economies

Review

The ARDL Method in the Energy-Growth Nexus Field; Best Implementation Strategies

Angeliki N. Menegaki

Department of Economics & Management of Tourist and Culture Units, Agricultural University of Athens, 33100 Amfissa, Greece; amenegaki@aua.gr

Received: 7 August 2019; Accepted: 14 October 2019; Published: 18 October 2019

Abstract: A vast number of the energy-growth nexus researchers, as well as other "X-variable-growth nexus" studies, such as for example the tourism-growth nexus, the environment-growth nexus or the food-growth nexus have used the autoregressive distributed lag model (ARDL) bounds test approach for cointegration testing. Their research papers rarely include all the ARDL procedure steps in a detailed way and thus they leave other researchers confused with the series of steps that must be followed and the best implementation paradigms so that they not allow any obscure aspects. This paper is a comprehensive review that suggests the steps that need to be taken before the ARDL procedure takes place as well as the steps that should be taken afterward with respect to causality investigation and robust analysis.

Keywords: ARDL bounds test; energy-growth nexus; "X-variable-growth nexus" review

1. Introduction

Since the seminal work by Kraft and Kraft (1978) on the energy-growth nexus, various cointegration and causality methods have been used in this field and the "X-variable growth nexus" framework in general. The most common of them have been the Engle and Granger (1987) method based on residuals, the Phillips and Hansen (1990) with a modified ordinary least square procedure, Johansen (1988) and Johansen and Juselius (1990) maximum likelihood method.

However, some years later, it was realized that these methods may not be appropriate for small samples (Narayan and Smyth 2005). Foremost, studies before the ARDL establishment, and this was much the case for the energy-growth nexus, used cross sectional analysis through their panel data configuration. This entailed that the countries included in those samples were not homogeneous enough with respect to their economic development level (Odhiambo 2009). Unless results became country specific, results from these studies were of little use for policy-making. This generated the need for more sophisticated cointegration and causality methods. These econometric methods employed in the older energy-growth nexus, have thrown light to other fields such as the tourism-growth nexus or others, which this paper, for reasons of simplicity, terms as the "X-variable- growth nexus."

The initiation of the autoregressive distributed lag (ARDL) method or Bounds test is due to Pesaran and Shin (1999), while its further development is due to Pesaran et al. (2001). It is acknowledged as one of the most flexible methods in the econometric analysis of the energy-growth nexus, particularly when the research framework is shaped by regime shifts and shocks. The latter change the pattern of energy consumption or the evolution of covariates in the energy-growth models. Moreover, the fact that the ARDL method may tolerate different lags in different variables, this makes the method very attractive, versatile, and flexible.

The ability to host sufficient lags enables best capturing of the data generating process mechanism. This translates into that the method can be applied irrespective of whether the time series is I(0), namely stationary at levels, I(1) namely stationary at first differences or fractionally integrated

(Pesaran et al. 2001). Nevertheless, within the ARDL framework, the series should not be I(2), because this integration order invalidates the F-statistics and all critical values established by Pesaran. Those have been calculated for series which are I(0) and/or I(1).

Furthermore, the ARDL method provides unbiased estimates and valid t-statistics, irrespective of the endogeneity of some regressors (Harris and Sollis 2003; Jalil and Ma 2008). Actually, because of the appropriate lag selection, residual correlation is eliminated and thus the endogeneity problem is also mitigated (Ali et al. 2016). As far as the short-run adjustments are concerned, they can be integrated with the long-run equilibrium through the error correction mechanism (ECM). This occurs through a linear transformation without sacrificing information about the long-run horizon (Ali et al. 2017). One other aspect is that the method allows the correction of outliers with impulse dummies (Marques et al. 2017, 2019) and the approach distinguishes between dependent and independent variables.

Last but not the least, the interpretation of the ARDL approach and its implementation is quite straightforward (Rahman and Kashem 2017) and the ARDL framework requires a single form equation (Bayer and Hanck 2013), while other procedures require a system of equations. The ARDL approach is more reliable for small samples as compared to Johansen and Juselius's cointegration methodology (Haug 2002). Halicioglu (2007) also mentions two more advantages of the method, which are: The simultaneous estimation of short- and long-run effects and the ability to test hypotheses on the estimated coefficients in the long-run. This is not done in the Engle–Granger method.

This paper is organized as follows: After the introduction, follows the methodology as Section 2, together with best practice guidelines. Section 3 contains other versions of the ARDL approach and ARDL implementation strategies to follow in one's energy-growth nexus paper, and Section 4 concludes the paper.

