_0 : \beta_1 = \beta_2 = ... = \beta = 0 \\ H_1 : \beta 1 = \beta_2 = ... = \beta \prec 0 \end{cases};$$

Where the test statistic is:

$t_{\beta_i} = \frac{\hat{\beta}_i}{\sigma(\hat{\beta}_i)}$, $\hat{\beta}_i$ is the OLS estimate of β_i in the equation (4) and $\sigma(\hat{\beta}_i)$ is his standard error.

Im et al (2003) proposed a test procedure based on the middle group approach. The starting point for the IPS test is also the ADF regressions given in equation (1). But the null and alternative hypotheses are different from the LLC test, where rejection of the null hypothesis implies that all series are stationary. We now have :

H0: β1 = β 2 = … = β N = 0 vs H1: Some but not necessarily all β i 0

IPS developed two test statistics and called them LM-bar and t-bar tests. The alternative t-bar statistics to test the null hypothesis of the unit root for all people (βi = 0) is as follows:

$$\bar{t} = \frac{\sum_{i=1}^{N} t\beta_i}{N} \qquad (3)$$

Where t is the calculated ADF statistics of the individual panel members. Using Monte Carlo simulations, IPS shows that t-bar convertiris normally distributed under the null hypothesis and outperforms M-bar in small samples. They then use estimates

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of the mean and variance to convert ($\bar{t}$) in a standard z-bar ($\bar{z}$)statistics so that conventional critical values can be used to assess its significance. The test statistic ($\bar{z}$) is defined as follows:

$$\bar{z} = \frac{\sqrt{N}\ (\bar{t} - E[\bar{t}\,|\beta_i = 0])}{\sqrt{\mathrm{var}[\bar{t}\,|\beta_i = 0]}} \rightarrow N(0,1) \qquad (4)$$

Where $\bar{t}$ is as previously defined , $E[\bar{t}\,|\,\beta_i = 0]$ and $\mathrm{var}[\bar{t}\,|\beta_i = 0]$ are the mean and variance of obtained from Monte Carlo simulations with i = 1,2,…, N.

The LLC and IPS unit root tests are used in this study to test the stationarity of the data used for the 30 African countries.

3.4 Cointegration tests in panel data

After checking that the series are integrated in the same order, we move on to the next step by testing the possibility of long-term convergence between our data series. Engle and Granger (1987) indicated that variable series can be stationary and are therefore interpreted as Co-integrated (having a long-run relationship) if there is a linear combination of two or more non-stationary variable series. The unique order of integration of the variables allows us to use the panel cointegration technique to test the long-run relationships between the variables in each model. The existing literature suggests several panel cointegration tests, such as Pedroni (1999, 2004), Kao (1999) and Westerlund (2007). For this study, we used the cointegration technique of Pedroni (1999). This test is based on a method similar to that of Engle and Granger (1987) on time series with the following data generation process:

$$Y_{it} = \alpha_i + X'_{it}\beta_i + \varepsilon_{it};\ N=1\ldots 14;\ T= 1 \ldots 25 \qquad (5)$$

Where Y_{it} is the dependent variable; αi is a fixed effect taking into account the unobserved heterogeneity between the dependent variables; and X'it is a vector of explanatory variables. To test the cointegrating relations, Pedroni constructed seven different statistics based on the cointegrating residual of εit , which are divided into two categories. The first includes statistics called "intra-dimensional" or "within".

3.5 Model with individual effects

We will now focus on heterogeneous panel models, where the only source of heterogeneity comes from individual constants. It is thus assumed that the coefficients of the different stochastic explanatory variables are identical for all individuals in the panel ($ß_1$ = ß). It is further assumed that these coefficients are deterministic constants. The individual constants α_1 ; The latter differ from one individual to another.

$$Y_{it} = \alpha_i + \sum_k ß_k\ x_{kit} + \varepsilon_{it}$$

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Innovations ε_{it} are supposed to be i: i: d: of zero mean, variance equal to σ_ε^2 ; $\forall i \in [1; N]$ and are assumed to be uncorrelated either in the individual dimension or in the time dimension.

Therefore, in this context, two cases must be distinguished: the case in which the parameters α_i are deterministic constants (fixed-effects model) and the case where the parameters α_i are realizations of a random variable of expectation and finite variance (random effects model). We will thus successively consider these two types of model.

