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by

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Abstract

Renewable electricity is a pillar of the sustainability transition being pursued through climate and energy policy strategies, and the European Green Deal represents a potential investment plan for this new phase of development. Economic growth can be influenced by the expansion of renewable electricity consumption, but the nature of their relationship is ambiguous and depends on various economic and policy factors. This paper investigates the long-run relationship between renewable electricity consumption and economic growth in selected countries over the period 1971-2015 using econometric panel data techniques that specifically address cross-country heterogeneity and cross-sectional dependence. Our findings suggest that, on average, there is a significant positive long-term relationship between renewable electricity consumption and economic growth, although Granger causality is not detected. Regarding causality, we do find per capita economic growth to be a causal factor for total electricity consumption.

Keywords:
Electricity Consumption, Economic Growth, Renewables, Cross-sectional Dependence, CS-ARDL Model, CS-DL Model.

1. Introduction

In efforts to pursue decarbonisation, electricity production and consumption are of particular interest, as electrification represents a key potential substitute for fossil fuels. In most processes, electricity can be fully sourced from renewable forms of energy. In this respect, the decarbonisation transition interacts with the digital transition. As the EEA (2019) observes, the same is true for ICT, which may introduce new appliances and services that require additional electricity and hence increase energy consumption above a baseline scenario. Furthermore, the increased use of mobile phones and smartphones has increased electricity use but may also modernise and replace existing processes, thereby reducing energy needs. The electricity consumption–economic growth nexus has been studied extensively in recent years but with conflicting results; researchers have identified unidirectional, bidirectional and neutral relationships between electricity consumption and economic growth (Payne, 2010, Apergis and Payne, 2012). In general, most of these approaches assume cross-sectional independence and short-run dynamics. This paper revisits the nexus of renewable electricity consumption and economic growth in selected countries by using somewhat new econometric techniques and focuses particularly on means of addressing the cross-sectional heterogeneity in the long-run estimates. The paper adopts two specific types of estimators to address cross-country heterogeneity as proposed by the Chudik and Pesaran, 2015 cross-sectionally augmented distributed lag (CS-ARDL) and Chudik et al., 2013 cross-sectionally augmented distributed lag (CS-DL) models. We investigate the long-run effects of renewable electricity consumption on the economic growth of thirty-three countries over the period 1971-2015. In contrast to the previous literature on the electricity consumption–economic growth nexus, as explained in Section 3, the CS-ARDL and CS-DL econometric approaches used here take into account three important features of panel data (i.e., dynamics, heterogeneity and cross-sectional dependence). The panel techniques adopted in this paper also allow countries to be affected by common factors (such as oil price, monetary policy and fiscal shocks) due to slope coefficients differing across countries and cross-country averages (and their lags) being proxies for unobserved common factors. The econometric modelling approach is a complement to other modelling analyses, such as system dynamics and dynamic computable general equilibrium models (see EEA, 2019, section 5). Among other compelling features, the GTAP framework provides an interesting modelisation of the energy structure, including a separate and detailed representation of the renewable and non-renewable electricity sectors (see, e.g., the GDynEP-AG general equilibrium model in EEA, 2020). Our findings suggest that a significant positive long-term relationship exists between per capita economic growth and renewable electricity consumption, although Granger causality is not confirmed in the analysis. A similar analysis of the relation between per capita economic growth and per capita total electricity consumption does not yield any significant relationship. However, when checking for causality, we find per capita economic growth to be a causal factor for total electricity consumption. The remainder of this paper is organised as follows: Section 2 reviews the literature, Section 3 discusses the type of estimation techniques adopted, Section 4 describes the data and the model applied, Section 5 presents the results, and Section 6 concludes the paper.

2. Electricity–Growth Nexus

Energy is undeniably the most important contributor to economic progress, with current trends in energy demand expected to reach double the present level by 2050 (World Energy Council, 2007). This makes questions related to climate change and non-renewable energy consumption and economic growth truly important. The nexus between economic growth and energy consumption has been studied extensively by applied researchers, beginning with Kraft and Kraft, 1978. Various forms of energy consumption measures have been used to understand electricity consumption using different data samples (cross-sectional and time-series data) and econometric methodologies to investigate this relationship and have obtained different results. A review of previous research from an empirical perspective allows one to state four possible hypotheses.

- Growth hypothesis: There is unidirectional causality from energy (electricity) to growth. In this scenario, the consumption of energy (electricity) tends to have a considerable influence on the economic growth process. If the relationship is positive, then the implementation of pollution reduction measures will reduce domestic output. However, if the relationship is negative, then reducing energy (electricity) consumption will increase economic output. A positive relationship is most commonly observed in countries that tend to have high energy intensity or low energy efficiency sectors.

- Conservation hypothesis: There is unidirectional causality from growth to energy (electricity), and there is scope for energy (electricity) conservation policies to be effective without harming growth. In this case, real GDP growth influences the consumption of energy (electricity). Thus, decisions to reduce energy (electricity) consumption will have only a limited or marginal impact on the economy.

- Feedback hypothesis: There is bidirectional causality. In this scenario, increasing energy (electricity) consumption drives economic growth, which further increases energy (electricity) consumption; that is, energy (electricity) consumption and economic growth are highly interdependent. Therefore, if new emission reduction environmental policies are introduced, growth and consumption will decrease, but if economic stimuli are adopted, then there will be a surge in GDP and energy (electricity) consumption.

- Neutrality hypothesis: Energy (electricity) and growth have a neutral relationship, meaning that energy (electricity) conservation policies have no effect on growth. This is possible for countries in which real GDP growth is considerably reliant on the service sector, which exhibits relatively low energy (electricity) consumption. Therefore, policies intended to reduce energy consumption with a focus on reducing emissions do not affect or reduce domestic output. The economy can be considered to be decoupled from the dynamics of energy (electricity) consumption.