2. The Methodology

For reasons of educative demonstration, we assume two series, the Y_t and the X_t in this paper but the reader can easily generalize into more variables. Nevertheless, the production function equation in the energy-growth nexus, has more variables. In a bivariate energy-growth nexus model, the Y_t stands for economic growth and the X_t stands for energy consumption. It is also typical in the energy growth nexus to use logarithms of the variables in order to translate variable coefficients as elasticities. The series of steps in the ARDL procedure is the investigation of: (i) stationarity, (ii) cointegration, and last but not least (iii) causality. There are other ways to proceed to causality analysis without the first two steps, but this occurs within other methodological frameworks.

2.1. Stationarity

After a presentation of the descriptive statistics of the series (mean, median, minimum and maximum values, skewness, kurtosis, as well as the standard deviation, Bera–Jacque normality test and pairwise correlation), the first step in the ARDL analysis, is the unit root analysis. It informs about the degree of integration of each variable. To satisfy the bounds test assumption of the ARDL models, each variable must be I(0) or I(1). Under no circumstances, should it be I(2). De Vita et al. (2006) also noted that the dependent variable should be I(1). However, this is not widely claimed in the current literature. Unit root analysis is performed with a long array of tests such as for example the augmented Dickey Fuller (ADF) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS), the Phillips–Perron (PP), the Ng–Perron test, the cross-sectional augmented IPS-CIPS (Pesaran 2007), the LS (Lee and Strazicich 2003), and many others. Each one is more compatible with different data characteristics, but this paper will not discuss them for brevity reasons. However, it should be stressed that researchers should apply both the traditional and structural break unit root tests to make sure that the variables are not I(2).

2.2. Cointegration

The essence models in the ARDL bounds test framework are the following unrestricted error correction models:

$$\Delta LY_t = a_0 + a_1 t + \sum_{i=1}^{m} \alpha_{2i} \Delta LY_{t-i} + \sum_{i=0}^{n} a_{3i} \Delta LX_{t-i} + a_4 LY_{t-1} + a_5 LX_{t-1} + \mu_{1t} \quad (1)$$

$$\Delta LX_t = \beta_0 + \beta_1 t + \sum_{i=1}^{m} \beta_{2i} \Delta LX_{t-i} + \sum_{i=0}^{n} \beta_{3i} \Delta LY_{t-i} + \beta_4 LX_{t-1} + \beta_5 LY_{t-1} + \mu_{2t} \quad (2)$$

Δ is the first difference operator, μ is the error term that must be a white noise or put in other words it represents the residual term which is supposed to be well behaved (serially independent, homoskedastic and normally distributed). All α and β coefficients are non-zero with a_4 and β_4 also being negative (this represents the speed of adjustment). The parameters α_{2i} and a_{3i} represent the short-run dynamic coefficients, while a_4 and a_5 are long-run coefficients in the energy-growth nexus relationship. The a_0 and β_0 are drift components, μ_{1t} and μ_{2t} are white noise. What type of explanatory variables must be incorporated in the energy-growth relationship is provided in detail by Inglesi-Lotz (2018) in a chapter written specifically on this topic. The interested reader is advised to read that. Generally, one can decide first on the framework one is going to work, namely whether that is a production function approach or a demand function approach or others such as the Kuznets curve hypothesis and then decide on the variables and other components. Other deterministic components are included on a trial and error basis and to corroborate further the stability of an estimated relationship.

Overall, we observe in Equations (1) and (2) that each variable is represented as dependent on the past values of itself, the past values of the other variable(s), and the past values of differenced values of itself and the past values of differenced values of the other variable(s). Models (1) and (2) can be formulated either as intercept or trend ARDL models, or both. Equations (1) and (2) contain both. Halicioglu (2007) claims that it is possible to end up with two models, one with trend and one without a trend. There is a method described in Bahmani-Oskooee and Goswami (2003), according to which one ends up with a single long-run relationship through consecutive eliminations of the rest of the relationships. The first stage of the ARDL estimation produces a $(p+1)^k$ number of regressions so that the optimal lag length for each variable is obtained, with p being the maximum number of lags and k is the number of variables in the equation. In our simplistic example, there is only one X_t variable. In the framework described in Equations (1) and (2), the ARDL bounds cointegration test is carried out. These equations are estimated with ordinary least squares (OLS).

2.3. More on the ARDL Analysis

The ARDL analysis occurs as follows: If the existence of cointegration is confirmed in Equations (1) and (2), then the long-run and the short-run models are estimated and both long and short-run elasticities are derived, namely the ARDL equivalent of the UECM (Unrestricted error correction model). Cointegration, in the ARDL bounds test approach, is examined under the following hypothesis set up:

$$H_0 : a_1 = a_2 = a_n = 0$$

$$H_1 : a_1 \neq a_2 \neq a_n \neq 0$$

The setup of the hypotheses reads as follows: there is cointegration if the null hypothesis is rejected. The F-statistics for testing are compared with the critical values developed by Pesaran et al. (2001). Narayan critical values are more appropriate for small samples. Pesaran et al. (2001) provide a table enumerated as CI and entitled: “Asymptotic critical value bounds for the F-statistic. Testing for the existence of a levels relationship” in five versions. These are (i) no intercept and no trend, (ii) restricted intercept and no trend, (iii) unrestricted intercept and no trend, (iv) unrestricted intercept and restricted trend, (v) unrestricted intercept and unrestricted trend. They also provide a table CII entitled "Asymptotic critical value bounds for the t-statistic. Testing for the existence of a levels relationship" in three versions: (i) No intercept and no trend, (ii) unrestricted intercept and no trend, (iii) unrestricted intercept and unrestricted trend. Next we reproduce a part of these tables (CI-iii and CI-v) in order to explain how the decision for cointegration was made in Bölük and Mert (2015) based on Pesaran tables. Note that Pesaran tables are not valid for I(2) variables (Ali et al. 2016). The interested reader can find these tables in Pesaran et al. (2001).

Narayan and Smyth (2005) on the other hand, has estimated critical values for the bounds test for four cases at three significance levels and up to seven independent variables up to eighty observations. The critical values of the four cases are entitled as: (i) Case II: restricted intercept and no trend, (ii) case III: unrestricted intercept and no trend, (iii) case IV: unrestricted intercept and restricted trend, (iv) case V: unrestricted intercept and unrestricted trend. In Narayan tables, k stands for the number of regressors, n is the sample size, I(0): stationary at levels, I(1): stationary at first differences. The interested reader can find these tables in Narayan and Smyth (2005).

When no cointegration is confirmed, we can proceed with simple Granger causality (unrestricted VAR). The VAR equation should be specified on stationary data. There are various reasons why cointegration is not confirmed (e.g., no relationship between the examined variables or due to omitted variables). The Toda and Yamamoto (1995) test is a solution for Granger causality testing in this case. After all, even when a long-run relationship does not exist in the data, this does not mean that no short-run relationship exists either. Moreover, it needs to be remembered that the cointegration equation provides the long-run elasticities. Short-run elasticities are presented by the coefficients of the first differenced variables. In cases where more than one coefficient for a particular variable has been estimated for the short-run case, these are added and their joint significance is tested with a Wald test (Fuinhas and Marques 2012). However, if cointegration is the case (which occurs very commonly, when there is a known and established theoretical connection between some variables), then we can proceed with the establishment of the error correction mechanism (ECM). Evidence of cointegration implies that there is a long-run relationship between the variables and their connection is not a short-lived situation, but a more permanent one, which can be recovered every time there is a disturbance. Alternatively to the above described F-test, a Wald test can be applied which is used to test the null hypothesis of no cointegration when there is more than one short-run coefficient of the same variable (Tursoy and Faisal 2018).

2.4. Diagnostic Tests after Cointegration

A model to be trusted, it must be robust. To support robustness of an estimated model, one needs to peruse various diagnostic tests. Typical diagnostic χ^2 tests follow to investigate the goodness of fit, stability, parsimoniality, functional form, and a well-behaved model in general. The Breusch Godfrey serial correlation LM test, the Breusch–Pagan Godfrey Heteroskedasticity test or the White test, and the Jarque–Bera test are some of the tests encountered in these applications. In addition to that, the Ramsey reset test is used for the functional form. Besides the latter, the variance inflation factor (VIF) for multicollinearity might be useful in cases where there is evidence of multicollinearity.

The Impulse Response Function (IRF), Shifts, and Dummies

The impulse response functions can be of use because they reveal the effect of a standard deviation shock on the dependant variable. IRF are formed through the moving average (MA) of the vector autoregressive (VAR) equation[1]. Some energy-growth researchers use them as an indispensable tool

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[1] A VAR model is a generalization of univariate AR models for multiple time series. Within a VAR framework, all variables are represented by an equation that explains its evolution based on its own lags and the lags of the other variables in the multivariate framework. The number of variables k are measured over a period of time t as a linear evolution of their past values.

for valuable information in their ARDL models. The impulse response function mainly shows what happens when the model is transferred to the one side of a dummy variable. For example, if the value of 1 represents war time and the value of 0 represents peace time, then if we take the ones or zeros only and separately, we have an impulse response function, one for war time and one for peace time. Thus, they are also a useful tool to test the stability of a model across structural breaks. There are various hypotheses that underlie the models after cointegration is confirmed. After the identification of the long-run relationship in Equations (1) and (2), we can continue with the examination of the short-run and the long-run Granger causality. The Granger causality refers to a situation where the past can be used to predict the future. Thus, if past values of X_t significantly contribute to forecasting future values of Y_t, the X_t is said to Granger cause the Y_t. However, evidence of correlation is not necessarily an evidence for causality.

