



Renewable energy and growth: Evidence from heterogeneous panel of G7 countries using Granger causality



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ABSTRACT

In this paper we examine the causal relationship between renewable energy consumption and economic growth across the G7 countries, using annual data for the period of 1990–2011. By employing the causality methodology proposed by Emirmahmutoglu and Kose (2011) [8], we investigate if there is a causal relationship between the variables. The advantage of this methodology is that it takes into account possible slope heterogeneity and cross-sectional dependency in a multivariate panel. The empirical results support the existence of a bi-directional causal relationship between economic growth and renewable energy for the overall panel. However, looking at the individual results for each country, the neutrality hypothesis is confirmed for Canada, Italy and the US; while for France and UK there is a unidirectional causality from GDP to renewable energy, and the opposite for Germany and Japan.

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1. Introduction

Among the main factors that influence the intensity of energy use (energy to economic growth ratio) around the world is the composition of the energy mix [1]. There is a growing body of the literature that specifically fossil-fuel based energy generation has detrimental effects on the environment. On top of that, the

environmental impact can have substantial negative consequences for economic growth as well as society at large. According to Sadorsky [2], power generation is the fastest growing energy sector in terms of both demand and emissions. There is thus a critical need to balance our future energy needs with the environmental impact of energy generation. Since energy is a major driver of economic growth and prosperity, and with demand for world energy predicted to grow in excess of 50% by 2030 according to International Energy Agency (IEA) [3], it is imperative that cleaner alternatives of energy generation be introduced for the sake of reducing the climate change effects.

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The use of renewable energies, as a whole, is considered a cleaner alternative to fossil fuel energy generation. According to IEA [4], renewable energy is projected to be the fastest growing world energy source. The growing investment in this type of energy generation is considered to be linked with economic growth and development, however the existing literature has not reached a general consensus as to whether higher economic growth improves the use of renewable energies or vice versa. Renewable energy is expected to increase its contribution to the energy supply mix from 13% in 2012 to 18% in 2035 [5]. However, not all renewable types are so promising for the future: wind and solar although growing fast (7.8% annually) they are still accountable for less than 1% of the global energy consumption [5].

Obtaining energy from renewable sources has advantages other than reduced output of harmful substances that cause climate change, such as less reliance on foreign imports for import dependent nations (oil and coal energy), meaning greater energy security and the ability to generate energy domestically, as well as the decreased impact on the environment. Renewable energy can contribute to growth in the new world economy by means of the investment in infrastructure, which is potentially massive, with a predicted \$20 trillion worth of infrastructure spending worldwide necessary to meet the rising demand for energy over the course of the next 17 years [2].

Renewable energy technologies are relatively new and have not yet reached cost-effective levels due to a lack of high competition. Given this high cost, it is expected that only high-income, developed countries have a measurable renewable energy contribution to the power grid, even though developing countries have abundance of natural resources, but not the means or the capital to exploit them. Thus we make use of the G7 countries, which are all highly developed and use the greatest share of renewable energy, illustrated in REN21 [6]. In 2013 the share of renewable energy (including hydro) in primary energy demand for the G7 countries was Canada (8.20%), France (1.88%), Germany (3.02%), Italy (2.17%), Japan (2.47%), United Kingdom (1.05%), and the United States (10.58%) [7].

In this paper, we examine the existence as well as the direction of the causal relationship between renewable energy consumption and economic growth across the G7 countries, using annual data for the period of 1990–2013. We employ the causality methodology proposed by Emirmahmutoglu and Kose [8] that controls for heterogeneity and cross-sectional dependence among cross-sections, addressing a shortcoming in the current literature. The members of the G7, although being the strongest economies are not similar in all aspects, and may have differentiating factors such as geography, climate, education, population size and government policy. However, all the G7 countries are linked by growing economic and financial integration, interlinked trade, policy similarity, etc. Thus a shock in one of the G7 may have an effect on one or many of the other countries in the G7. We thus control for the presence of cross sectional dependency in our analysis, which tells us that a shock in one of the G7 countries will have spill-over effects in the other countries.

The paper is structured as follows. In Section 2, we review briefly recent studies on the relationship between renewable energies and economic growth while in Section 3 we describe the data and methodology. Section 4 discusses the empirical results and concluding remarks are given in Section 5.