Due to space limitations, we do not wish to devote attention to a more detailed review of the recent literature, and the following papers provide extensive surveys in this context: Ozturk, 2010, Payne, 2010, Omri, 2014, Halkos and Tzeremes, 2014, Tiba and Omri, 2017, and Marina et al., 2018. The idea of including sustainability and social inclusion while measuring economic development can be attributed to the Stiglitz-Sen-Fitoussi Report (Stiglitz et al., 2009) and the Sustainable Development Goals. A scarcity of energy affects development, especially quality of life. Recently, an increase in energy prices and strategic goals to reduce emission rates have encouraged more detailed study of the linkages between renewable energy consumption and economic growth. The question of the relationship between renewable electricity consumption and economic growth has been relatively overlooked by researchers. Much of the economic growth in market-based economies can be attributed to industrial output, which is energy intensive. Given their future energy policies and inclination towards a greener future, countries have been investing in renewable electricity and energy infrastructure. In this context, it is very important to understand the implications of such plans for economic growth. The analysis of the nexus is also relevant to the development of the EU's broader green industrial policy. Through the introduction of the Juncker Plan-Invest EU and recent EU Green Deal, Brussels is planning to be carbon neutral and have a strong 'real economy'. Since its formation, the EU has lacked effective industrial policy (Pianta and Lucchese, 2020, Lucchese and Pianta, 2020). Through the introduction of various integration policies, the EU has encouraged its member states towards limited state intervention in the industrial arena. This lack of further insight has led to loss of EU competitiveness and a decline in manufacturing. In the ten-year period between 2007 and 2016, with the exception of Germany and some Eastern European countries, every major European player experienced a decline in its share in high-end manufacturing (Pianta et al., 2020). It is thus vital to integrate climate and energy policies with a process of re-manufacturing and green industrialisation, where eco innovations and renewable energy investments play a key role (EEA, 2016, EEA, 2019, UNIDO, 2012, UNIDO, 2015).

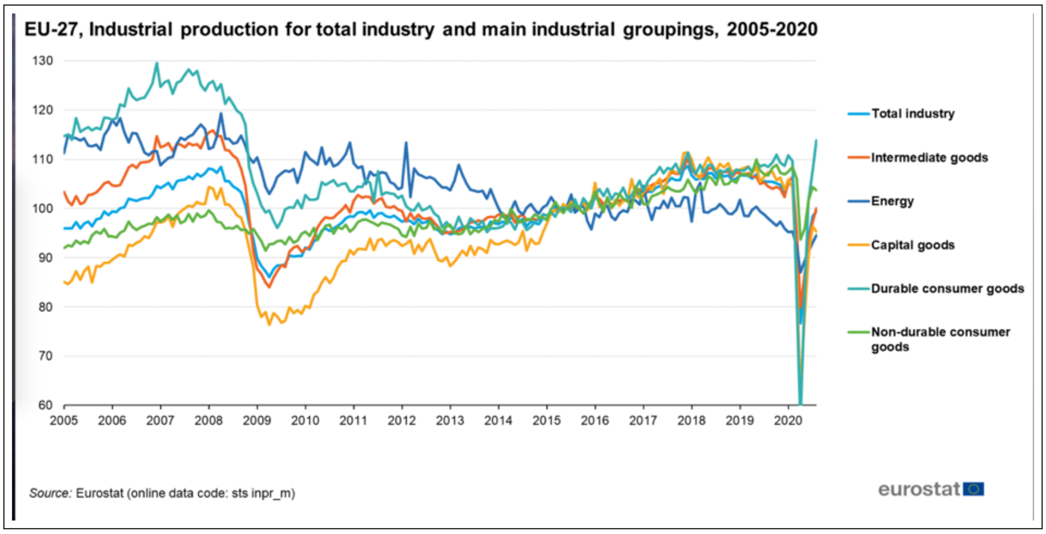

Figure 1: Industrial production in the EU [1]

3. Empirical Approaches

In this section, we propose the approach applied to examine renewable electricity consumption and economic growth in the long run.

We begin with a simple panel data model that can summarise much of the existing work on the empirics of economic growth:

$$\Delta y_{it} = (\phi - 1)y_{it} + \beta' x_{it} + c_{yi} + \eta_t + \epsilon_{it} \tag{1}$$

$$i = 1, ...N; t = 1, ...T$$

where Δy_{it} is the growth rate of real GDP per capita of country i; y_{it-1} is the lagged value; x_{it} is a vector of explanatory variables; η_t is the time-specific effect; c_{yi} is the country-specific effect; and ϵ_{it} is the error term.

Much of the empirical growth literature is based on estimating Eq. (1) using various fixed/random effects or cross-sectional techniques. Most of these techniques clearly suffer from endogeneity problems because y_{it-1} and ϵ_{it} are correlated; this correlation is of much greater magnitude if there are unobserved country-specific factors (such as global financial or monetary shocks and oil price shocks). Traditional static fixed or random estimators are not effective in such cases due to the presence of serial correlation and heteroscedasticity. Since the interlinkage between economic growth and electricity consumption (renewable in our case) is highly complex, we include the lagged value of GDP per capita on the right-hand side to eliminate fixed effects from Eq. (1), which in any standard OLS-based technique implies violation of orthogonality between the error term and independent variables. Although a GMM-type estimator might be appropriate in this regard, we do not apply this technique because it restricts slope coefficients to be identical across *i*. GMM techniques also assume homogeneity in time effects and cross-sectional independence in error terms; for details, please refer to Pesaran and Smith, 1995 and Mohaddes and Raissi, 2017. We choose two different types of estimators that address such problems, namely, CS-ARDL and CS-DL, which we describe below.