2.5. Combined Cointegration Methods for the Robustness of the ARDL Model

In the particular case of a unique order of integration, Bayer and Hanck (2013) have developed a test which borrows elements from a variety of previously developed cointegration tests. The combined test borrows elements from Engle and Granger (1987); Johansen (1988); Boswijk (1994) and Banerjee et al. (1998). The combined cointegration test uses Fisher's formulae and the p-values of the aforementioned individual tests.

$$\text{Engle and Granger} - \text{Johansen} = -2\left[\ln\left(P_{\text{Engle \& } Granger}\right) + \ln\left(P_{\text{Johansen}}\right)\right]$$

$$\begin{aligned}\text{Engle and Granger} \quad & -\text{Johansen} - \text{Boswijk} - \text{Banerjee et al.} \\ & = -2\left[\ln\left(P_{\text{Engle \& } Granger}\right) + \ln\left(P_{\text{Johansen}}\right) + \ln\left(P_{\text{Boswijk}}\right)\right. \\ & \left. + \ln\left(P_{\text{Banerjee}}\right)\right]\end{aligned}$$

The null hypothesis of no cointegration is rejected if the aforementioned Fisher statistic exceeds the critical value as produced by Bayer and Hanck (2013). The above test balances the decisions produced by the independent tests which suffer from various weaknesses, each one of them.

2.6. Causality after the ARDL Bounds Test and the Importance of the Error Correction Term (ECT)

The investigation of causality is the third step in the energy-growth nexus analysis. The lagged error correction term is derived from the cointegration equation. Thus the long-run information that is missed through the differencing of the variables for stationarity purposes, is re-introduced in the system of causality equations. This is a necessary step when variables are cointegrated. Cointegration implies that there must be causality of some direction, however, it does not reveal to which direction that causality goes. Therefore, additional causality analysis is required. Thus, before going to the estimation of Equations (3) and (4) below, one needs to run another set of regressions in order to get the residuals which will be inserted to Equations (3) and (4) as the ECT term.

There are many strategies to follow in the examination and direction of causality. One such strategy is the VECM approach (vector error correction model), which is a restricted form of unrestricted VAR and is suitable, once the variables are integrated at I(1). According to this model setup, the dependent variable is dependent on its own lagged values, as well as the lagged values of the independent variables, the error correction term, and the residual term. This is shown in the following set of equations.

$$\Delta lnY_t = a_1 + \sum_{i=1}^{l} a_{11}\Delta LY_{t-i} + \sum_{j=0}^{m} a_{22}\Delta X_{t-j} + n_1 ECT_{t-1} + \mu_{1i} \quad (3)$$

$$\Delta lnX_t = a_1 + \sum_{i=1}^{l} a_{21}\Delta LX_{t-i} + \sum_{j=0}^{m} a_{22}\Delta Y_{t-j} + n_2 ECT_{t-1} + \mu_{2i} \quad (4)$$

Residual terms in the above equations, are assumed to distribute normally. The coefficient of the ECT must be negative to assure system convergence from the short run toward the long run. An ECT equal to x% is interpreted as such that x% of economic growth is corrected by deviations in the short run that lead eventually to the long-run equilibrium path. The significant variables on the right hand side of each equation show short-run causality for the dependent variable.

FMOLS and DOLS Estimators for Robustness

The FMOLS (fully modified OLS) and the DOLS (dynamic OLS) were developed by Phillips and Hansen (1990) and Stock and Watson (1993). They lead to the generation of asymptotically efficient coefficients, because they take into account the serial autocorrelation and endogeneity. They are applied only in the I(1) case for all variables. The latter makes them less flexible and attractive methods. OLS is biased when variables are cointegrated but nonstationary, while FMOLS is not. DOLS performs better than the FMOLS approach (Kao and Chiang 2000) for several reasons: DOLS is computationally simpler and it reduces bias better than FMOLS. The t-statistic produced from DOLS approximates the standard normal density better than the statistic generated from the OLS or the FMOLS. DOLS estimators are fully parametric and do not require pre-estimation and non parametric correction. Ali et al. (2017) reports that the most significant benefit of DOLS is that the test considers the mixed order of integration of variables in the cointegration framework.

2.7. Additional Ways to Study Causality

Literature reports additional types of causality: (a) The weak causality/short-run causality, (b) the long-run causality, (c) the strong causality (joint causality), (d) the pairwise causality. Each one serves a particular purpose.

(a) Weak causality/short-run causality

Each variable is caused by its own past only.

