Non-Hydro Renewable Energy and Employment: A Bootstrap Panel Causality Analysis for Countries with Different Income Levels

Selahattin BEKMEZ
Gaziantep University, Faculty of Economics and Administrative Sciences
Department of Economics
Gaziantep, Turkey

Fatma AĞPAK
Gaziantep University, Institute of Social Sciences
Gaziantep, Turkey

Abstract

The contribution of renewable energy to overall energy consumption has been growing significantly all around the world due to its undisputable role in improving energy security and in reducing emissions. However, the existing literature has not reached a general consensus about renewable energy's employment and welfare effects. Especially net employment impact of renewable energy is a pressing issue as many countries facing high unemployment rates. This study contributes to the field by investigating the existence and the direction of causality between non-hydro renewable energy consumption and employment for 80 countries categorized into three panels as high, middle, and low income countries. For this purpose a bootstrap panel causality test, which takes into account slope heterogeneity and cross section dependence, has been employed. The empirical results support the existence of a unidirectional causal relationship from employment to non-hydro renewable energy consumption for low and middle income countries. For high income countries, on the other hand, test results reveal the absence of Granger-causality between the variables. These findings do not favor the view that the use of renewable energy has the big potential to stimulate employment, unless a well-designed multi-objective policy mix is enacted.

Keywords: Employment, Renewable Energy, Panel Causality.

1. Introduction

Global warming has long been a hot topic among the scientists. But recently it has become more evident and destructive than ever, leading to sea level rise, drought, famine, floods, misery, and diseases. In order to avoid further unmanageable risks of global warming, the attention is directed towards the environmental issues by the international community. To this end, restrictions/taxes on harmful gas emissions, boosting energy efficiency and environment-friendly renewable energy technologies became prominent solutions. Along with the energy security concerns of energy importing countries, efficiency gains and improvements in the competitiveness of renewable power generation technologies have made renewable even more attractive. Driven by all these factors, almost every country invested in green energies over last decades.

Also the Kyoto Protocol, negotiated in 1997, barely was able tocome into force with Russia's ratification in 2005. The Kyoto Protocol was an undoubtedly well-intentioned step but the world's biggest greenhouse polluters US, China and India didn't ratify the protocol and Canada pulled out of the protocol in 2011. Mainly due to the reasons mentioned above, the progress made under Kyoto looks extremely poor. And after United Nations Framework- Convention on Climate Change's 21st Conference of the Parties (COP 21), intended nationally determined contributions (INDCs) took place instead of Kyoto commitments. Representing the nationally determined nature of contributions, INDCs vary significantly in form, scope, and coverage; mostly not satisfying the environmentalists for a real improvement. Briefly, a large number of countries are cautious to take a stand on climate action- mainly because of increasing energy costs and its impacts on growth and employment. Without analyzing these impacts, employing any renewable energy policy would be counterproductive in the long-term.

Especially net employment effect matters, because employment problems can be defined as the most compelling social and economic problem of all times. Low employment rates are closely associated with poverty, social peace and political stability. There are three main types of studies can be seen while focusing on the employment impacts of renewable energy: input-output analysis, employment factor based on analytical methods, and macroeconomic modelling. Different findings regarding these approaches may be seen in the field, but there is no single convincing result whether renewable energy positively or negatively effects employment. Still it can be said that first two approaches generally in favor of renewable energy deployment and argue that renewable energies and low carbon sources generate more jobs than the conventional energy sources (Wei, Patedia, and Kammen, 2010; Rutovitz and Atherton, 2009; Lehr, Lutz, and Edler, 2012). Nevertheless the globalization has increased integration of economies and strengthened the spill-over effect of shocks. This evolution usually made one country based analyses insufficient for developing realistic policies. Panel data methods are suitable under these circumstances. Panel data analysis also allows researchers to control for heterogeneity between cross sections. But there is hardly any panel data evidence on the causality between employment and renewable energy consumption. To the best of author's knowledge there are only a few exceptions such as Apergis and Salim (2015) and Menegaki (2011). Their findings documented mixed results across studies, regions and periods. It can be said that more studies are needed in this field for better understanding of this causality.

This paper attempts to contribute this research gap and to draw some policy implications especially for the long term. Thus, in this paper, the existence as well as the direction of the causal relationship between employment to population ratio and renewable energy consumption is investigated across 80 countries covering the period 1991-2012. As a main contribution, different from previous studies, this study employs a bootstrap panel causality methodology, therefore applied methodology can control for cross sectional dependency and also slope heterogeneity. Again unlike previous papers non-hydro renewable energy consumption is used as an indicator of renewable energy deployment.

The focus is on non-hydro renewables, because hydroelectricity technology has been mature for decades and is at a very different stage of its deployment than, for instance, wind, solar, tidal. This disaggregation will be detailed in Section 3. The other important difference in this study is countries are grouped in three different panels according to gross national income per capita levels, as low income-middle income- high income countries. By doing so, along with the non-hydro renewable consumption and employment to population ratio, income levels are considered implicitly. Before exploring the causality between renewable energy and employment, possible presences of cross section dependence and heterogeneity of slope coefficients are examined respectively.