3.5.1 Fixed-effect model

It is now hypothesized that the individual effects αi are represented by constants (hence the name fixed-effect model). We will determine the general shape of the estimators of the parameters αi et β in this fixed-effect model.

Assumptions:

- The individual fixed effects model has a residue structure that tests standard OLS assumptions. It is in fact a classical model with individual indicator variables.
- We're going to make an additional assumption about the nature of the residue process. This hypothesis is simply the generalization in the panel dimension of the definition of a white noise $\forall i \in 1; N\ et\ t \in 1; T$:

- $E\ \varepsilon it = 0$
- $E\ (\varepsilon it\ \varepsilon is) = \sigma_\varepsilon^2 t = s\ 0\ \forall t \neq s$
- $E\ (\varepsilon it\ \varepsilon js) = 0\ \forall j \neq i, \forall\ (t, s)$

<u>Estimateur Within ou LSDV (Least Square Dummy Variables)</u> : The Ordinary Least Squares (OLS) estimator of the parameters αi et β in the fixed-effects model is called the Within estimator; or the fixed-effects estimator or the Least Square Dummy Variable (LSDV) estimator. As we have seen, the term Within is explained by the fact that this estimator takes into account the within-group variance of the endogenous variable.

The third name LSDV is only because this estimator leads to the introduction of dummy variables.

The OLS estimators of this model are the best linear, unbiased and convergent (BLUE) estimators. In practice, the OLS or LSDV estimator is obtained from a transformed model where the different model variables are centred with respect to their respective individual means. The following specification is then retained :

$$\tilde{y}\,it = \sum_k \beta k\ \tilde{x}\,kit + \tilde{\varepsilon}\,it \quad \text{With} \quad \tilde{y}\,it = yit - \bar{Y}it$$

$$\tilde{x}\,it = xit - \bar{X}\,it \quad \text{and } \bar{Y}it = \frac{1}{T}\sum_{t=1}^{Ti} yit$$

$$\tilde{\varepsilon}\,it = \varepsilon it - \varepsilon\ it$$

The realizations of the estimators of the constants αi are deduced at the mean point, after estimation of the parameters βk by MCO on the previous transformed model.

$$\tilde{\alpha}\,i = \bar{Y}i - \sum_{k=1}^{p} \tilde{\beta}\,k\ \bar{X}\,ki$$

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3.5.2 Random effects model

In the standard practice of econometric analysis, it is assumed that there are a large number of factors that can affect the value of the variable being explained and yet are not explicitly introduced as explanatory variables. These factors are then approximated by the structure of the residuals. The problem arises in a similar way in panel econometrics. The only difference is that three types of omitted factors can be considered. First, there are factors that affect the endogenous variable differently depending on the period and the individual under consideration. In addition, there may be factors that affect all individuals identically, but whose influence depends on the period under consideration (temporal effects). Finally, other factors may, on the contrary, reflect differences between individuals of a structural type, i.e. independent of time (individual effects). Therefore the residual, noted εit ; of a panel model can be decomposed into three main components as follows (Hsiao 1986):

$$\forall i \in 1; N \; et \; t \in 1; T \; ; \; \varepsilon it = \alpha i + \lambda t + \vartheta i$$

The variables αi s here refer to the individual effects that represent the set of structural or a-temporal specificities of the endogenous variable, which differ from one individual to another. It is assumed here that these effects are random. Random variables λt represent strictly identical temporal effects for all individuals. Finally, the stochastic process ϑit designates the component of the total residue εit orthogonal to individual and temporal effects. In general, a number of technical assumptions are made about this tailings structure.

Assumptions:

It's assumed that the residue $\varepsilon it = \alpha i + \lambda t + \vartheta it$ are i.i.d. and satisfy the following conditions, $\forall i \in [1; N] \; et \; t \in [1; T]$:

$$E\,(\alpha i) = E\,(\lambda t) = E\,(\vartheta it) = 0$$
$$E\,(\alpha i \lambda t) = E\,(\lambda t \vartheta it) = E\,(\vartheta it \alpha i) = 0$$
$$E\,(\alpha i \alpha j) = \{\sigma_\alpha{}^2 \; i = j$$
$$\{0 \; \forall i \neq j$$
$$E\,(\lambda t \lambda s) = \{\sigma\lambda \; 2 \; s = t$$
$$\{0 \; \forall s \neq t$$
$$E\,(\vartheta it \vartheta js) = \{\sigma\vartheta \; 2 \; s = t \; ; \; i = j$$
$$\{0 \; \forall s \neq t \; ; \; \forall i \neq j$$
$$E\,(\alpha ixit) = E\,(\lambda txit) = E\,(\vartheta itxit) = 0$$