(b) Long-run causality

The error correction term is zero. This is a VAR (vector autoregression) causality leading to Toda and Yamamoto (1995) method. Granger causality can be checked for existence through a VAR model (note that data are not in differences, namely they are in level form):

$$Y_t = g_0 + \alpha_1 Y_{t-1} + \ldots + \alpha_p Y_{t-p} + b_1 X_{t-1} + \ldots + b_p X_{t-p} + u_t$$

$$X_t = h_0 + c_1 Y_{t-1} + \ldots + c_p Y_{t-p} + d_1 X_{t-1} + \ldots + d_p X_{t-p} + v_t$$

$$H_0 : b_1 = b_2 = \ldots = b_p = 0$$

$$H_1 : X\ Granger\ causes\ Y$$

A similar hypothesis set up can be constructed for the second equation, but this will not be done here for space considerations. Please note the following rationale:

If $b_i \neq 0$ and di=0, then X_t will lead Y_t in the long run.
If $b_i = 0$ and $d_i \neq 0$, then Y_t will lead X_t in the long run.
If $b_i \neq 0$ and $d_i \neq 0$, then the feedback relationship is present.
If $b_i = 0$ and $d_i = 0$, then no cointegration exists.

After we have calculated the diagnostics of the model and we have verified that the model is well behaved, then the next step is the bounds test. The existence of a long-run relationship can be further corroborated with the investigation of significance of the individual terms.

(c) Strong causality: The joint causality investigation process

This is altogether the case described in (a) and (b). The joint causality test also known as strong causality test (Lee and Chang 2008) identifies two sources of causation, one the short run and the other the long run, to which the variables re-adjust after a short-run perturbation. This is tested with the short-run coefficients of the lagged variables and the significance of the lagged error correction term. Granger causality can be investigated in two other known ways: It can be investigated with the F-test to decide about the significance of first difference stationary variables (Asafu-Adjaye 2000; Masih and Masih 1996) or by including the ECT as a source of variation. This is most commonly checked with a *t*-test.

(d) Pairwise Granger causality test

This is another solution toward the investigation of causality when cointegration is not confirmed. An additional usage is for the corroboration of VECM results. Menegaki and Tugcu (2016) have employed this method for the investigation of the energy-sustainable growth nexus in Sub-Saharan African countries for the years 1985–2013. In addition to that, Menegaki and Tugcu (2018) have employed the same method for the investigation of the energy-sustainable growth nexus in Asian countries.

3. Other Versions of the ARDL Approach

3.1. The Asymmetric Nonlinear or the Nonlinear Autoregressive Distributed Lag (NARDL) Approach

This version of the ARDL approach was introduced by Shin et al. (2011, 2014) and is an extension of the method introduced by Pesaran et al. (2001). The nonlinear ARDL is used for testing whether the positive shocks of the independent variables have the same effect as their negative shocks on the dependent variables. In the typical ARDL, there is a symmetric relationship between the dependent and the explanatory variables. This is not the case with the NARDL in which the ARDL relationship is formulated as follows:

$$y_t = a^+ {x_t}^+ + a^- {x_t}^- + \varepsilon_t$$

The alphas are the long-run parameters, while x_t is the following vector regressor:

$$x_t = x_0 + {x_t}^+ + {x_t}^-$$

With ${x_t}^+$ being the positive partial sum and ${x_t}^-$ being the negative partial sum as follows:

$${x_t}^+ = \sum_{i=1}^{t} \Delta {x_i}^+ = \sum_{i=1}^{t} max(\Delta x_i, 0)$$

$${x_t}^- = \sum_{i=1}^{t} \Delta {x_i}^- = \sum_{i=1}^{t} max(\Delta x_i, 0)$$

This means that the corresponding error correction model can be written as:

$$\Delta y_t = \rho y_{t-1} + \theta^+ {x_{t-1}}^+ + \theta^- {x_{t-1}}^- + \sum_{i=1}^{j-1} \varphi_i \Delta y_{t-i} + \sum_{i=0}^{p} \left({\pi_i}^+ \Delta {x_{t-i}}^+ + {\pi_i}^- \Delta {x_{t-i}}^- \right) + \varepsilon_t$$

where $\theta^+ = \frac{\alpha^+}{\rho y_{t-1}}$ and $\theta^- = \frac{\alpha^-}{\rho y_{t-1}}$.

Using the F-statistic developed by Pesaran et al. (2001), one can test the hypothesis that $\theta^+ \ \theta^- = \theta = 0$. The rejection of the null hypothesis indicates the presence of cointegration. The hypothesis of $\theta = 0$ versus the alternative that $\theta < 0$ is examined through a *t*-test (Banerjee et al. 1998).

