Renewable Energy and Growth: Evidence from Heterogeneous panel of G7 countries using Granger Causality

Tsangyao Chang

Department of Finance, Feng Chia University, Taichung, Taiwan

Rangan Gupta, Roula Inglesi-Lotz*,

Department of Economics, University of Pretoria, South Africa

Beatrice Simo-Kengne,

Department of Economics, University of Johannesburg, South Africa

Devon Smithers, Amy Trembling

Department of Economics, University of Pretoria, South Africa

*Corresponding author: Email Roula.inglesi-lotz@up.ac.za

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 to 2011. By employing the causality methodology proposed by Emirmahmutoglu and Kose (2011), 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.

Keywords: Renewable energy; economic growth; G7 countries; panel causality

JEL classification codes: C23, C33, Q42, Q43

1. Introduction

There is a growing body of literature that 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 [1], 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) [2], it is imperative that cleaner alternatives of energy generation be introduced for the sake of reducing the climate change effects.

The use of renewable energies, as a whole, is considered a cleaner alternative to fossil fuel energy generation. According to IEA [3], 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.

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 [1].

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 [4]. In 2006 the share of renewable energy (including hydro) in primary energy demand for the G7 countries was Canada (16%), France (6.0%), Germany (5.6%), Italy (6.5%), Japan (3.2%), United Kingdom (1.7%), and the United States (4.8%).

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 to 2011. We employ the causality methodology proposed by Emirmahmutoglu and Kose [5] 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 [6, 7, 8, 9, 10, 11, 12, 13, 14, 14] 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 [6] showed that real income per capita and renewable energy consumption per capita have a positive relationship for emerging economies. Sadorsky [6] 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 [7] 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 [15,16]. 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 [13] 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 [13] focuses more on the difference of the results between developed and developing countries as groups and not individually.

Menegaki [12] concluded similar results to Inglesi-Lotz [13] 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 [14] 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 [17] and Narayan and Smyth [18]) or other non-renewable types of energy such as electricity (for example Narayan et al. [19]).

Recently, Tugcu, Ozturk and Alsan [20] employed the lately developed causality method by Hatemi [21] 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 times-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 in two main points methodologically where our paper makes a contribution to the literature and take their technical analysis a step forward: a) our paper uses a more recent time period including a few years after the financial crisis of 2008/09; b) Tugcu et al. [20] use only time series analysis for the individual countries not taking into account cross-sectional dependence like in our analysis.

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 [22] has been extensively used in empirical studies. The procedure to compute the LM test requires the estimation of the following panel data model:

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it} \text{ for } i = 1, 2, ..., N;\ t = 1, 2, ..., T \tag{1}$$

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 - $H_0 : Cov(u_{it}, u_{jt}) = 0$ for all t *and* $i \neq j$ - is tested against the alternative hypothesis of cross-section dependence - $H_1 : Cov(u_{it}, u_{jt}) \neq 0$, for at least one pair of $i \neq j$. In order to test the null hypothesis, Breusch and Pagan [22] developed the LM test as:

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

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals from Ordinary Least Squares (OLS) estimation of equation (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 [23]. 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. [23] 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:

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

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. [23]. Under the null hypothesis with first T→∞ and then N→∞, 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 [24]. Moreover, the homogeneity assumption for the parameters is not able to capture heterogeneity due to region specific characteristics [25].

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 [26] 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 [27] proposed a standardized version of Swamy's test (the so-called $\tilde{\Delta}$ test) for testing slope homogeneity in large panels. The $\tilde{\Delta}$ 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 the Swamy's test as in Pesaran and Yamagata [27]:

$$\tilde{S}=\sum_{i=1}^{N}\left(\widehat{\beta}_i-\tilde{\beta}_{WFE}\right)'\frac{x_i'M_\tau x_i}{\tilde{\sigma}_i^2}\left(\widehat{\beta}_i-\tilde{\beta}_{WFE}\right) \tag{4}$$

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

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

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:

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

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

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 [5] will be employed here that is based on the meta analysis of Fisher [28]. They extended the Lag Augmented VAR (LA-VAR) approach by Toda and Yamamoto [29], 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 $k_i + d\max_i$ lags in heterogeneous mixed panels:

$$x_{i,t} = \mu_i^x + \sum_{j=1}^{k_i + d\max_i} A_{11,ij} x_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} A_{12,ij} y_{i,t-j} + \mu_{i,t}^x \tag{7}$$

$$y_{i,t} = \mu_i^y + \sum_{j=1}^{k_i + d\max_i} A_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} A_{22,ij} y_{i,t-j} + \mu_{i,t}^y \tag{8}$$

where i (i = 1,……N) denotes individual cross-sectional units and t (t = 1,…….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 $d\max_i$ is the maximal order of integration in the system for each i. Following the bootstrap procedure by Emirmahmutoglu and Kose [5], testing causality from x to y is summarized as follows:

Firstly, we will determine the maximal order $d\max_i$ 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 kis via information criteria (AIC or SB) by esteeming the regression (2) using the OLS method. Next, we will re-estimate equation (2) using the $d\max_i$ and k_i under the non-causality hypothesis and attain the residuals for each individual as in (9).

$$\hat{u}_{i,t}^y = y_{i,t} - \hat{u}_i^y + \sum_{j=1}^{k_i + d\max_i} \hat{A}_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} \hat{A}_{22,ij} y_{i,t-j} \tag{9}$$

The next step is to have the residuals centred using Stine’s [30] suggestion, as in (10):,

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

Where $\hat{\mu}_t = (\hat{\mu}_{1t}, \hat{\mu}_{2t}, \ldots\ldots, \hat{\mu}_{Nt})'$, $k = \max(k_i)$ and $l = \max(d\max_i)$. Next, we develop the $[\tilde{\mu}_{i.t}]_{N\times T}$ 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 $\tilde{\mu}_t^*$ where $(t = 1, \ldots., T)$.

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

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

where $\hat{\mu}_i^{y}$ $\hat{A}_{12,ij}$ 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 equation (2) without imposing any parameter restrictions. Using individual p-values (pi) that correspond to the Wald statistic of the ith individual cross-section, the Fisher test statistic λ is obtained as follows:

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

Finally, the bootstrap empirical distribution of the Fisher test statistics are generated by repeating steps 3 to 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 [5] 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 to 2011. 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. The energy data used is measured in Terawatt Hours (TWh), 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 2012. 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 Germany 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 the Appendix, Figure A1.

Table 1: Descriptive statistics for GDP in G7 countries

	GDP							
	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**
CANADA	27.59385	27.62623	27.84977	27.31969	0.188074	-0.155942	1.515488	2.109293
FRANCE	28.25625	28.28152	28.40492	28.08739	0.116685	-0.143398	1.470294	2.220398
GERMANY	28.59745	28.62012	28.74472	28.42228	0.093352	-0.136563	1.926309	1.125127
ITALY	28.13126	28.16052	28.2416	28.00959	0.07632	-0.263153	1.632706	1.967615
JAPAN	29.07579	29.07384	29.18023	28.95399	0.064857	-0.052643	1.999954	0.926912
UK	28.30679	28.33951	28.5035	28.06402	0.158363	-0.294412	1.58958	2.141333
US	30.01006	30.05515	30.22206	29.72261	0.178227	-0.345461	1.634075	2.147864

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

	Renewable Energy							
	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**
CANADA	2.110356	2.170424	2.957305	1.385642	0.43405	-0.031484	2.293318	0.461417
FRANCE	2.082696	2.176013	2.434674	1.544197	0.286399	-0.676901	2.220432	2.237131
GERMANY	1.379201	1.14747	2.945365	0.570879	0.72338	0.848703	2.467214	2.901294
ITALY	2.138623	2.04407	3.530757	1.217996	0.706709	0.327276	1.872781	1.557472
JAPAN	3.017046	2.957044	3.492803	2.500475	0.334757	-0.067061	1.715901	1.527991
UK	1.579229	1.639036	3.378031	-0.502857	1.147902	-0.228585	1.990665	1.125449
US	4.496166	4.349924	5.298746	4.155031	0.314142	1.342447	3.655626	7.001958

4. Empirical findings

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

Table 3: Cross-sectional Dependence and Slope Homogeneous Tests

Test	Test statistic	Conclusion
CD_{BP}	164.627***	Cross-Sectional dependency confirmed.
CD_{LM}	22.162***	Cross-Sectional dependency confirmed.
CD	12.430***	Cross-Sectional dependency confirmed.
LM_{adj}	57.6947***	
$\tilde{\Delta}$	12.4245***	Slope Heterogeneity confirmed
$\tilde{\Delta}_{adj}$	0.6306	Slope Heterogeneity not confirmed
Swamy Shat	67.5094***	Slope Heterogeneity confirmed

Note: *,** and *** indicate significance at the 10%, 5% and 1% levels respectively.