Under these assumptions, the variance of the endogenous variable yit conditional on the explanatory variables xit is then equal to $\sigma_y{}^2 = \sigma_\alpha{}^2 + \sigma_\lambda{}^2 + \sigma_\vartheta{}^2$. The variances $\sigma_\alpha{}^2$, $\sigma_\lambda{}^2$ and σ_ϑ correspond to the different components of the total variance. For this reason, the random effects model is also called the Error Component Model.

In this course, due to simplification, the time effect is neglected. We will assume that it does not exist (static panel).

3.6 The ARDL models "Autoregressive Model with Scaled Distributed Delays"

The "AutoRegressive Distributed Lag/ARDL" or "Autoregressive Distributed Lag/ARRE" models are dynamic models. The latter have the particularity of taking into account time dynamics (adjustment lag, expectations, etc.) in the explanation of a variable (time series), thus improving forecasts and the effectiveness of policies (decisions, actions, etc.), unlike the simple (non-dynamic) model whose instantaneous explanation (immediate effect or not spread over time) only restores part of the variation of the variable to be explained. Within the family of dynamic models, there are three types of models. If we consider the dependent variable « Yt » and the independent variable « Xt », noteworthy:

Autoregressive (AR) models: these are dynamic models in which the explanatory variables include (Xt), the lagged dependent variable (its past values). In general, they are as follows (implicit form)

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Yt = f (Xt, Yt-p) … (1a)

The term "autoregressive" reflects the regression of a variable on itself, i.e. on its own lagged values.

- Staggered lag or distributed lag (DL) models: these are dynamic models that have as explanatory variables: and its past or lagged values. In general, their form is:

Yt = f (Xt, Yt-q) … (1b)

The term "staggered delays" shows that the short-term effects of Xt on Yt are different from the long-term ones. From one point in time to another, the response scales of Yt at the change of Xt differ.

Autoregressive staggered-delay (ARDL) models: these models combine the features of the two previous ones; among the explanatory variables are the following (Xt), the shifted dependent variable (Yt-p) and the past values of the independent variable (Xt-q). They have the following general form:

Yt = f (Xt, Yt-p, Xt-q) …(1c)

Or

$$\mathbf{Yt = \varphi + \sum_{i=1}^{p} \alpha\ Yt\text{-}i + \sum_{i=1}^{p} bj\ Xt\text{-}j + e_t ...(1d)}$$

With e_t ~ iid (0,ϭ) : error term; « b0» reflects the short-term effect of Xt on Yt Considering the following long-term or equilibrium relationship «Yt = k + φXt + µ », it is possible to calculate the long-term effect of X_t on Y_t (or « ») as follows:

$$Ø = \sum bj / (1 - \sum \boldsymbol{\alpha} i)$$

As with any dynamic model, the following information criteria will be used (AIC, SIC and HQ) to determine the optimal offset (p* or q*) ; An optimal shift is one where the estimated model offers the minimum value of one of the stated criteria. These criteria are: Akaike's (AIC), Schwarz's (SIC) and Hannan and Quinn's (HQ). Their values are calculated as follows:

$$\text{AIC (p)} = \log \|\Sigma\| + \frac{2}{T} n2p$$

$$\text{SIC (p)} = \log \|\Sigma\| + \frac{\log T}{T} n2p$$

$$\text{HQ (p)} = \log \|\Sigma\| + \frac{2\log T}{T} n2p$$

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With : $\sum$ = variance-covariance matrix of estimated residuals; T = number of observations ; p = lag of the estimated model; and n = number of regressors. All of these dynamic models can help capture the short-term dynamics and long-term effects of one or more explanatory variables on a variable to be explained. This will only be possible if the time series under study are cointegrated, thus allowing the estimation of an error-correction/ERM model. In fact, two series are said to be "cointegrated" if they are integrated of the same order; and, a series will be said to be "d-integrated" if it has to be differentiated "d" times to make it stationary. A stationary series is stationary in terms of mean and variance, if its mean ($E(Y_t) = c$) remains invariant or constant over time and that its variance does not increase with time ($Var(Y_t) = б$), as well as its covariances ($E(Y_{t}-_{c})(Y_{t-p}-c) = y_p$).