Overall, the procedure steps are exactly as the conventional ARDL approach that has been already presented in this paper. In addition to that, the method provides the cumulative dynamic multiplier effects of x^+ and x^- on y_t as follows:

$$m_k{}^+ = \sum_{i=0}^{k} \frac{\partial y_{t+i}}{\partial x_t{}^+} \; and \; m_k{}^- = \sum_{i=0}^{k} \frac{\partial y_{t+i}}{\partial x_t{}^-}$$

When k increases to infinity, the multipliers converge to the alphas. This method has been applied by Shahbaz (2018) in a case study for the energy-growth nexus in Al-hajj et al. (2018) for the investigation of the oil price and stock returns nexus in Malaysia. The NARDL method is applicable if all variables are integrated at I(1) or they have a flexible order of integration. The approach solves multicollinearity through the choice of the appropriate lag length of variables (Shin et al. 2014). Thus, the bounds test proposed by Shin et al. (2014) examines the presence of cointegration while at the same time hosting asymmetries. As far as causality is concerned, a complete account of asymmetric causality is presented in Apergis (2018) who provides a detailed account also on linear versus the nonlinear causality.

3.2. The Pool Mean Group (PMG) Estimator for Panel Data

The PMG allows for heterogeneity only in the short-run compared to the mean group which allows for heterogeneity both in the short and the long-run. The pool mean group estimates are superior to the fixed effects estimates, because they are robust to endogeneity and to the presence of unit roots. Overall the PMG is an estimator that allows pooling and averaging. Besides the short-run and long-run effects that are captured among the variables of a model, the PMG additionally investigates the dynamic effects of the independent variables on the dependent variable.

The general form of the PMG can be seen in the following Equation:

$$Y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,\, t-j} + \sum_{j=0}^{q} \delta_{ij} X_{i,t-j} + \mu_t + \varepsilon_{it}$$

The following notation applies for the Equation:

I = number of panels with $I = 1 \ldots N$
T = time, $t = 1, \ldots T$
X_{it} = a vector of $K \times 1$ regressors
λ_{ij} = is a scalar
μ_i = is a group specific effect

The error correction equation can be derived from the previous equation as:

$$\Delta Y_{it} = \varphi_i y_{i,t-j} - \theta_i X_{i,t-j} \sum_{j=1}^{p-1} \lambda_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij} \Delta_{i,t-j} + \mu_t + \varepsilon_{it}$$

With φ_i indicating the speed of adjustment which needs to be negative and significant in order to have convergence in the long-run horizon. If the speed of adjustment is zero, then no long-run relationship would be present. This equation provides the short-run dynamics that correspond to the long-run ones described in the cointegration equation. Besides the sign of the adjustment coefficient, the researcher must pay attention to the rest of the signs both I the cointegration and the error correction equation and decide whether they are consistent with economic theory and established research in the energy-growth nexus field. After short-run and long-run causal findings have been corroborated, it is useful to document them with policy reasons, namely find out why a causal direction is happening, whether it is due to some energy or environmental policy or whether it is due to the lack of some relevant policy. Comparison with the findings of other studies is also essential at this point. The estimates from the PMG estimator are consistent and asymptotically normal for both stationary and non-stationary regressors. As with conventional ARDL, the appropriate lag length in the PMG can be determined by the AIC and SBC criteria. Foremost, the more homogeneous the panels are, the more efficient the PMG estimator is.

Additional attention is advised for researchers with panel data who are advised to perform both the Pesaran (2004) CD test and the Pesaran and Yamagata's slope homogeneity tests. The Pesaran (2004) CD test was formulated as an answer to the shortcomings faced in the scaled LM test (Pesaran 2004; Breusch and Pagan 1980). Large panel data sets could not be handled with the Breusch and Pagan test. Thus, Pesaran (2004) suggested the standardized version of that LM test. Again, however, this solution had its own restrictions with large panels where cross sections were large but the time span was not long enough. The CD test was proposed as a final solution that could accommodate both smaller cross sections and shorter data spans. In many studies we make the comfortable assumption that the slope coefficients are homogeneous. While, when the time span is long and the cross section dimension short, this can be tested with seemingly unrelated regressions (SURE), but these dimensions are not always the case. Pesaran and Yamagata (2005) have proposed a modified Swamy's test of slope homogeneity. Swamy (1970) bases his test of the slope homogeneity on the dispersion of individual slope estimates from a suitable pooled estimator. For more on these tests, the interested reader should read the suggested bibliography.

3.3. What Are the ARDL Best Implementation Strategies to Follow in One's Energy-Growth Nexus Paper?

This paper deals with the general outline of the research in the ARDL analysis and not the specific direction that various studies may end up with, because of specific handlings dictated by data, theory, and research demands. For example Liu (2009) ends his/her ARDL analysis with a factor decomposition model (FDM) analysis, which shows the yearly causal contribution of each variable onto the dependent variable. This is not how most ARDL energy-growth nexus studies end with. The typical outline of most of these studies is an investigation of the integrational properties of the variables, followed by an ARDL cointegration analysis that ends with a causality analysis. In the following two tables (Tables 1 and 2), the ARDL implementation strategies are provided with guidelines for every step and variant. Table 1 contains guidelines for the time series data, while Table 2 contains guidelines for the panel data version of the ARDL implementation. For more detailed discussions on time series and panel data causality tests dependent on cointegration and integration results, the reader is advised to consult the studies by Tugcu (2018) and Apergis (2018) in the book by Menegaki (2018) entitled as "The Economics and the Econometrics of the energy-growth nexus" and by Marques et al. (2019) in the book by Fuinhas and Marques (2019) entitled as "The extended energy-growth nexus."