The remainder of the study is structured as follows. Second section covers a brief literature review and theoretical framework. Third section is devoted to the data and methodology. Section 4 reports a summary of test results and main findings. In the last section concluding remarks and policy implications are presented.

1. Literature Review and Theoretical Framework

There is a huge body of research on impacts of energy consumption on the economy (Sari, Ewing, and Soytas, 2008; Fowowe, 2012; Mercan and Karakaya, 2015; Khatun and Ahamad, 2015; Sharma (2010); Carley, Lawrence, Brown, Nourafshan, and Benami, 2011; Ramos and Veiga, 2014; Ozturk, 2010; Payne, 2010 and references therein). In general, these studies have shown that energy consumption is significantly related to economic growth, energy prices, inflation, terms of trade, capital account, and stock markets. Paradoxically, renewable energy literature is not that comprehensive and clear for now. Especially the relationship between renewable energy consumption and employment has not been sufficiently studied yet. In the meantime in several developed countries and developing countries have been facing high unemployment rates in the recent decades due to local/global crises, labor market inefficiencies, hysteresis etc. So attention of researchers has shifted to (renewable) energy-employment nexus. This relationship deserves all attention because energy is both an input and output of an economy. Energy issues may constraint not only growth but also the demographic dividend and human capital development. Moreover, increasing employment to population rates means increasing energy demand to meet (Arouri, Youssef, M'Henni, and Rault, 2014).

Renewable energy deployment triggers various impacts on employment through four main different economic mechanisms: price and cost effects (income/budget effect, substitution effect, and revenue effect), structural demand effect (investment impulse, operation & management impulse, trade impulse, consumption impulse), income multipliers and accelerator effects, productive effects of investments (The European Commission, 2009).

These adjustments create or destroy direct, indirect or induced jobs, and the economy-wide total employment change is called net employment effect of renewable. It is seen that researches dealing with employment effect of renewable energy principally based on three different approaches: employment factor based analytical approach, input-output approach, macroeconomic modelling. All three approaches have their own limitations and strengths (Breitschopf, Nathani and Resch, 2013; Lambert and Silva, 2012) and are reviewed briefly here. First approach is easy to understand and calculate. Yet, the quality of the results is limited by reason of the employment factors usually derived from previous empirical studies, reports or surveys. In order to get reliable results from this approach employment factors should be country and technology specific, and also should be up-to-date and accurate. This type of studies mostly argues that deployment of renewable energy is an opportunity for creating jobs (Moreno and Lopez, 2008; Wei, Patedia, and Kammen, 2010; Blanco and Rodrigues (2009), Rutovitz and Atherton (2009) and Arli Yilmaz (2014), among others).

The second approach, input-output models are designed to encompass both the direct and indirect employment effects. This approach requires up-to-date and sectoral disaggregated data. But for many countries this is a big problem. Overall, it is said that this approach is a good proxy of net employment effects of renewable energy and very useful if data is available. For instance, Lehr et al. (2008, 2012) argue that net employment effect of renewable energy is significantly affected by income/budget effect and technology export in Germany. The last approach, macroeconomic modelling is the most comprehensive assessment to capture overall economic effects. But macroeconomic modelling is rather complex and difficult to understand or communicate. Besides, data requirement and work load is rather high. By employing a computable general equilibrium analysis Böhringer, Keller, and van der Werf (2013) shows that the choice of the financing option affects both the magnitude and the sign of employment and welfare impacts of renewable energy deployment.

Beyond documented disadvantages of above mentioned approaches, they are country or technology specific. So these approaches are not suitable for a joint policy implication for a group of economy or for a healthy comparison. In the highly integrated open-economy conditions, taking into consideration these ties and developing a common perspective would be useful in the long term. Also these approaches do not give information about causality. Panel data causality methods are useful tools in this sense. There are many studies investigating the dynamic causal relationship between energy consumption and employment. But very few of them addressed renewable energy. To the best of our knowledge, Payne (2009) is the first research in this field. Payne (2009) investigates causality between aggregate energy (renewable and non-renewable) consumptionand employment using time series data for the period of 1976-2006 in Illinoi and reveals a unidirectional causality from energy consumption to employment. Menegaki (2011) employs panel causality test for 27 European countries over the period 1997-2007, finds bidirectional causality between renewable energy and employment in the short run. The most recent study in the field is Apergis and Payne (2015) which examines the causality between aggregate renewable energy consumption and unemployment using panel data of Latin America, Europe, Asia and Africa. Test results revealed a unidirectional causality from renewable energy consumption to unemployment across all regions, as long as the recent time period is approached. Authors claim that recent time period closely associated with the specific activities in favor of renewable energy that occurred across the regions under investigation. As this literature review shows there is a research gap in this field.