To test the stationarity of a time series (absence of unit root), several tests are available in most software: Augmented Dickey-Fuller/ADF test, Phillippe-Perron/PP test, Andrews and Zivot/AZ test, Ng-Perron, Kwiatkowski, Phillips, Schmidt and Shin/KPSS test, Ouliaris-Park-Perron, Eliott-Rothenberg-Stock, etc. The first three tests are easy to apply and are commonly used. It should be noted that the ADF test is effective in the presence of error autocorrelation, the PP test is recommended in the presence of heteroskedastic errors, the AZ test is suitable for series that are victims of endogenously identified regime change (trend break), and the KPSS test decomposes a series into three components (deterministic part, random part, white noise) with the null hypothesis of stationarity. It should be noted that, as part of the family of dynamic models, an ARDL model makes it possible to estimate short-term dynamics and long-term effects for series that are co-integrated or even integrated at different orders, as will be seen with the boundary test approach of Pesaran et al. (1996), Pesaran and Shin (1995), and Pesaran et al. (2001). However, an ARDL model cannot be applied to integrated series at orders greater than 1.

4. Results and discussion

4.1 Results and discussion

To study the stationarity of the series used, we used unit root tests on panel data (Levin Lin and Chu, IM Persaran and Shin, Hadri, ...). The next table 2 summarizes the results of the (Summary) tests, applied to the different variables of the model. The unit root tests show that all the statistical series at the level are assigned a unit root. Moving on to first differences, we can see that all the series are stationary. We conclude that they are integrated of order I (1) and I(0).

Table 2. Unit root test results

Variables / methods	Integration Order	Levin et al.	Im et al.	ADF-Fisher chi-square	PP-fisher chi-square
GDP	I(1)	*-8.13344 (0.0000)*	*-8.91040 (0.0000)*	*125.563 (0.0000)*	*130.484 (0.0000)*
stationarty		**Hadri Z-stat**		**Heteroscedastic Consistent Z-stat**	
		5.47912 (0.0000)		*3.10673 (0.0000)*	
FDI	I(1)	*-2.94203 (0.0016)*	*-4.46400 (0.0000)*	*59.9463 (0.0000)*	*54.5151 (0.0001)*
stationarty		**Hadri Z-stat**		**Heteroscedastic Consistent Z-stat**	
		3.58597 (0.0000)		*3.35800 (0.0000)*	
		Levin et al.	**Im et al.**	**ADF-Fisher chi-square**	**PP-fisher chi-square**

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		En niveau	Différence première	En niveau	Différence première	En niveau	Différence première	En niveau	Différence première
Log CE	I(0)	*-0.9882 (0.1615)*	*-16.9238 (0.0000)*	*1.18831 (0.8826)*	*-16.4708 (0.0000)*	*20.3619 (0.5604)*	*202.044 (0.0000)*	*20.5153 (0.5508)*	*220.380 (0.0000)*
stationarty		**Hadri Z-stat**				**Heteroscedastic Consistent Z-stat**			
		10.8187 (0.0000)				9.10802 (0.0000)			
CER	*I(0)*	*1.06230 (0.8560)*	*-11.4987 (0.0000)*	*0.70665 (0.7601)*	*-12.9988 (0.0000)*	*21.2863 (0.5031)*	*181.082 (0.0000)*	*26.5511 (0.2288)*	*175.253 (0.0000)*
stationarty		*5.99423 (0.0000)*				*5.99423 (0.0000)*			
Log Pop	*I(0)*	*1.64641 (0.9502)*	*-3.12926 (0.0009)*	*3.92872 1.0000*	*-7.65503 (0.0000)*	*15.4128 (0.8439)*	*101.834 (0.0000)*	*46.2751 (0.0018)*	*82.1472 (0.0000)*
stationarty		*12.8872 (0.0000)*				*13.1507 (0.0000)*			

Notes: Probability values are given in brackets. Significance thresholds * (1%), ** (5%), and *** (10%)

Source: Author elaboration on Eviews9

4.2 Co-integration

After checking the non-stationarity properties for all the variables in the panel, we study the existence of a short- and long-term relationship between these variables. That is to say, the study of the existence of a Co-integration relationship, by applying the Co-integration tests of Pedroni, Kao and Johansen which are based on unit root tests on estimated residuals. Table 3 summarizes the results of the seven (7) Pedroni Co-integration statistics.