2. Literature review

Due to the interest in renewable energies only growing in recent years, the literature has not extensively studied the

relationship between renewable energy and economic growth. However, there are few efforts [9–17] that conclude the importance of renewable energy to economic growth in various countries. Here, we will discuss briefly the findings of selected recent studies on the topic.

Sadorsky [9] showed that real income per capita and renewable energy consumption per capita have a positive relationship for emerging economies. Sadorsky [9] uses a bivariate panel error correction model for eighteen emerging economies over the period 1994–2003. The model presents evidence of bi-directional causality between renewable energy consumption and economic growth.

Apergis and Payne [10] confirmed the results for a larger group of countries (20 OECD members). To do so, they used the panel unit root and cointegration testing approach of Pedroni [18,19]. This heterogeneous panel cointegration test advanced by Pedroni, allows for cross-section interdependence with different individual effects, accounting for heterogeneity across countries. Parameters are included in the tests that allow for the possibility of country-specific fixed effects and deterministic trends. Extending the above group to include more OECD countries, Inglesi-Lotz [16] used the renewable energies as an input in a production-function context, concluding that there is a long-run equilibrium relationship between real GDP or real GDP per capita, total renewable energy consumption or share of total renewable energy consumption, real gross fixed capital formation, employment and the R&D expenditures of the countries. Both studies, however, did not account for cross-dependence among the OECD countries, although both used panel cointegration techniques. Also, Inglesi-Lotz [16] focuses more on the difference of the results between developed and developing countries as groups and not individually.

Menegaki [15] concluded similar results to Inglesi-Lotz [16] for European countries, a 1% increase in the share of renewable energies to total supply mix will increase GDP by 4.4%. In more disaggregated analysis, Sari and Soyotas [17] showed that three types of renewable energies (waste, hydraulic power and wood) explained around 31% of the variation in GDP in real terms for Turkey.

Although the group of G7 countries has received substantial attention in the energy literature, the majority of studies focused on the nexus between economic growth and energy in total (for example Bildirici [20] and Narayan and Smyth [21]) or other non-renewable types of energy such as electricity (for example Narayan et al. [22]).

Recently, Tugcu, Ozturk and Alsan [23] employed the lately developed causality method by Hatemi [24] to test for causality for the existence and direction of causality between non-renewable and renewable energy and economic growth for the G7 countries over the 1980–2009 period. Their methodology uses a modified Wald statistic, which accounts for the possibility of autoregressive conditional heteroscedasticity (ARCH) effects via a bootstrapping simulation. The paper uses classical and augmented production functions as a basis for their tests, and thus does not account for cross-sectional dependence or homogeneity among countries. Additionally, their study looks at each country individually in a time-series context, rather than in a panel. These factors may limit the inference one can make from the results.

So, although our paper also focuses on the group of G7 countries, the two papers differ firstly, methodologically where our paper makes a contribution to the literature and take the technical analysis a step forward. Tugcu et al. [23] use only time series analysis for the individual countries not taking into account cross-sectional dependence like in our analysis. That is, with us using the Toda–Yamamoto based approach (which can handle non-stationary data), we do not need to test for existence of

cointegration, and neither do we need to transform the data into stationary variables, which essentially changes the definition of the variable per se. More importantly, unlike Tugcu et al. [23], which only provides evidence or lack of it for the entire panel, we are not only able to provide evidence for the entire panel, but also each of the cross-sectional unit comprising the panel. This is very important, since we now have information as to which cross-sectional units drives the results of the panel, and also the fact that there could be cross-sections which show results different from the entire panel taken together. In other words, unlike previous studies using panel data, we can design country specific policies if requires, even though we are in a panel setting, since we do have causality test results for each of the panel members. A sweeping policy statement based on the panel set-up hence might be quite misleading, if information is not available for each of the cross-sections. In addition, our paper uses a more recent time period including a few years after the financial crisis of 2008/09.

In the literature, various techniques are employed to control for a number of different issues. Despite this, all the results are in agreement; there is a positive relationship between renewable energy and economic growth for both emerging and developed economies; however no agreed upon methodology to test for causality has arisen in the literature. Given certain shortcomings of the papers discussed above, we make use of a multivariate panel setup. This allows for greater inference due to the greater degrees of freedom stemming from the larger data set a panel provides. Panel also allows us to control for omitted variables. Further, cognisance of the potential for cross-sectional dependence and homogeneity among countries, for reasons discussed in our methodology below.