Table 1. Autoregressive distributed lag model (ARDL) implementation for time series data in the energy-growth nexus.

	Stages in Time-Series ARDL Implementation
	First: Stationarity, Unit roots, and order of integration
	ADF: Augmented Dickey Fuller, PP: Philips–Perron (Note: They have low power properties, but since literature is still using them, it is good to use them as reference)

Table 1. *Cont.*

	KPSS: Kwiatowksi–Phillips–Schmidt–Shin	
	ADF-WS: Augmented Dickey Fuller-Weighted Symmetric (Note: Good size and power properties)	
	LS: Lee and Strazicish for breaks	
	and various other tests depending on the assumptions made about the data or the knowledge of them . . .	
	When contradictory results are reached, observing the correlogram is a good idea.	
	Are the series I(0) or I(1)? If yes, proceed with ARDL cointegration	
Yes: Stationarity		**No: Stationarity**
	Second stage: Cointegration	
	Maximum lag value is decided on AIC and BIC basis and HQC. The F value for the cointegration test should be applied for all criteria (BIC, AIC, HQC).	
Yes: Cointegration	If cointegration evidence is inconclusive, then the decision about the long-run relationship is based on the ECT.	**No: Cointegration**
	Are long-run coefficients significant? Do they have the correct sign?	
We need to augment the Granger-type causality test model with one period lagged ECT		If we find no evidence of cointegration, then the specification will be a vector autoregression (VAR) in 1st difference form (Liu 2009)
		Even if the ECT is incorporated in all equations of the Granger causality model, only in the equations where the null hypothesis of no cointegration is rejected, will be estimated with an ECT (Narayan and Smyth 2006).
	Is the cointegration equation robust? Answer: Use the FMOLS, DOLS to check.	
	Third stage: Causality	
	Granger causality is ideal both for small and large samples (Geweke et al. 1983)	
	The ECT model allows the inclusion of the lagged ECT derived from the cointegration equation. Thus the long-run information lost through differencing is reintroduced.	
	Does the ECM have a negative sign?	
	Are the estimated coefficients stable?	
	Work with diagnostics to prove robustness of your model	

Source: Author's compilation. Note: BIC: Bayesian (Schwarz) information criterion, AIC: Akaike information criterion, HQC: Hannan–Quinn criterion, ECT: error correction model, FMOLS: fully modified OLS, DOLS: dynamic OLS.

Table 2. ARDL implementation for panel data in the energy-growth nexus.

	Stages in Panel Data ARDL Implementation	
	First stage: Cross sectional dependence	
	This is examined with various tests (Some examples are shown below): Breusch Pagan LM test (Breusch and Pagan 1980) Pesaran CD test (Pesaran 2004) (Baltagi et al. 2012) bias corrected scaled LM test	
No: Cross Sectional dependence		Yes: Cross Sectional dependence
	Second stage: Stationarity and order of integration	
Apply tests assuming cross sectional independence (first generation) EXAMPLES: Im et al. (2003) Levin et al. (2002) Choi (2001) Breitung (2000) Maddala et al. (1999) Hadri (2000)	LS for 2 structural breaks and large size of data	Apply tests assuming cross sectional dependence (second generation) EXAMPLES: Pesaran (2007) Moon and Perron (2004) Bai and Ng (2004) Chang (2002) Harris and Sollis (2003) CIPS test (Pesaran 2007)
Yes: Stationarity		No: Stationarity
	Third stage: Panel cointegration	
	There are residual based tests, likelihood based tests and error correction based tests.	
No: Cross sectional dependence EXAMPLES OF TESTS: Gutierrez (2003) Larsson et al. (2001) Pedroni (higher explanatory power, mostly preferred with 7 statistics) (Pedroni 2004, 2007) McCoskey and Kao (1998)—(ideal for small samples) Kao (1999) —(ideal for small samples)		Yes: Cross sectional dependence EXAMPLES OF TESTS: Groen and Kleibergen (2003) It allows for multiple cointegration equations. Westerlund (2007) 4 statistics (good for structural breaks)
	Use a resilient estimator such as Driscoll and Kraay (1998)	
	Is cointegration confirmed?	
Yes: Cointegration		No: Cointegration
FMOLS DOLS MG PMG (does not consider cross-sectional dependence; constrains long-run coefficients be the same across units) CCEP (allows cross sectional dependence, endogeneity, serial correlation) CCEMG (as above but better for small cross sections)		Pooling is a good idea: Opt between random effects models or fixed effects models depending on Hausman test.
	Fourth stage: Panel Causality	
	Granger causality: It is a traditional method that assumes panels are homogeneous with no interconnections among cross-section units	Dumitrescu and Hurlin (2012): good sample properties and cross-sectional dependence resilient. Able to report individual specific causal linkages. Bai and Kao CUP-FM estimator

Source: Author's compilation. Note: FMOLS: fully modified OLS, DOLS: dynamic OLS, MG: mean group (estimator), PMG: panel mean group (estimator), CIPS: CCEP: common correlated effects pooled (estimator), CCEMG: common correlated effects mean group (estimator), CUP-FM: continuously updated fully modified (estimator).