They were established by Eviews 9.0 which has an appropriate program to handle Co-integration on heterogeneous panel data. The Co-integration of the variables depends on the probability value associated with each statistic. From the results of Pedroni's Co-integration tests we can see that out of the seven statistics, four have probability values less than 5%. These are mainly (Panel pp- statistic) and (Panel ADF-Statistic) for the intra-individual tests "Pedroni (1999), (Weighted statistic)", and (Group PP-Statistic) and (Group ADF-Statistic) for the inter-individual tests "Pedroni (1999)". Therefore, all of these tests show the existence of a Co-integration relationship. In what follows, we will estimate the long-term relationship of Co-integration using the most adequate methods for this type of approach.

Table 3. Co-integration model results

No deterministic trend	Intra dimensions (four statistics)				Inter dimension (3 statistics)		
Pedroni	Panel v-statistic	Panel rho-statistic	Panel PP-statistic	Panel ADF-statistic	Group rho-statistic	Group PP-statistic	Group ADF-statistic
Staistic	*-0.772857*	*-3.372856*	*-10.82630*	*-8.643915*	*-1.912110*	*-17.11109*	*-8.810620*
prob	*(0.7802)*	*(0.0004)*	*(0.0000)*	*(0.0000)*	*(0.0279)***	*(0.0000)*	*(0.0000)*
kao	***ADF***				***RESID(-1)***		
stastic	*-5.269950*				*-11.68755*		
Prob	*(0.0000)*				*(0.0000)*		
Johansen	**Fisher (from trace test)**				**Fisher (from max-eigen test)**		
	Statistic		**Prob**		**Statistic**		**Prob**
None	*470.5*		*(0.0000)*		*344.0*		*(0.0000)*
At most 1	*413.9*		*(0.0000)*		*272.4*		*(0.0000)*
At most 2	*233.4*		*(0.0000)*		*155.1*		*(0.0000)*

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At most 3	*115.8*	*(0.0000)*	*93.08*	*(0.0000)*
At most 4	*64.62*	*(0.0000)*	*64.62*	*(0.0000)*

Notes: Probability values are given in brackets. Significance thresholds * (1%), ** (5%), and *** (10%)

Source: Author elaboration on Eviews9

4.3 Casuality of Granger Panel

The existence of Co-integration implies the existence of causality in at least one direction. Having found that there is a long-term relationship between GDP, FDI, RCE, CET and Pop.the next step is to test the causal links between these variables using the Granger panel test Causality. A Granger causality analysis is performed to determine whether there is potential predictive power across indicators. The results of the Granger Panel Causality test for all individuals are summarized in the following table 4.

Table 4. The Panel VECM Granger Casuality Results

Dependent variables	Source of short-term causality (independent variables)					Long term
	ΔGDP	ΔFDI	ΔCER	ΔCE	ΔPop	ECT
ΔGDP	-	*0.051942* *(0.051942)***	*0.001617* *(0.00371)*	*-0.005544* *(0.00110)*	*5.06* *(6.1)*	*0.051942* *(0.04927)*
ΔFDI	*0.045439* *(0.08979)****	-	*0.004624* *(0.00480)*	*0.001820* *(0.00142)*	*6.47* *(7.8)*	*-0.005544* *-0.005544*
ΔCER	*-0.212568* *(1.30807)*	*-0.683442* *-0.683442*	-	*0.003703* *(0.02068)**	*0.000922* *(0.00114)*	*0.001617* *(0.00371)*
ΔCE	*4.649756* *(4.17685)*	*1.783248* *(2.96392)*	*-0.024501* *-0.024501*	-	*0.002028* *(0.00364)*	*-0.276848* *(0.12601)****
ΔPop	*-7.83706* *(37.0688)*	*-27.43068* *(26.3043)*	*2.058512* *(1.98284)*	*-2.163168* *(0.58612)*	-	*0.042438* *(0.23936)*

Notes: Probability values are given in brackets. Significance thresholds * (1%), ** (5%), and *** (10%)

Source: Author elaboration on Eviews9

The aim of our study is to demonstrate the interactive relationships between the set of variables GDP, FDI, CER, CET and Pop, but this does not preclude the study of all possible relationships. From the results of the Granger Panel Causality tests presented in the table above, we can deduce the meanings of the causal relations that can be found between the variables at the critical threshold (probability of error) of 1%, 5% and 10%.