3.1. CS-ARDL

The most important econometric methodology for addressing long-run relationships is cointegration, which was proposed by Engle and Granger, 1987. Pesaran and Smith, 1995 introduced a methodology for panel data and named it the autoregressive distributed lag (ARDL) model. In a panel data framework, two extreme alternative approaches exist to address parametric heterogeneity, one being the mean group (MG), which estimates equations differently for each country, and the average of each coefficient is then examined. Pesaran and Smith, 1995 notes that the results of MG-type estimators are consistent when the time-series dimension is large enough. Fixed effects (FE), random effects (RE) and generalised method of moments (GMM) estimators, which might be considered to be situated at the other extreme, simply pool the dynamic nature of the data and treat observations homogeneously. Between these two extreme approaches lies the pooled mean group (PMG) type of estimator proposed by Pesaran et al., 1999. This approach involves aspects of both averaging and pooling estimators, allowing for heterogeneity in the intercepts, short-run coefficients and error variances, with the long-run coefficients being homogeneous across cross-sectional units. The PMG estimator takes the average of each cross-sectional unit and generates consistent short-run estimates for these cross-sectional units.

Chudik and Pesaran, 2015 and Chudik et al., 2016 introduced CS-ARDL, a new ARDL type estimator, to address cross-sectional dependence in the presence of I(0) or I(1) order of integration irrespective of the order and obtain pooled long-run type estimates. The estimator also takes into account omitted variable bias. The only requirement in this type of estimator, apart from the existence of a long-term relationship between the variables considered, is that the model have a dynamic specification, so that the weak exogeneity among the regressors is taken into account and the residuals are no longer correlated.

We will discuss the CS-ARDL model in detail, but let us start with a basic ARDL model of order 1 with a multifactor error structure:

$$y_{it} = c_{it} + \phi y_{it-1} + \beta'_{0i} x_{it} + \beta'_{1i} x_{it-1} + u_{it} \tag{2}$$

$$u_{it} = \gamma'_i f_t + \epsilon_{it} \tag{3}$$

$$\omega_{it} = \begin{pmatrix} x_{it} \\ g_{it} \end{pmatrix} = c_{\omega i} + \alpha_i y_{it-1} + \Gamma'_i f_t + v_{it} \tag{4}$$

where $i = 1, ...N; t = 1, ...T$, x_{it} is a $k_x \times 1$ vector of regressors of *i* cross-sectional units at time *t*, c_{yi} and $c_{\omega i}$, g_{it} is $k_g \times 1$ is a vector of covariates specific to the i^{th} cross-sectional unit, $k_g \geq 0$,$k_x + k_g = k$, ϵ_{it} represents the idiosyncratic errors, and f_t is an $m \times 1$ vector of unobserved common factors, which can be stationary on non-stationary. Γ_i is an $m \times k$ matrix of factor loadings ($k \geq m$), α_i is a $k \times 1$ vector of unknown coefficients, and the assumption behind v_{it} is that it follows a general linear covariance stationary process distributed independently of the idiosyncratic error terms, ϵ_{it}. ; see Kapetanios et al., 2014. The main intrinsic feature of this technique is that the unobserved common factors or heterogeneous time effects can be proxied by adding cross-sectional averages of the observables (see Pesaran, 2006 and Chudik and Pesaran, 2015). Chudik and Pesaran, 2015 derive that the unobserved common factors f_t can be proxied by detrended common averages of z_t = $(y_{it}, x'_{it}, g'_{it})'$ and their respective lags, with the necessary condition being that N is sufficiently large.

$$f_t = G(L)\tilde{z}_{wt} + O_P(N^{-1/2}) \tag{5}$$

where G(L) is a distributed lag function, $\tilde{z}_{wt} = \bar{z}_{wt} - \bar{c}_{zw}$ is a $k+1$ dimensional vector of detrended cross-sectional averages, $\bar{c}_{zw} = \Sigma_{i=1}^N w_i (I_{k+1} - A_i)^{-1} c_{zi}$ with $A_i = A_{0i}^{-1} A_{1i}$,

$$A_{0i} = \begin{bmatrix} 1 & -\beta'_{0i} & 0 \\ 0_{k_x \times 1} & I_{k_x} & 0_{k_x \times k_g} \\ 0_{k_g \times 1} & 0_{k_g \times k_x} & I_{k_g} \end{bmatrix}$$

and

$$A_{1i} = \begin{bmatrix} \phi_i & -\beta'_{1i} & 0_{1\times k_g} \\ \alpha_{x_i} & 0_{k_x\times k_x} & 0_{k_x\times k_g} \\ \alpha_{g_i} & 0_{k_g\times k_x} & 0_{k_g\times k_g} \end{bmatrix}$$

The weights are specified by the normalisation condition: $\Sigma_{i=1}^{N} w_i = 1$. Finally, substituting (5) into (2), the final form can be written as

$$y_{it} = c^*_{yi} + \phi_i y_{it-1} + \beta'_{0it} x_{it} + \beta'_{1i} x_{it-1} + \delta'_i(L)\bar{z}_{wt} + O_P(N^{-1/2}) + \epsilon_{it} \tag{6}$$

$$\delta_i(L) = \sum_{l=0}^{\infty} \delta_{il} L^l = G'(L)\gamma_i \tag{7}$$

and

$$c^*_{yi} = c_{yi} - \delta'_i(1)\bar{c}_{zw}$$

To estimate (2) using MG and PMG estimators, certain conditions need to be fulfilled.

- The number of cross-sectional averages must be at least as large as the number of unobserved common factors.
- A sufficient number of lags of cross-sectional averages needs to be included in the individual equations of the panel.
- The model needs the time-series dimension to be large enough to estimate the values of each cross-sectional unit.

For the MG-type estimator, θ can be written as $\theta = E(\theta_i)$, so the long-run coefficients are

$$\theta_i = \frac{\beta_{0i} + \beta_{1i}}{1 - \phi_i} \tag{8}$$

For the PMG-type estimator, the individual long-run coefficients must be the same across all cross-sectional units, and the PMG estimator uses a maximum likelihood approach to calculate estimates using a variant of the Newton-Raphson algorithm:

$$\theta_i = \theta, i = 1, ..., N \tag{9}$$

3.2. CS-DL

The CS-ARDL approach has some conceptual shortcomings because it first estimates the short-run coefficients and then computes the long-run coefficients based on (8) with the short-run estimates being replaced by their long-run counterparts (Pesaran, 2015). However, a problem arises if the rate of convergence towards the long-run estimate is slow and if the time dimension is not sufficiently long. Another problem might arise if the sampling uncertainty is of large dimension and the short-run coefficient is subject to small T bias (see Pesaran, 2015, page 782). Therefore, one of the most important requirements is the correct specification of the lag order.