3. Methodology and data

3.1. Methodology

In the current interconnected and open world economy, panel causality analysis must take into consideration two important issues: cross-section dependence and slope heterogeneity.

Firstly, concerning cross-sectional dependence, in the recent past there has been a growing economic and financial integration of countries and financial institutions. Given this integration, panel data literature has concluded that panel data sets are likely to exhibit substantial cross-sectional dependence, which may occur due to the presence of common shocks, as well as unobserved components that ultimately form part of the error term.

Additionally, concerning slope heterogeneity, when dealing with panel data methodologies, it is assumed that variations in between cross sectional units are captured by fixed constants, using either fixed or random effects. However, not all unobserved individual variation can conclusively be ruled out, and some individual variability in the slopes of the cross-sections may exist. If this variability is not taken account of, it may bias our results, and cause incorrect inference.

Thus, before exploring the causality between renewable energy and economic growth, the issues of cross-sectional dependence and heterogeneity of slope coefficients are examined. In what follows, we outline the essentials of econometric methods used in this study.

3.1.1. Testing cross-section dependence

To test for cross-sectional dependence, the Lagrange multiplier (LM hereafter) test of Breusch and Pagan [25] has been extensively

used in empirical studies. The procedure to compute the LM test requires the estimation of the following panel data model:

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it} \text{ for } i = 1, 2, \dots, N; \quad t = 1, 2, \dots, T \quad (1)$$

where i is the cross section dimension, t is the time dimension, x_{it} is $k \times 1$ vector of explanatory variables, α_i and β_i are respectively the individual intercepts and slope coefficients that are allowed to vary across states. In the LM test, the null hypothesis of no-cross section dependence – $H_0 : \text{Cov}(u_{it}, u_{jt}) = 0$ for all t and $i \neq j$ – is tested against the alternative hypothesis of cross-section dependence – $H_1 : \text{Cov}(u_{it}, u_{jt}) \neq 0$, for at least one pair of $i \neq j$. In order to test the null hypothesis, Breusch and Pagan [25] developed the LM test as follows:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2 \quad (2)$$

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals from Ordinary Least Squares (OLS) estimation of Eq. (1) for each i . Under the null hypothesis, the LM statistic has asymptotic chi-square with $N(N-1)/2$ degrees of freedom. It is important to note that the LM test is valid only for relatively small N and sufficiently large T – as we have in this study.

However, the Cross sectional Dependence (CD) test is subject to decreasing power in situations that the population average pair-wise correlations are zero, although the underlying individual population pair-wise correlations are non-zero [26]. Furthermore, in stationary dynamic panel data models the CD test fails to reject the null hypothesis when the factor loadings have zero mean in the cross-sectional dimension. In order to deal with these problems, Pesaran et al. [26] propose a bias-adjusted test, which is a modified version of the LM test, by using the exact mean and variance of the LM statistic. The bias-adjusted LM test is

$$LM_{adj} = \sqrt{\left(\frac{2T}{N(N-1)} \right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{\nu_{Tij}^2}} \quad (3)$$

where μ_{Tij} and ν_{Tij}^2 are respectively the exact mean and variance of $(T-k)\hat{\rho}_{ij}^2$, that are provided in Pesaran et al. [26]. Under the null hypothesis with first $T \rightarrow \infty$ and then $N \rightarrow \infty$, LM_{adj} test is asymptotically distributed as standard normal.

3.1.2. Testing slope homogeneity

The second issue investigated here is to test whether or not the slope coefficients are homogenous. The causality from one variable to another variable by imposing the joint restriction for the whole panel is the strong null hypothesis [27]. Moreover, the homogeneity assumption for the parameters is not able to capture heterogeneity due to region specific characteristics [28].