The results indicate the existence of two unidirectional causalities: FDI to GDP and CER to GDP.

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4.4 Models with individual effects

If the main objective is the estimation of the coefficients of the variables other than the constant and if they differ little.

Table 5. Results of individual effect models

Variables	Effet fixe	Effet aléatoire	Test Hausman
FDI	*0.865040*	*0.352954*	*0.002507*
	*(0.865040)****	*(0.7244)****	*(0.00250)*
CER	*-1.884330*	*-0.016893*	*3.740207*
	*(0.0606)****	*(0.9865)****	*(0.0548)***
LCE	*-0.304002*	*0.852544*	*1.035037*
	*(0.7614)****	*(0.3946)****	*(0.6463)****
LPop	*-3.716112*	*-3.214474*	*1.650091*
	(0.0002)	*(0.0015)*	*(0.0024)*

Notes: Probability values are given in brackets. Significance thresholds * (1%), ** (5%), and *** (10%)

Source: Author elaboration on Eviews9

4.5 Models ARDL

This approach was introduced by Pesaran and Shin (1999) and further developed by Pesaran et al (2001). This approach has many advantages over Johansen's cointegration technique. The variables are integrated of different orders. Another advantage is that the error correction model (ECM) can be derived from the ARDL which integrates the CT dynamics with the LT equilibrium without losing the LT information.

Table 6. Results from Models ARDL

Dependent variable(GDP)	**Coefficient**	**Z-statistics**	Probability
Log run results			
FDI	*0.154327 (0.076262) ****	*2.023651*	*(0.0454)**
LCE	*6.62561 (1.431944)*	*4.627010*	*(0.0000)*
LCER	*0.357443 (0.638771) ****	*0.559580*	*(0.5769)***
LPop	*-3.728982 (0.771053) ****	*-4.836217*	*(0.0000)**
Short run results			
ECT	*0.288799 (0.288799) ****	*2.241166*	*(0.0270)**
ΔIDE_{t-1}	*0.152298 (0.272353)****	*0.559194*	*(0.5771)****

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ΔIDE_{t-2}	*0.365498 (0.340335) ****	*1.073937*	*(0.2851)****
ΔCE_{t-1}	*0.024823 (9.603603)*	*0.002585*	*(0.9979)****
ΔCE_{t-2}	*11.35308 (7.457255)*	*1.522420*	*(0.1307)****
ΔCER_{t-1}	*3.321993 (2.702170)*	*1.229380*	*(0.2215)****
ΔCER_{t-2}	*3.555253 (2.299951)*	*1.545795*	*(0.1250)*
ΔPop_{t-1}	*-3002.347 (3211.346)*	*-0.934919*	*(0.3518)*
ΔPop_{t-2}	*2711.985 (2711.985)*	*1.763306*	*(0.0806)****

*Notes: Probability values are given in brackets. Significance thresholds * (1%), ** (5%), and *** (10%)*

Source: Author elaboration on Eviews9

The long and short terms of the ARDL methodology are presented in Table 6. The ARDL results for the relationship between economic growth and foreign direct investment are positive and important in both the long and short term given the same importance of the relationship between energy consumption and economic growth, which indicates foreign direct investment and energy consumption as in MENA countries Increases economic growth in the long and short term.

6. Conclusion

Bridging the gap between foreign direct investment and energy consumption is one solution to achieving development goals. The role of foreign direct investment and energy consumption in achieving these goals is becoming an important topic in some of the discussions in the current literature. International organizations, economists and policy makers have considered them as a means to achieve the future development of society as a whole.

Despite this growing interest and importance, the relationship between foreign direct investment, energy consumption and economic growth is not yet clear. Therefore, the main objective of this study is to clarify this relationship by showing the ability of foreign direct investment and energy consumption to achieve economic growth at a given point in time, reduce environmental degradation and improve social conditions in 11 transition countries over the period 1990 to 2015.

The Granger results revealed that FDI and energy consumption are closely linked to the pillars of economic growth. The result can be summarized as follows. First, the adoption of FDI has positive effects on economic growth, as well as on the use of renewable energy. In addition, the study indicates that foreign direct investment and energy use cannot stimulate growth simultaneously in economic terms and advance the environmental and social dimension without certainty of requirements, especially in countries in transition.

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