Chudik and Pesaran, 2015 proposed a different estimation approach in which the long-run coefficients are estimated directly without estimating the short-run coefficients. This approach also derives from the ARDL approach and can be written as:

$$y_{it} = \theta_i x_{it} + \alpha_i'(L)\Delta x_{it} + \tilde{u}_{it} \tag{10}$$

where $\tilde{u}_{it}$ = $\lambda_i(L)^{-1}u_{it}$, $\lambda_i(L) = 1 - \lambda_i L^l$ and $\alpha_i(L) = \Sigma_{l=0}^{\infty}\Sigma_{s=l+1}^{\infty}\lambda_i^s\beta_i L^l$. θ_i is directly estimated from (10) with some assumptions, $|\lambda_i| < 1$, and exponents of $\alpha_i(L)$ decay exponentially in the absence of feedback effects of lagged values of the dependent variable on the explanatory variables. A consistent estimate of θ_i can be obtained by least squares regressing y_{it} on x_{it}, $\{\Delta x_{it-l}\}_{l=0}^{\rho T}$ and using cross-sectional averages to address unobserved common factors present within u_{it}.

The final CS-DL estimator is as follows:

$$y_{it} = c_{yi} + \theta_i' x_{it} + \sum_{l=0}^{p-1}\delta_{il}x_{i,t-l} + \sum_{l=0}^{p\bar{y}}\omega_{yil}\bar{y}_{t-l} + \sum_{l=0}^{p\bar{x}}\omega_{xil}'\bar{x}_{t-l} + \epsilon_{it} \tag{11}$$

where $\bar{x}_t = N^{-1}\sum_{i=1}^{N}x_{it}$ and $\bar{y}_t = N^{-1}\sum_{i=1}^{N}y_{it}$ and $p_{\bar{x}}$ is set equal to integer of $T^{1/3}$, $p = p_{\bar{x}}$ and $p_{\bar{y}}$ is set to 0.

Therefore, the cross-sectional augmented distributed lag (CS-DL) mean group estimator can be written as

$$\widehat{\theta}_{MG} = \frac{1}{N}\sum_{i=1}^{N}\widehat{\theta}_i \tag{12}$$

and

$$\widehat{\theta}_i = (\tilde{X}_i' M_{qi}\tilde{X}_i')^{-1}\tilde{X}_i' M_{qi}\tilde{y}_i \tag{13}$$

The CS-DL pooled estimator of the long-run coefficients can be written as

$$\widehat{\theta}_P = \left(\sum_{i=1}^{N} w_i\tilde{X}_i' M_{qi}\tilde{X}_i'\right)^{-1}\sum_{i=1}^{N} w_i\tilde{X}_i' M_{qi}\tilde{y}_i \tag{14}$$

The CCE estimator of Pesaran (2006) only includes a fixed number of regressors, but in the CS-DL estimator, θ_{MG} and θ_P include ρ_T lags of Δx_{it} and its cross-sectional averages. The length of ρ_T increases with T, and following Pesaran, 2006, Chudik and Pesaran, 2015 and Chudik et al., 2016, the optimal lag length can be determined.

4. Data

This section presents the data we used to examine the long-term effects of renewable electricity consumption on economic growth in the OECD, using both CS-ARDL and CS-DL.

We obtain per capita renewable electricity consumption (REN) in GWh and per capita gross domestic product (GDP) in billions of 2005 US dollars, which represents economic growth in our case, from the International Energy Agency (IEA) (IEA, 2018); finally, we convert every variable into its natural logarithmic form to reduce heteroscedasticity. Since our analysis allows for slope heterogeneity across our sample of countries, we need a sufficient number of time periods to estimate country-specific coefficients. One of the requirements of CS-DL is $30 \leqslant T < 100$ (Chudik et al., 2013, Pesaran, 2015), where T is the number of time periods. For the above reason, we only select countries that have the maximum number of time data points available, and we ultimately have 33 countries as listed in Table 1 for a period of 45 years (1971-2015). We also compare our results with total electricity consumption (ele), and these data are also from the IEA (IEA, 2018).

Table 1: List of countries in our sample

Australia	Greece	New Zealand
Austria	Hungary	Norway
Belgium	Iceland	Poland
Canada	India	Portugal
Chile	Ireland	Slovak Republic
China	Italy	Spain
Czech Republic	Japan	Sweden
Denmark	Korea (South)	Switzerland
Finland	Luxembourg	Turkey
France	Mexico	United Kingdom
Germany	Netherlands	United States of America

~~In Table 2, we display the descriptive statistics of each variable in our sample.~~ We present the

~~Descriptive Statistics~~

~~Variables~~	~~GDP~~	~~REN~~	~~ELE~~
~~Mean~~	~~26.14622105~~	~~3109.468307~~	~~7047.162228~~
~~St. Dev~~	~~13.93018802~~	~~6672.208809~~	~~6670.866862~~
~~Min.~~	~~0.481767437~~	~~0~~	~~117.1609852~~
~~Max.~~	~~91.30977131~~	~~56782.47734~~	~~56794.56193~~
~~Skewness~~	~~0.82933714~~	~~4.143397245~~	~~2.963922057~~
~~Kurtosis~~	~~2.152172355~~	~~21.95513886~~	~~14.25913855~~

total and decadal simple correlation coefficients between REN and GDP for each country in our sample in Table 2 ~~3~~.

Figure 2 illustrates a simple bivariate relation between GDP and REN for our sample of countries in the time period we consider. It provides a clear indication of a positive relationship between the two variables. For comparative purposes, we also display the bivariate relation between GDP and ELE in Figure 3.