The most familiar way to test the null hypothesis of slope homogeneity – $H_0 : \beta_i = \beta$ for all i – against the hypothesis of heterogeneity – $H_1 : \beta_i \neq \beta_j$ for a non-zero fraction of pair-wise slopes for $i \neq j$ – is to apply the standard F test. The F test is valid for cases where the cross section dimension (N) is relatively small and the time dimension (T) of panel is large; the explanatory variables are strictly exogenous; and the error variances are homoscedastic. By relaxing homoscedasticity assumption in the F test, Swamy [29] developed the slope homogeneity test on the dispersion of individual slope estimates from a suitable pooled estimator. However, both the F and Swamy's test require panel data models where N is small relative to T . Pesaran and Yamagata [30] proposed a standardized version of Swamy's test (the so-called $\hat{\Delta}$ test) for testing slope homogeneity in large panels. The $\hat{\Delta}$

test is valid as $(N, T) \rightarrow \infty$ without any restrictions on the relative expansion rates of N and T when the error terms are normally distributed. In the $\tilde{\Delta}$ test approach, the first step is to compute the following modified version of Swamy's test as in Pesaran and Yamagata [30]:

$$\tilde{S} = \sum_{i=1}^N (\hat{\beta}_i - \tilde{\beta}_{WFE})' \frac{X_i' M_{\tau} X_i}{\hat{\sigma}_i^2} (\hat{\beta}_i - \tilde{\beta}_{WFE}) \quad (4)$$

where $\hat{\beta}_i$ is the pooled OLS estimator, $\tilde{\beta}_{WFE}$ is the weighted fixed effect pooled estimator, M_{τ} is an identity matrix, the $\hat{\sigma}_i^2$ is the estimator of σ_i^2 . Then the standardized dispersion statistic is developed as follows:

$$\tilde{\Delta} = \sqrt{N} \left(\frac{N^{-1} \tilde{S} - k}{\sqrt{2k}} \right) \quad (5)$$

Under the null hypothesis with the condition of $(N, T) \rightarrow \infty$ so long as $\sqrt{N/T} \rightarrow \infty$ and the error terms are normally distributed, the $\tilde{\Delta}$ test has asymptotic standard normal distribution. The small sample properties of $\tilde{\Delta}$ test can be improved under the normally distributed errors by using the following bias adjusted version:

$$\tilde{\Delta}_{adj} = \sqrt{N} \left(\frac{N^{-1} \tilde{S} - E(\tilde{z}_{it})}{\sqrt{\text{var}(\tilde{z}_{it})}} \right) \quad (6)$$

where the mean $E(\tilde{z}_{it}) = k$ and the variance $\text{var}(\tilde{z}_{it}) = 2k(T - k - 1)/T + 1$.

If the presence of cross-sectional dependence and heterogeneity over the sample period exists, it implies that the panel causality test that imposes the homogeneity restriction and does not account for spill-over effects across units, may result in misleading inferences; hence providing the rationale of using the bootstrap panel causality approach.

3.1.3. Panel Granger causality analysis

The causality test proposed by Emirmahmutoglu and Kose [8] will be employed here that is based on the meta-analysis of Fisher [31]. They extended the Lag Augmented VAR (LA-VAR) approach by Toda and Yamamoto [32], which uses the level VAR model with extra $dmax$ lags to test Granger causality between variables in heterogeneous mixed panels. Consider a level VAR model with $k_i + dmax_i$ lags in heterogeneous mixed panels:

$$x_{i,t} = \mu_i^x + \sum_{j=1}^{k_i + dmax_i} A_{11,ij} x_{i,t-j} + \sum_{j=1}^{k_i + dmax_i} A_{12,ij} y_{i,t-j} + \mu_{i,t}^x \quad (7)$$

$$y_{i,t} = \mu_i^y + \sum_{j=1}^{k_i + dmax_i} A_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i + dmax_i} A_{22,ij} y_{i,t-j} + \mu_{i,t}^y \quad (8)$$

where i ($i = 1, \dots, N$) denotes individual cross-sectional units and t ($t = 1, \dots, T$) denotes time periods, μ_i^x and μ_i^y are two vectors of fixed effects, $\mu_{i,t}^x$, $\mu_{i,t}^y$ are column vectors of error terms, k_i is the lag structure which is assumed to be known and may differ across cross-sectional units, and $dmax_i$ is the maximal order of integration in the system for each i . Following the bootstrap procedure by Emirmahmutoglu and Kose [8], testing causality from x to y is summarised as follows:

Firstly, we will determine the maximal order $dmax_i$ of integration of variables in the system for each cross-section unit based on the Augmented Dickey Fuller (ADF) unit root test and select the lag orders k_i 's via information criteria (AIC or SB) by esteeming the regression (2) using the OLS method. Next, we will re-estimate Eq. (2) using the $dmax_i$ and k_i under the non-causality hypothesis

and attain the residuals for each individual as in (9):

$$\hat{u}_{i,t}^y = y_{i,t} - \hat{y}_{i,t}^y + \sum_{j=1}^{k_i + dmax_i} \hat{A}_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i + dmax_i} \hat{A}_{22,ij} y_{i,t-j} \quad (9)$$

The next step is to have the residuals centred using Stine's [33] suggestion, as in (10):

$$\tilde{u}_t = \hat{u}_t - (T - k - l - 2)^{-1} \sum_{t=k+l+2}^T \hat{u}_t \quad (10)$$

where

$\hat{\mu}_t = (\hat{\mu}_{1t}, \hat{\mu}_{2t}, \dots, \hat{\mu}_{Nt})'$, $k = \max(k_i)$ and $l = \max(dmax_i)$ and. Next, we develop the $[\tilde{\mu}_{it}]_{N \times T}$ from these residuals. We select randomly a full column with replacement from the matrix at a time to preserve the cross covariance structure of the errors. We denote the bootstrap residuals as $\hat{\mu}_t^*$ where $(t = 1, \dots, T)$.

Subsequently, a bootstrap sample of y is generated under the null hypothesis:

$$y_{i,t}^* = \hat{\mu}_t^y + \sum_{j=1}^{k_i + dmax_i} \hat{A}_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i + dmax_i} \hat{A}_{22,ij} y_{i,t-j}^* + u_{i,t}^* \quad (11)$$

where $\hat{\mu}_t^y$, $\hat{A}_{12,ij}$ and $\hat{A}_{22,ij}$ are the estimations from step 3.

For each individual, Wald statistics are calculated to test for the non-causality null hypothesis by substituting $y_{i,t}^*$ for $y_{i,t}$ and estimating Eq. (2) without imposing any parameter restrictions. Using individual p -values (p_i) that correspond to the Wald statistic of the i th individual cross-section, the Fisher test statistic λ is obtained as follows:

$$\lambda = -2 \sum_{i=1}^N \ln(p_i) \quad i = 1, \dots, N \quad (12)$$

Finally, the bootstrap empirical distribution of the Fisher test statistics are generated by repeating steps 3–5 10,000 times and specifying the bootstrap critical values by selecting the appropriate percentiles of these sampling distributions. Using simulation studies, Emirmahmutoglu and Kose [8] demonstrate that the performance of LA-VAR approach under both the cross-section independency and the cross-section dependency seem to be satisfactory for the entire values of T and N .

3.2. Data

The annual data used in this analysis covers the time period 1990–2013. The variables used are renewable energy and real GDP. Real GDP is measured in constant 2005 dollars, and the series was obtained from the World Bank [34]. The energy data used is measured in Terawatt Hours (TW h), and is based on generation from renewable sources, including wind, geothermal, solar, biomass and waste, while cross border electricity supply is not accounted for. This data was obtained from the BP Statistical Review of world energy [7]. All series are in natural logarithm form.

Tables 1 and 2 summarise the descriptive statistics of the two variables of interest for each of the G7 countries. Based on these tables, we find that France and US have the lowest and highest mean of renewable energy generation respectively, and that Canada and US have the lowest and highest mean levels of real GDP, respectively. For more detailed per country graphs, please refer to Appendix, Fig. A1.

4. Empirical findings

As per the methodology section, firstly the panel dataset was examined for possible cross-sectional dependency and slope

Table 1
Descriptive statistics for GDP in G7 countries.

GDP								
	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque–Bera
CANADA	27.65122	27.68811	27.90799	27.35417	0.189015	−0.28069	1.616705	2.228657
FRANCE	28.30377	28.33341	28.44384	28.11581	0.120235	−0.29631	1.530988	2.509193
GERMANY	28.61463	28.63198	28.75827	28.42684	0.097615	−0.17386	1.923211	1.28038
ITALY	28.13987	28.17065	28.2496	28.00304	0.077883	−0.45176	1.84709	2.145547
JAPAN	29.10286	29.09651	29.19267	28.97942	0.06292	−0.21175	1.934023	1.315664
UK	28.32233	28.36002	28.53405	28.01321	0.183554	−0.44758	1.732817	2.407056
US	30.06013	30.09671	30.30507	29.73795	0.190258	−0.42096	1.754022	2.261276

Table 2
Descriptive statistics for renewable energy generation in G7 countries.