The last three rows of Table 3 show the results of the slope homogeneity tests. Although according to $\tilde{\Delta}$ the slope homogeneity assumption fails to be rejected, according to Swamy-Shat, and $\tilde{\Delta}_{adj}$ the null hypothesis of homogenous slopes can be rejected at a 10% 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 [5] based on meta-analysis of Fisher [28] 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 3. 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 can be rejected at 5% level of significance.Under AIC, the Fisher test statistic (47.523) is greater than the bootstrap critical value (44.809) and under SIC, the Fisher test statistic (53.755) is greater than bootstrap critical value (38.244) both at a 5% level of significance. For the Renewable Energy Led Hypothesis, under AIC the Fisher test statistic (59.966) is greater than the 5% bootstrap critical value (43.382) indicating that there is a causality running from renewable energy consumption to economic growth for the overall panel. However the results under SIC show a Fisher statistic of 23.102 that is smaller than the bootstrap critical values confirming that the null hypothesis of no causality from renewable energy to economic growth cannot be rejected.

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) can only be confirmed for France and the United Kingdom; their Wald statistics indicate that the null hypothesis of no causality can be rejected at 1% level of significance. For the rest of the G7 countries, there is no causality running from GDP to renewable energy consumption indicated.

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 Japan. The same is confirmed for Germany but only under AIC. As with the overall result, this may suggest that there is some delay in the causality, for example the AIC criterion suggested 3 lags for Germany but the SIC only 1, showing that the causal relationship is statistically significant in a 3-lagged period, and not sooner in a 1-lagged period. For the rest of the G7 countries, there is no causality running from renewable energy consumption to GDP.

Table 4: Results of Granger Causality test using AIC selection criteria

Country	Lag length	**GDP Led Hypothesis**			**Renewable Energy Led Hypothesis**		
	k_i	Wald Statistic	p- value		Wald Statistic	p- value	
Canada	2	8.013	0.018		4.592	0.101	
France	3	28.339	0.000***		3.728	0.292	
Germany	3	0.282	0.963		40.044	0.000***	
Italy	3	1.933	0.586		0.729	0.866	
Japan	1	0.004	0.949		7.72	0.005***	
United Kingdom	3	12.572	0.006***		4.761	0.19	
United States	2	2.536	0.281		2.129	0.345	
Fisher Test Statistic value (λ)		47.523			59.966		
Critical values		CV 1%	CV 5%	CV 10%	CV 1%	CV 5%	CV 10%
		69.922	44.809	36.293	67.506	43.382	34.704

Note: *,** and *** indicate significance at the 10%, 5% and 1% levels respectively and hence conclusion of causality.

Table 5: Results of Granger Causality test using SIC selection criteria

Country	Lag length	GDP Led Hypothesis		Renewable Energy Led Hypothesis	
	k_i	Wald Statistic	p- value	Wald Statistic	p- value
Canada	2	8.013	0.018	4.592	0.101
France	3	28.339	0.000***	3.728	0.292
Germany	1	2.701	0.1	0	0.993
Italy	1	1.325	0.25	0.01	0.92
Japan	1	0.004	0.949	7.72	0.005***
United Kingdom	3	12.572	0.006***	4.761	0.19
United States	2	2.536	0.281	2.129	0.345

	GDP Led Hypothesis			Renewable Energy Led Hypothesis		
Fisher Test Statistic value (λ)		53.755			23.102	
Critical values	CV 1%	CV 5%	CV 10%	CV 1%	CV 5%	CV 10%
	55.659	38.244	31.398	54.612	36.552	29.989

Note: *,** and *** indicate significance at the 10%, 5% and 1% levels respectively and hence conclusion of causality.

All in all, the tests confirm the neutrality hypothesis for Canada, Italy, and the United States indicating that economic growth and renewable energy consumption are indicators that do not affect each other. For France and UK, the GDP Led Hypothesis is confirmed indicating GDP causes renewable energy consumption while for Japan and Germany the Renewable Led Hypothesis is confirmed indicating that renewable energy consumption causes economic growth in these countries.