[2] we considered original values and not after logarithmic transformation, so the variables are per-capita gdp and per-capita renewable energy consumption.

Table 2: Time correlation between GDP and Renewable Electricity consumption

Countries[2]	total sample	71-80	81-90	91-00	01-10	11-15
Australia	0.48	0.34	-0.02	-0.50	0.20	0.82
Austria	0.90	0.94	0.57	0.83	0.50	0.14
Belgium	0.67	0.86	0.34	0.89	0.79	0.50
Canada	0.71	0.98	0.48	0.45	0.43	0.67
Chile	0.89	0.09	-0.04	-0.13	0.31	0.66
China	0.98	0.83	0.95	0.95	0.99	0.99
Czech Republic	0.83	0.85	-0.19	0.86	0.68	0.42
Denmark	0.85	0.64	0.75	0.95	0.55	0.97
Finland	0.90	-0.16	0.24	0.71	0.70	-0.52
France	0.09	0.74	-0.67	-0.05	-0.12	0.04
Germany	0.77	0.77	-0.58	0.89	0.91	0.95
Greece	0.50	0.35	-0.60	0.75	0.37	-0.85
Hungary	0.84	0.46	0.48	0.51	0.76	0.98
Iceland	0.90	0.95	0.79	0.97	0.55	0.95
India	0.96	0.88	0.55	-0.24	0.93	0.74
Ireland	0.73	0.51	-0.45	0.76	0.26	0.98
Italy	0.31	0.52	-0.83	0.60	-0.81	-0.94
Japan	0.50	-0.41	0.57	0.08	0.14	0.76
Korea	0.73	0.61	0.83	0.12	0.46	0.89
Luxembourg	0.76	0.67	-0.43	0.80	0.86	0.59
Mexico	0.66	-0.33	0.67	0.19	0.69	0.25
Netherlands	0.86	0.86	0.51	0.99	0.83	0.65
New Zealand	0.52	0.21	0.50	-0.02	0.24	0.14
Norway	0.75	0.80	0.61	0.24	0.37	0.64
Poland	0.87	0.60	-0.28	0.95	0.93	0.97
Portugal	0.62	0.55	0.16	0.33	0.31	-0.21
Slovak Republic	0.79	0.73	-0.05	0.60	0.27	0.63
Spain	0.58	0.03	-0.17	0.43	0.15	-0.51
Sweden	0.65	0.55	0.78	0.40	0.20	0.44
Switzerland	-0.05	0.08	-0.71	0.30	-0.29	0.42
Turkey	0.89	0.87	0.69	0.60	0.48	0.44
United Kingdom	0.68	0.82	0.58	0.88	0.59	0.99
United States	0.29	-0.33	-0.24	-0.33	0.53	0.77

5. Model

In accordance with previous empirical literature, we use a standard log-linear functional specification of the long-run relationship between renewable electricity consumption and real gross

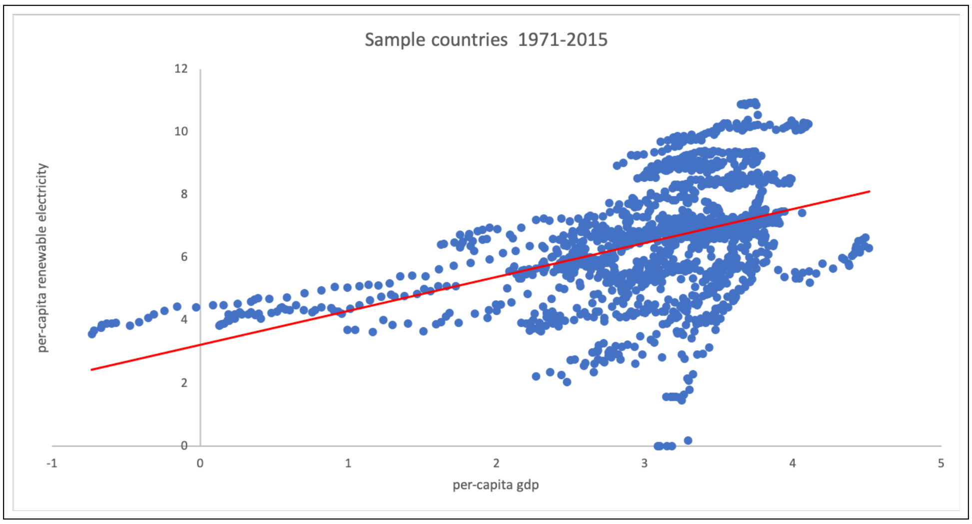

Figure 2: Renewable Electricity – GDP: 1971-2015 on a logarithmic scale

domestic product in our sample of countries. The function can be expressed in the following way:

$$GDP_{it} = \alpha + \beta REN_{it} + \epsilon_{it}$$

we also provide the results for total electricity consumption using the same specification:

$$GDP_{it} = \alpha_{it} + \beta ELE_{it} + \epsilon_{it}$$

To examine the long-run effects of renewable electricity consumption on economic growth, we estimate the following panel CS-ARDL model:

$$y_{it} = c^*_{yi} + \sum_{l=1}^{p} \phi_{il} y_{i,t-l} + \sum_{l=0}^{p} \beta'_{il} x_{i,t-l} + \sum_{l=0}^{q} a_{il} \overline{y}_{t-l} + \sum_{l=0}^{q} b'_{il} \overline{x}_{t-l} + \epsilon_{it} \tag{15}$$

where y_{it} is the GDP per capita of country i at time t and x_{it} represents renewable electricity consumption per capita for country i during that same time period t. $\overline{y}_t$ and $\overline{x}_t$ denote the cross-sectional averages of y_{it} and x_{it} for time period t. The important decision in specifying ARDL models is to set a lag length long enough to ensure that the residuals become serially uncorrelated with the error correction term, although choosing too many lags imposes excessive parameter requirements on the data. We keep the lag length at 3, i.e., we set p$\leq$ 3, according to similar approaches employed by Chudik and Pesaran, 2015, Mohaddes and Raissi, 2017 and Chudik et al., 2016 following Pesaran, 2007.