Experienced researchers will have so far realized that the panel data are many shorter time series data, pooled together. The data generation process may be, or may not be, the same across panels (sub-groups of data). Therefore, several time series tests and procedures have been adapted from time series into panel data through a kind of averaging across panels (groups of data). Panel data are a convenient way in energy economics to overcome problems such as collinearity. Furthermore, that data provide more degrees of freedom and a more informed speed of adjustment. On top of that, with this approach one can control for heterogeneity and efficiency in the identification and measurement of economic issues (Tugcu 2018).

Panel data suffer from limitations such as the cross-sectional dependence, which is attributed to globalization and unification of policies across panel units (e.g., countries). This makes energy consumption patterns follow similar movements among the various countries in a panel, particularly if countries are signatories to the same environmental and emissions cutting agreement. The other limitation comes from the fact that panel data are in essence two entry level data and thus the error term in modeling contains both unit-specific (e.g., country) information and time-specific information. This may contribute to the endogeneity problem if the aforementioned error components are correlated to explanatory variables. However, these drawbacks do not discourage researchers from using panel data, which are the main type of data to expect in the energy-growth nexus research field.

Before closing this paper, it is useful to recommend the sites for the implementation of ARDL and NARDL coding in EVIEWS and STATA softwares:

ARDL and NARDL coding and implementation in EVIEWS available from: http://www.eviews.com/help/helpintro.html#page/content/ardl-Estimating_ARDL_Models_in_EViews.html.

ARDL and NARDL coding and implementation in STATA available from: https://www.statalist.org/forums/forum/general-stata-discussion/general/1434232-ardl-updated-stata-command-for-the-estimation-of-autoregressive-distributed-lag-and-error-correction-models.

Note: As far as NARDL coding and implementation in EVIEWS and STATA are concerned, since it is an ARDL model, it is just an estimation with lags of variables. One can specify that as a non-linear estimation with the least squares estimator.

4. Conclusions

The energy-growth nexus economics is a field that attracts major research attention, because of the significant information it provides to policy-makers who consider energy conservation measures. The ARDL method has been mostly favored and used in the past decade owing to its merits (flexibility, interpretability, eloquence, and statistical properties that are explained in the introduction of this paper). The paper meets the needs of two groups of researchers: one group is the new researchers who have recently started using the ARDL method. As a result of that, some points of its implementation are not fully clarified to them yet, because those are fragmented in various research papers and lecture notes on the internet. This fragmentation causes delays in research and paper writing and always leaves room for journal reviewers to reject a paper or advise major reviews. The other group is the more experienced researchers who have used the method a lot of times, but there is always an aspect in the method that will be benefited from throwing additional light into. Besides, the method is continuously enriched it its applied dimension and the reading of this paper by experienced researchers will grant them the opportunity to stay up-to-date with the method's evolution.

The paper is referencing applied work and knowledge throughout. Sometimes, it happens that even experienced researchers are using a test of a statistical concept, whose exact meaning needs brushing-up since the days they learned that during their undergraduate years at university. Furthermore, the paper guides the ARDL energy-growth researcher about the steps that need to be taken and the exact way that results should be presented and written in a paper in order to create the readers a feeling of transparency when they read a research paper. Moreover, this point will offer comparability among papers and will enable apt meta-analysis which is so valuable for the progress of science and the evolution of society.

The paper can also serve as a review and reference paper for post-graduate students writing their MA/MSc (not lest PhD) dissertation and need to employ this method. The quintessence of the paper lies in the last two tables of the fifth section, which separate the ARDL steps between the time-series and panel-data frameworks. Degree of integration, cointegration, and causality steps are explained and presented in a vertebrate and well-tied nature and relieves students from the stress of selecting the correct test in every step of the implementation.

Last but not the least, the content of this paper is useful not only for the researchers of the energy-growth nexus, but also for the researchers of other fields such as the tourism-growth nexus or the broader environment-growth nexus and the Kuznets curve studies.

Author Contributions: The author is the sole contributor in this paper.

Funding: The author has received no funding for writing this paper.

Conflicts of Interest: The author declares no conflict of interest.

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