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 to 2011. For the overall panel, the results confirm a bidirectional relationship between economic growth and renewable energy, with some evidence that the causality from renewable energy to economic growth has a delayed response. Looking at the results for each country individually, the neutrality hypothesis is confirmed for Canada, Italy and the US;

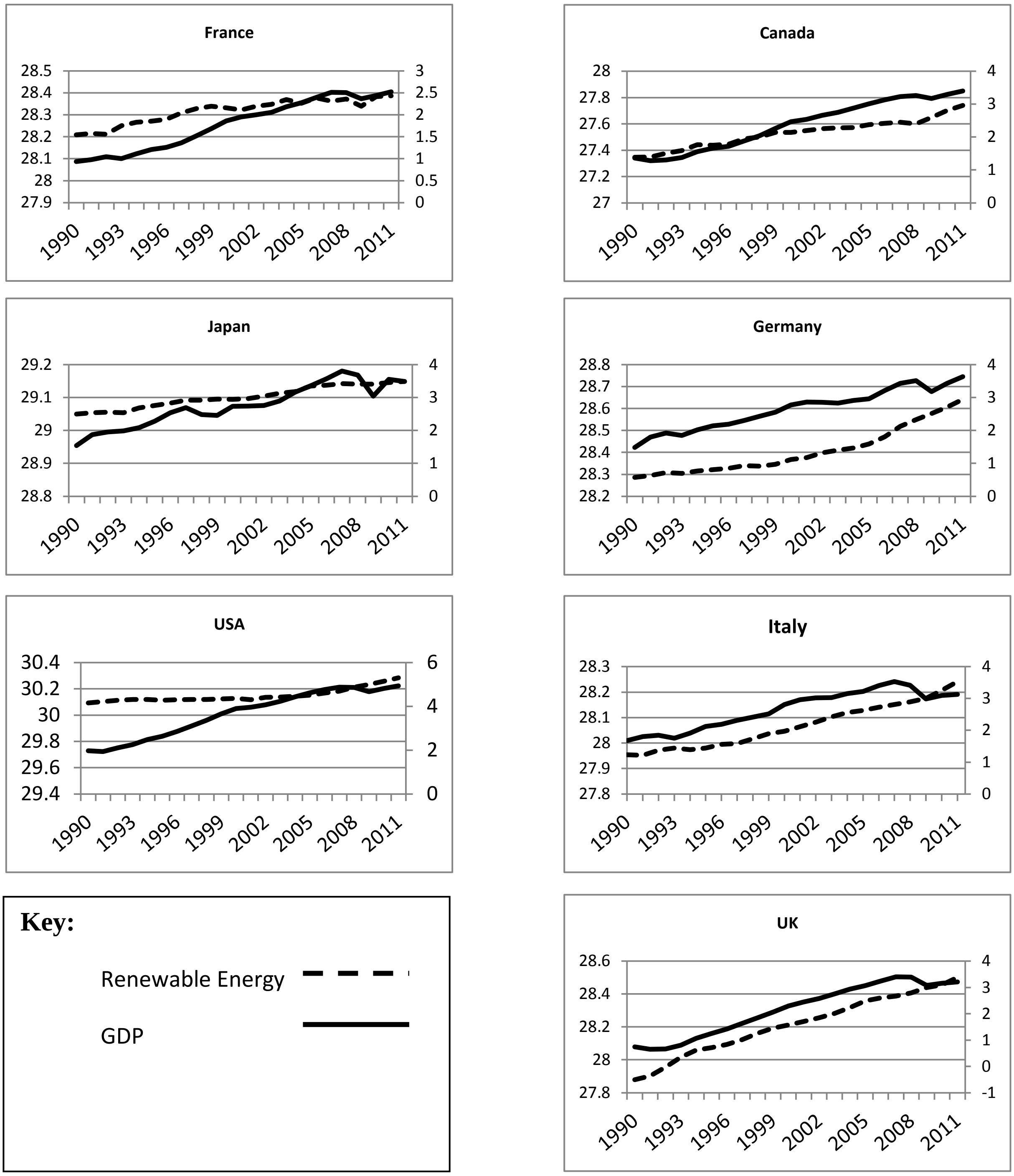
while for France and UK there is a unidirectional causality from GDP to renewable energy and the opposite for Japan and Germany, with a lagged response for the latter.

From a policy perspective, for Canada, Italy and the 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.

For France and UK, however, the exit of the international "dead end" and a higher economic growth rate might be the "green light" for more investments in renewable energies. Consequently, macroeconomic policies with the main purpose to boost the economy for these two countries will be translated to higher renewable energy generation. On the other hand, for Germany and Japan, the generation and hence, consumption of renewable energy and substitution of fossil-fuel generation will boost the economic activity through job creation, as Frondel et al. [31] suggested for Germany, and investment.

Appendix

Figure A1. Real GDP per capita and Renewable energy consumption across G7 countries: 1990 - 2011



*Note: The right axis represents renewable energy consumption, while the left axis represents GDP.

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