Renewable energy								
	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque–Bera
CANADA	2.219192	2.273382	2.945818	1.436468	0.460524	−0.09254	2.077223	0.88577
FRANCE	1.533154	1.249123	3.261074	0.570879	0.865884	0.76228	2.218691	2.934725
GERMANY	2.770793	2.925404	4.877013	0.410121	1.530671	−0.17086	1.589523	2.106216
ITALY	2.295925	2.183757	4.049654	1.217996	0.858628	0.520212	2.215387	1.6981
JAPAN	3.070887	3.00474	3.731212	2.500475	0.36868	−0.00487	1.835882	1.355267
UK	1.759458	1.775342	3.873095	−0.50286	1.254946	−0.1492	2.027086	1.035602
US	4.578236	4.387588	5.557354	4.155031	0.409848	1.185328	3.067818	5.624607

Table 3
Cross-sectional dependence and slope homogeneity tests.

Test	Test statistic
CD _{BP}	174.966***
CD _{LM}	23.757***
CD	12.627***
LM _{adj}	66.8013***
$\hat{\Delta}$	18.795***
$\hat{\Delta}_{adj}$	0.8701
Swamy Shat	77.326***

Note: **, * and *** indicate significance at the 10%, 5% and 1% levels respectively (in this Table only *** statistical significance at 1% is only concluded).

homogeneity. To do so, four different tests are employed (CD_{BP}, CD_{LM}, CD, LM_{adj}), with a null hypothesis of no cross-sectional dependence. The results conclude that the null hypothesis can be rejected at 1% level of significance and hence, there is evidence of cross-sectional dependence (Table 3–first four rows) meaning that a shock originating in one country may spill over onto other countries. As shown in the methodology, the causality tests control for this dependency.

The last three rows of Table 3 show the results of the slope homogeneity tests. Although according to $\hat{\Delta}_{adj}$ the slope homogeneity assumption fails to be rejected, according to Swamy-Shat, and $\hat{\Delta}$ the null hypothesis of homogenous slopes can be rejected at a 1% level of significance. This implies that the panel causality analysis by imposing homogeneity restriction on the variable of interest may result in misleading inferences. Therefore country specific characteristics should be taken into account.

The establishment of the existence of cross-sectional dependence and heterogeneity across G7 countries suggests the suitability of the bootstrap panel causality approach developed by

Emirmahmutoglu and Kose [8] based on meta-analysis of Fisher [31] in heterogeneous mixed panels which accounts for these econometric issues. Our bootstrap test causality results are reported in Tables 4 and 5. The appropriate lag length was chosen based on the Akaike Information Criterion (AIC) in Table 4 and the Schwarz Information Criterion (SIC) in Table 5 for each individual country ranging between 1 and 2. The results are almost identical confirming the robustness of the results.

The overall results for the panel of G7 countries suggest that the null of no Granger causality from economic growth to renewable energy consumption cannot be rejected at 5% level of significance. Under AIC, the Fisher test statistic (12.757) is smaller than all bootstrap critical values and under SIC, the Fisher test statistic (12.425) is also smaller than all bootstrap critical value. For the Renewable Energy Led Hypothesis, under AIC the Fisher test statistic (31.248) is greater than the 5% bootstrap critical value (30.206) similarly under SIC, the Fisher test statistic (32.945) is greater than the 5% bootstrap critical value (29.791) indicating that there is a causality running from renewable energy consumption to economic growth for the overall panel.

Moreover individual country results are presented in Tables 4 and 5 too. Both using AIC and SIC selection criteria, the GDP Led Hypothesis (GDP causing renewable energy consumption) cannot be confirmed for any country; the Wald statistics indicate that the null hypothesis of no causality cannot be rejected at 1%, 5% or 10% level of significance.

With regards to the Renewable Energy Led Hypothesis, under AIC and SIC, the null hypothesis of no causality from renewable energy consumption to economic growth can be rejected for Canada, France and Japan. For the rest of the G7 countries, there is no causality running from renewable energy consumption to GDP.