We also employ CS-DL to estimate the long-run effects of renewable electricity consumption on the economic growth of our sample of countries for different truncation lag orders, $p = 1, 2, 3$,

$$y_{it} = c_{yi} + \theta'_i x_{it} + \sum_{l=0}^{p-1} \delta_{il} x_{i,t-l} + \sum_{l=0}^{p\overline{y}} \omega_{yil} \overline{y}_{t-l} + \sum_{l=0}^{p\overline{x}} \omega'_{xil} \overline{x}_{t-l} + \epsilon_{it} \tag{16}$$

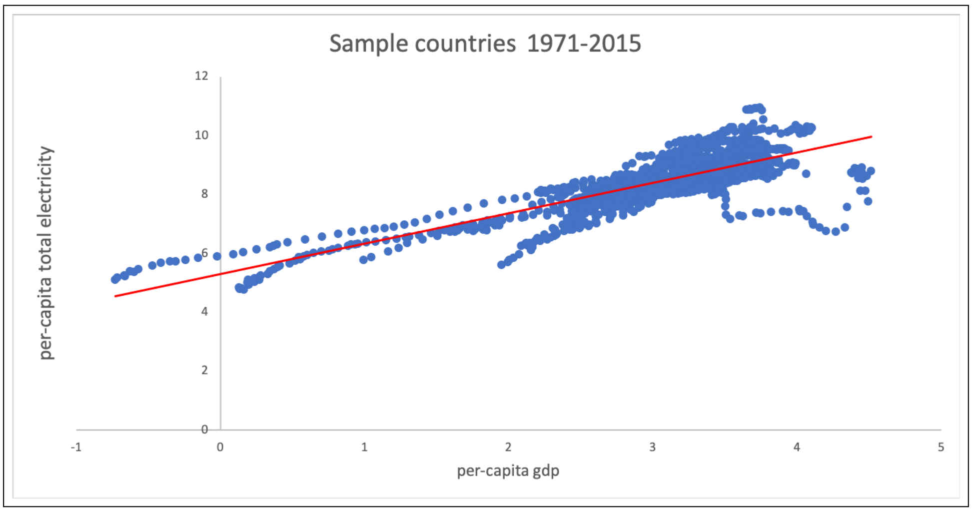

Figure 3: Total Electricity – GDP: 1971-2015 on a logarithmic scale

where y_{it} is the GDP per capita of country i at time t and x_{it} represents renewable electricity consumption per capita for country i during that same time period t. $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$ and $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, and $p_{\bar{x}}$ is set equal to the integer of $T^{1/3}$. Since in our case T = 45, $p_{\bar{x}}$ = 3

6. Results

6.1. Cross-sectional dependence test

We first check the nature of the cross-sectional relations between our variables, and we use Pesaran, 2004 to test the degree of magnitude of cross-sectional dependence. The results are depicted in Table 3 4. The null hypothesis is strict cross-sectional independence, which is rejected for all the variables considered.

Table 3: CD Results- I

Var.	CD-test	p-value	mean ρ	mean abs (ρ)
gdp	144.727	0.000	0.94	0.94
ren	92.551	0.000	0.60	0.60
ele	130.784	0.000	0.85	0.85

Then, we follow Pesaran, 2015, Bailey et al., 2016 and Ertur and Musolesi, 2017 to calculate the degree of the cross-sectional dependence statistic along with estimated confidence bands of α, the exponent of cross-sectional dependence defined over the range [0,1] for our required variables, as depicted in Table 4 ~~5~~, the null of the CD test depending upon the increase in T and N. When T is fixed and N $\rightarrow \infty$, the null for CD test is given by $0 \leqslant \alpha \leqslant$0.5 and when T and N $\rightarrow \infty$ at the same rate, the null for CD test is given by $0 \leqslant \alpha \leqslant 0.25$ (which is our case). To this extent, the value of α in the range of [0.5,1] depicts different degrees of strong cross-sectional dependence and a value in the range [0, 0.5] depicts different degrees of weak cross-sectional dependence.

Table 4: CD Results- II

Variables	CD statistic	$\widehat{\alpha_{0.5}}$	$\widehat{\alpha}$	$\widehat{\alpha_{0.95}}$
gdp	140.122	0.958	1.002	1.047
ren	94.03	0.92	0.99	1.065
ele	122.12	0.95	1.002	1.049

In our case, for all the variables, the CD statistic strongly rejects the null hypothesis, suggesting that the exponent of cross-sectional dependence lies in the range [0.25, 1]. To determine the degree of cross-sectional dependence, one must examine the bias-corrected estimates of α and the 90$\%$ confidence bands around it. In our case, the exponent of cross-sectional dependence is estimated at approximately one for all variables in levels and more than 0.90 for all variables in first differences. In addition, the 90$\%$ confidence bands are substantially above 0.5 and include unity. This confirms our preliminary finding and suggests the presence of strong cross-sectional dependence in both the dependent and explanatory variables used in our analysis.

6.2. *Second-generation Panel Unit root tests*

Table 5 ~~6~~ reports the outcomes of three first-generation unit root tests with cross-sectionally demeaned data (Im et al., 2003), along with the first difference of each variable, we use BIC lags for each case.

Table 5: Second-generation Panel Unit root tests – I

Variable	Statistic	p-value
gdp	7.45	1.00
ren	3.44	0.997
ele	5.54	1.00
dgdp	-19.8	0
dren	-40.62	0
dele	-30.54	0

We then apply Pesaran, 2007 and Pesaran et al., 2013 to understand the non-stationarity in a multifactor error structure framework, and as in our previous case, the variables become stationary in first differences. The results are presented in Table 6 ~~7~~. We choose 3 lags. Following the literature that sets the lag number equal to integer of $T^{1/3}$, in our case T = 45, we choose the lag length to be 3.