All in all, the tests confirm the neutrality hypothesis for Germany, Italy, United Kingdom and United States indicating that economic growth and renewable energy consumption are indicators that do not affect each other. For Canada, France and Japan,

Table 4
Results of Granger causality test using AIC selection criteria.

Country	Lag length k_i	GDP Led Hypothesis		Renewable Energy Led Hypothesis	
		Wald statistic	p-Value	Wald statistic	p-Value
Canada	2	3.512	0.173	8.222	0.016**
France	3	0.245	0.621	4.274	0.039**
Germany	3	1.950	0.377	0.172	0.917
Italy	3	0.392	0.531	0.239	0.625
Japan	1	0.046	0.829	8.428	0.004***
United Kingdom	3	3.103	0.212	1.474	0.479
United States	2	1.598	0.450	2.735	0.255
Fisher test statistic value (λ)		12.757		31.248	
Critical values		CV 1% 40.333	CV 5% 29.903	CV 1% 40.585	CV 5% 30.206
			CV 10% 25.827		CV 10% 25.939

Note: *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively and hence conclusion of causality (in this Table only *** statistical significance at 1% level and ** statistical significance at 5% level are only concluded).

Table 5
Results of Granger causality test using SIC selection criteria.

Country	Lag length k_i	GDP Led Hypothesis		Renewable Energy Led Hypothesis	
		Wald statistic	p-Value	Wald statistic	p-Value
Canada	2	3.512	0.173	8.222	0.016**
France	3	0.245	0.621	4.274	0.039**
Germany	1	0.582	0.445	0.730	0.393
Italy	1	0.392	0.531	0.239	0.625
Japan	1	0.046	0.829	8.428	0.004***
United Kingdom	3	3.103	0.212	1.474	0.479
United States	2	1.598	0.450	2.735	0.255
Fisher test statistic value (λ)		12.425		32.945	
Critical values		CV 1% 39.713	CV 5% 29.555	CV 1% 39.346	CV 5% 29.791
			CV 10% 25.364		CV 10% 25.414

Note: *, ** and *** indicate significance at the 10%, 5%, and 1% levels respectively and hence conclusion of causality (in this Table only *** statistical significance at 1% level and ** statistical significance at 5% level are only concluded).

the Renewable Led Hypothesis is confirmed only indicating renewable energy consumption causes economic growth.

5. Conclusion

This study applies a panel Granger causality methodology that controls for heterogeneity and cross-sectional dependence in a panel, to test the existence and direction of a causal relationship between renewable energy and GDP growth, using data for the G7 countries over the period 1990–2013.

The advantage of the method used is the fact that we take into account cross-sectional dependence. There has been a growing economic and financial integration of countries and financial institutions recently. Given this integration, panel data literature has concluded that panel data sets are likely to exhibit substantial cross-sectional dependence, which may occur due to the presence of common shocks, as well as unobserved components that ultimately form part of the error term, resulting in biased estimates, in the sense that results might pick up causality between the two variables in concern, when there is none [35]. Also, our bootstrapping approach helps us to account for small-sample bias and hence guard against insignificant parameter estimates. However, we do accept the fact that, we take a linear approach, when nonlinearities in the relationship could exist due to structural breaks or regime changes.

For the overall panel, the results confirm a unidirectional relationship running from renewable energy consumption to

economic growth only. Looking at the results for each country individually, the neutrality hypothesis is confirmed for Germany, Italy, UK and the US; while for France Canada and Japan there is a unidirectional causality from renewable energy to GDP.

From a policy perspective, for Germany, Italy, UK and US, programmes that will promote the use of renewable energies will have little to no effect to the economic growth; at the same time, if all the current conditions remain constant, further economic growth and improvement of the economies after the financial crisis will not necessarily contribute towards generation of more renewable energy.

In Canada, the Clean Energy Fund, already in place since 2009, has been aiming to reduce their greenhouse gas emissions by promoting “green” technologies of generation among them encouraging investment on renewable energy sources [36]. In Japan, the need for a turn towards renewable energies became more apparent after the Great East Japan Earthquake and the accident at the Fukushima Daiichi Nuclear Power Station. That is when the Innovative Strategy for Energy and the Environment [37] was accepted. According to the strategy, investment to renewable energy sources will increase from 25 billion kW h in 2010 to 190 billion kW h (eight times) by 2030. More recently in France, the Energy Bill to be adopted in 2015 will be proposing a certain path towards specific climate and renewable energy targets to be reached in 2030: overall target of 32% of share of energy generated to be generated by renewable sources [38].

For these three countries, according to our results, by doing so, these policies will not only lead to a more sustainable, clean and

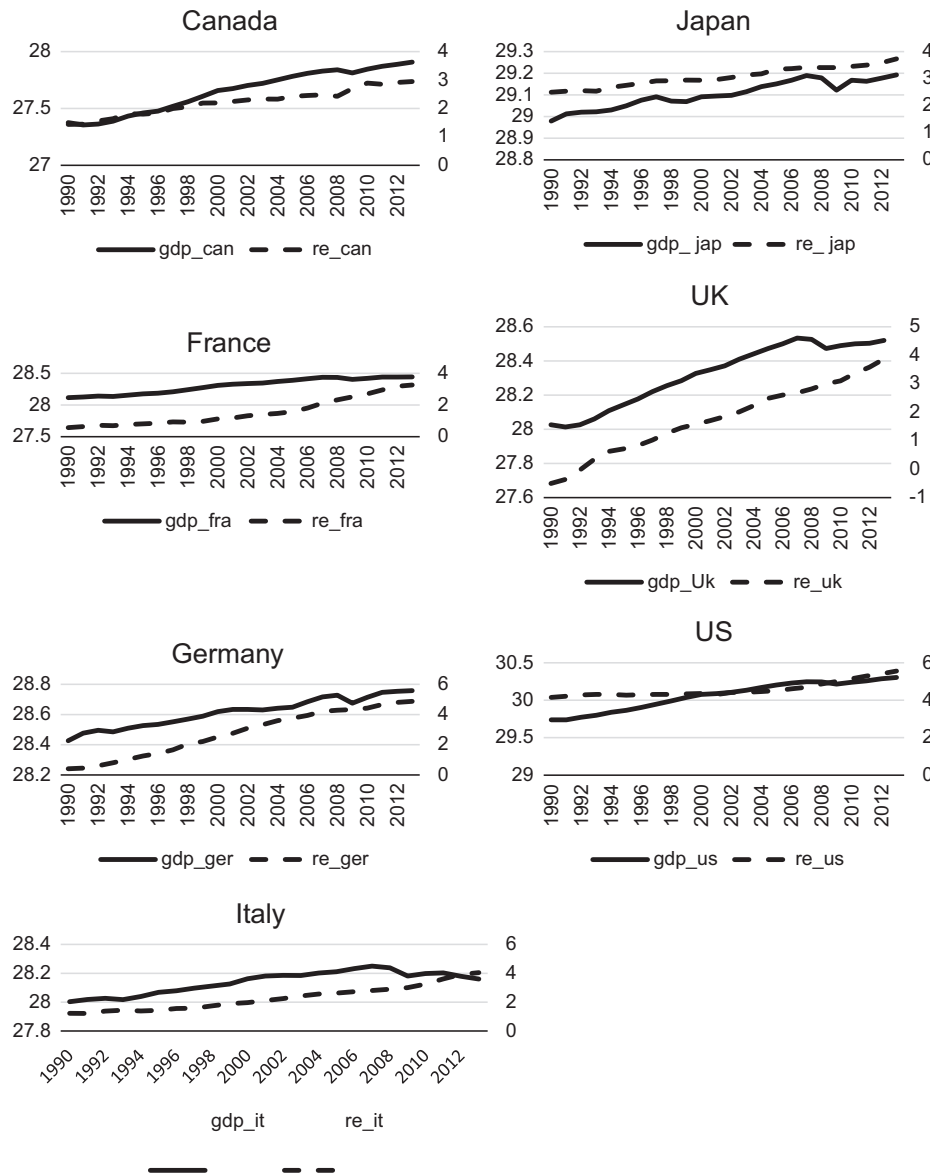


Fig. A1. Real GDP per capita and renewable energy consumption across G7 countries: 1990–2013.

free future but also the increasing consumption of renewable energies will be potentially the catalyst to unlock higher economic growth rates.

Appendix

See Fig. A1 here.

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