6.3. *Test for Panel Cointegration*

We finally apply Westerlund, 2007 and Persyn and Westerlund, 2008 to understand the order of integration among our variables. Table 7 ~~8~~ reports the relationship between per capita GDP and per capita renewable electricity consumption only. We conclude with the presence of cointegration among our variables. The mean-group test (G_τ) averages heterogeneous OLS estimates of the speed of adjustment of their standard errors, while the panel test (P_τ) provides estimates

Table 6: Second-generation Panel Unit root tests – II

Variable	t-bar	Z[t-bar]	p-value
gdp	-1.72	0.271	0.607
ren	-2.065	-1.8	0.036
ele	-1.472	1.823	0.966
dgdp	-2.611	-5.141	0
dren	-3.529	-10.747	0
dele	3.008	-7.565	0

Table 7: Cointegration Results

Statistic	Value	Z-value	P-value	Robust P-value
G_τ	-1.887	3.390	1.000	0.890
Ga	-7.485	3.824	1.000	0.890
P_τ	-10.074	2.356	0.991	0.680
Pa	-5.376	3.332	1.000	0.760

of the aggregate speed of adjustment and its standard error. Because both the G_τ and P_τ distributions assume error-correction models and are independently distributed, one can say that the tests take into consideration cross-sectional dependence through bootstrapped standard errors. We choose 3 lags and 100 bootstrap replications.

6.4. Long-run estimates

We first investigate the long-run effects of renewable electricity consumption on economic growth represented by per capita GDP using the traditional panel ARDL approach. In this approach, the long-run effects are calculated using OLS estimates of the short-term coefficients of (2). We use a lag range from 1 to 3, since we are using the economic growth variable with per capita GDP as the measure for advanced and developing countries, a lag order of 3 is sufficient to fully account for short-run dynamics and rule out feedback effects. Equation (2) also allows for a significant degree of cross-sectional dependence (particularly in the short run). Pesaran and Smith, 1995, Pesaran, 1997 and Pesaran et al., 1999 note that traditional ARDL models can be used for long-run estimation, taking into account both the endogeneity of regressors and the I(0) or I(1) nature of the variables. Additionally, following the argument of Pesaran and Smith, 2014, in which they argue in favour of parsimonious models when the object of interest is not the *ceteris paribus* impact of a regressor, we do not employ any control variables in our estimation.

In Table 8 ~~9~~, we report the results of the plain ARDL model for both fixed effects (FE) and mean group (MG) estimates with no cross-sectional correction. The first three columns of the first two rows of the table report the fixed effects estimates, and the last three columns report the mean group estimates. In the last two rows, we report the results when we use total electricity consumption instead of renewable electricity consumption.

The results show that renewable electricity consumption is significantly and positively related to economic growth except for the mean group type estimator with three lags, where it is

Table 8: Fixed Effects (FE) and Mean Group (MG) estimates of the Long-run effects based on the traditional ARDL approach

	FE (1,1)	FE (2,2)	FE (3,3)	MG (1,1)	MG (2,2)	MG (3,3)
$\widehat{\theta}$ ~~ren~~	0.006***	0.008***	0.004***	0.001***	0.009***	-0.014***
	(0.007)	(0.01)	(0.011)	(0.018)	(0.02)	(0.029)
$\widehat{\lambda}$ $\cancel{\lambda}$	-0.64	-0.68	-0.65	-0.66	-0.75	-0.713
	(0.037)	(0.034)	(0.041)	(0.03)	(0.035)	(0.044)
	FE (1,1)	**FE (2,2)**	**FE (3,3)**	**MG (1,1)**	**MG (2,2)**	**MG (3,3)**
$\widehat{\theta}$ ~~ele~~	0.116*	0.078**	0.079***	0.325	0.262	0.24
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)
$\widehat{\lambda}$ $\cancel{\lambda}$	-0.65	-0.69	-0.66	-0.705	-0.76	-0.74
	(0.039)	(0.037)	(0.041)	(0.032)	(0.039)	(0.04)

Notes: The ARDL estimation is given by: $y_{it} = c_{yi} + \sum_{l=1}^{p} \varphi_{il} y_{i,t-l} + \sum_{l=0}^{p} \beta_{il} x_{i,t-l} + u_{it}$, where y_{it} is the GDP per capita and x_{it}represents renewable electricity consumption per capita or electricity consumption per capita. Also, $p = 1, 2,$ and 3, $\lambda_i = 1 - \sum_{l=1}^{p} \varphi_{il}$. $\theta_i = \lambda_i^{-1} \sum_{l=0}^{p} \beta_{il}$

Values inside parentheses are standard errors.

The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

significant at the 1% level but the coefficient is negative. For total electricity consumption, the fixed effects model shows significance, and the level of significance increases with the introduction of lags, but for the mean group estimator, there exists no significant relationship, although the coefficients are positive.

6.4.1. CS-ARDL

We present the results of CS-ARDL in Table 9 ~~10~~, using the MG estimator for both renewable and total electricity consumption. The results of the CS-ARDL model are very similar to those of the ARDL model; renewable electricity consumption is significant at the 1% level for all three lag levels, but the coefficient becomes negative at the third lag, although it is positive for the first two lags. This strengthens the idea that in the short run, the effect of renewable electricity on economic growth is positive, but over time, the effect becomes less important. However, for total electricity in the case of CS-ARDL, no significance exists, but the coefficients are positive.

6.4.2. CS-DL

The MG estimates based on CS-DL regressions are summarised in Table 10 ~~11~~ for both renewable electricity and total electricity. For renewable electricity consumption, the mean group estimates are statistically significant and positive over time, and lag 1 is significant at the 5% level, whereas for lag 2 and lag 3, the significance is at the 1% level. However, in the case of total electricity consumption, the coefficients are positive and not significant at any of the chosen lag lengths.

Table 9: Mean Group (MG) estimates of the Long-run effects based on the CS-ARDL Approach

	CS-ARDL(1)	CS-ARDL(2)	CS-ARDL(3)
$\widehat{ren}$	0.022***	0.014***	-0.018***
	(0.015)	(0.02)	(0.03)
$\widehat{\lambda}$ $\cancel{\lambda}$	-0.683	-0.736	-0.689
	(0.042)	(0.05)	(0.058)
	CS-ARDL(1)	**CS-ARDL(2)**	**CS-ARDL(3)**
$\widehat{ele}$	0.259	0.238	0.249
	(0.08)	(0.06)	(0.07)
$\widehat{\lambda}$ $\cancel{\lambda}$	-0.761	-0.803	-0.763
	(0.044)	(0.047)	(0.055)

Notes:
Values inside parentheses are standard errors.
The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

6.5. Causality analysis

The ARDL (including CS-ARDL and CS-DL) type estimators are efficient at identifying the existence of long-run relationships among the variables included in the estimation, in our case, renewable electricity consumption and economic growth. However, this type of estimator does not indicate the direction of causality, which is a very important aspect in the literature on the energy/electricity–economic growth nexus. Accordingly, to determine the nexus of causality, we implement a new type of Granger causality test using the methodology proposed by Dumitrescu and Hurlin, 2012 and Lopez and Weber, 2017.

The null hypothesis of the test is of homogeneous non-causality against the alternative of heterogeneous causality. The test uses fixed coefficients in a vector autoregressive (VAR) framework. The framework assumes that the coefficients differ across cross-sectional units and is more reliable and robust to cross-sectional dependence than standard Granger causality tests. To consider cross-sectional dependence, the test uses a block bootstrap procedure to correct critical values. We use the BIC criterion to select the lag length, opting for 2 lags, and apply the first difference of the variables since the test requires stationarity among the variables. The test also uses dissimilar log structures and heterogeneous unrestricted coefficients. Another advantage of this test is the use of Wald statistics to test for Granger non-causality, which are calculated separately for each cross-section and then averaged to compute the result for the full panel. Dumitrescu and Hurlin, 2012 also verify the asymptotics behind the test and state that the panel test value converges to a normal distribution of homogeneous non-causality when T and N go to infinity with the rate of T being faster than that of N.

The empirical results of the short-run heterogeneous panel non-causality tests are presented in Table 11 ~~12~~. The findings show no evidence of causal relations between renewable electricity

Table 10: Mean Group (MG) estimates of the Long-run effects based on the CS-DL Approach

	CS-DL(1)	**CS-DL(2)**	**CS-DL(3)**
$\widehat{\theta}$ ~~ren~~	0.019^{**}	0.0211^{***}	0.0149^{***}
	(0.0103)	(0.0157)	(0.01911)
RMSE(σ)	0.0223	0.0219	0.0217
	CS-DL(1)	**CS-DL(2)**	**CS-DL(3)**
$\widehat{\theta}$ ~~ele~~	0.217	0.204	0.247
	(0.057)	(0.058)	(0.061)
RMSE(σ)	0.0201	0.0199	0.0196

Notes: The cross-sectionally augmented distributed lag (CS-DL) regressions include the cross-sectional average of the dependent variable and the three lags for the cross-sectiona averages of the regressor. The CS-DL estimates are based on the following specification$_{it} = c_{yi} + \theta_i' x_{it} + \sum_{l=0}^{p-1} \delta_{il} x_{i,t-l} + \sum_{l=0}^{p\bar{y}} \omega_{yil} \bar{y}_{t-l} + \sum_{l=0}^{p\bar{x}} \omega_{xil}' \bar{x}_{t-l} + \epsilon_{it}$, where y_{it} is the GDP per capita and x_{it}represents renewable electricity consumption per capita or electricity consumption per capita. Also, $p = 1, 2,$ and 3, $\lambda_i = 1 - \sum_{l=1}^{p} \varphi_{il}$. $\theta_i = \lambda_i^{-1} \sum_{l=0}^{p} \beta_{il}$

Values inside parentheses are standard errors.

The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

consumption and gross domestic product, although unidirectional causality exists between GDP and total electricity consumption.

Table 11: Heterogeneous Panel Causality results

Null hypothesis	w-bar	Z-bar Stat.	Prob
GDP does not Granger-cause REN	1.3819	1.5512	0.1209
REN does not Granger-cause GDP	1.0140	0.0570	0.9545
Null hypothesis	w-bar	Z-bar Stat.	Prob
GDP does not Granger-cause ELE	1.7753	3.1493	0.0016
ELE does not Granger-cause GDP	0.9744	-0.1039	0.9173

7. Conclusions and Policy Implications

The nexus between economic growth and energy consumption, especially electricity consumption, has gained considerable momentum given the role of (renewable) electricity as a potential structural change factor in the future of economic development based on a decarbonised economic system. Electricity is a key factor in the innovation-based sustainability transition; it drives manufacturing production, mobility, and energy sources for households. The bulk of the empirically oriented literature in applied environmental and energy economics has assessed long-run income–energy relationships by using methodologies that do not take cross-sectional dependence into specific consideration. Against this background, the present work uses panel data econometric techniques applied in a macroeconomic setting to examine whether a long-term relationship, and causality, exists between renewable electricity consumption and growth, and it does so using a sample of high-income countries over a fairly extended time period: 1971-2015. The paper has methodological and policy aims. Regarding methods, it focuses on the macroeconomics of sustainability and highlights new methods to properly assess long-run economic–environmental relationships. With respect to policy, it explores the specific realm of electricity in the energy transition. As economic development progresses, the evolution and extension of electricity is relevant, especially because it is the key pillar of an entirely fossil fuel-free economy and since it enhances the flexibility of the energy system along the transition to decarbonisation. Two recent methodologies that take into account cross-sectional dependence in a long-term framework, namely, CS-ARDL and CS-DL, are implemented to assess long-term relationships. The main conclusions are that a significant and positive long-term relationship exists between per capita economic growth and per capita renewable electricity consumption, but Granger causality does not emerge in any specifications. Nevertheless, whereas analyses of per capita economic growth and per capita total electricity consumption do not show any significant relationship, per capita economic growth appears to be a causal factor for total electricity consumption.

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