Meanwhile in energy-employment literature, it is highly recommended to understand the causality between growth and energy consumption before employing energy and employment policies (Arouri et al., 2014). For this and several other important reasons, most of the earlier renewable energy studies have been focused on growth-renewable energy consumption causality in order to better assess economic policies for employment and energy challenges. The direction of causality between economic growth and energy consumption can be reviewed in following testable hypotheses: growth, conservation, feedback, and neutrality. Firstly, the growth hypothesis suggests that energy consumption contributes directly to economic growth and energy conservation policies negatively effects growth and employment. The growth hypothesis cannot be rejected if there is unidirectional Granger-causality from energy consumption to growth/real output. For instance Pao and Fu (2013) explore causality between non-hydro renewable energy and growth, and lend support to growth hypothesis in Brazil for the period of 1980-2010. The conservation hypothesis implies that energy conservation policies can be employed safely. This hypothesis is cannot be rejected if there is unidirectional Granger-causality from growth/real output to energy consumption. Among many others Salim, Hassan, and Shafiei (2014), finds evidence supporting this hypothesis in 29 OECD countries spanning the period of 1980-2011. The feedback hypothesis argues that energy consumption and growth/real output are interdependent.

If this is the case it can be said that this variables acting as complementary to each other. The feedback hypothesis cannot be rejected if there is a bidirectional Granger-causality between growth/real outputs to energy consumption. Following studies Chang et al. (2015) in G7 countries, Apergis and Payne (2010a) in Euroasia, Apergis and Payne (2010b) in OECD countries, Pao and Fu (2013) in Brazil and Sadorsky (2009) in emerging countries support feedback hypothesis. Fourth and the last, the neutrality hypothesis asserts that there was no causality relationship among variables and in which case energy conservation policies may not have adverse impacts on economy. For US Yildirim, Sarac, and Aslan (2012) spanning the period 1949-2010 and for EU countries Menegaki (2011) in the period of 1997-2007 present evidence in favor of this hypothesis. Other than causality studies, impact assessment papers focusing on growth-renewable energy consumption can be seen in the literature. Fang (2011) for the period of 1978-2008 in China, Menegaki (2011) for the period 1997-2007 in EU, Tiwari (2011) for the period of 1965-2009 in Europe and Eurasia investigate impacts of renewable energy on growth. Their findings reveal positive impacts on employment. As is seen, renewable energy-growth literature is more developed than the previous renewable energy-employment causality branch and the number of published researches is rather large. It might be possible to draw some implications about employment from renewable energy-growth studies but the reliability and validity of implications can be arguable for many cases. For instance, Mandal and Mandal (2015) develops a simple model to explain how unemployment and growth go hand in hand in developing countries and finds that the initial level of unemployment has an important role in determining the required growth rate to improve employment. As a result, it is clear that more energy-employment causality studies are needed and the aim of this study is to contribute this field for a better understanding of this relationship.

2. *Data and Methodology*

This study covers a total of 80 countries in three separate panels: high income countries- middle income countries – low income countries. The categorization of countries by income level is based on the country's 2014 gross national income per capita (in accordance with the World Bank Atlas method). High income countries panel includes 33 countries, middle income countries panel includes 37 countries and low income countries panel includes 10 countries. Due to data unavailability other countries are not included. The annual data covers the time period of 1991–2012. As an indicator of employment, employment to population ratio (Emp) is used. This variable is calculated as number of people with ages between 15 and 64 years divided by the corresponding population size. Employment data is based on ILO estimates and obtained from World Bank, used in natural logarithm form.

On the other hand as a proxy for renewable energy deployment, non-hydro renewable energy consumption (Rceh) is used and this variable measured in TJ. Consumption data is obtained from World Bank and used in natural logarithm form. Different from previous researches, aggregate renewable energy consumption is not preferred.The reasons behind this disaggregation can be summarized as follows. First, hydroelectricity technology has been mature and cost competitive for long decades and it can be said that hydroelectricity is at a different stage of its development compared to other renewable energy resources. Second, though world has been deploying hydropower resources for more than a century, still have sufficient technical potential to fold many times current hydropower generation. But some geographic, ecological, and meteorological constraints limit hydroelectricity's development and in many countries hydroelectricity has stopped growing. For instance, in EU and in US hydroelectricity capacity has been essentially flat since 1980. Third, expert reports and projections reveal that hydro power will keep taking a different path from the other renewables (World Energy Council, 2013; BP, 2015). Regarding this separation, in line with the purpose of this study hydro power is excluded.

This study applies a panel Granger causality methodology proposed by Emirmahmutoglu and Kose (2011) which controls for heterogeneity and cross-sectional dependence in a panel, to test the existence and direction of a causal relationship between non-hydro renewable energy and employment.According to Monte-Carlo simulations presented in Emirmahmutoglu and Kose (2011), this approach performs satisfactory for whole values of T and N. Also this causality test does not require pre-test of unit root or cointegration rank; but maximal order of integration, cross-sectional dependence, and slope heterogeneity should be investigated in advance. Given the growing economic and financial integration of economies, panel data literature has concluded that panel data sets are likely to exhibit substantial cross-sectional dependence in the errors. Cross sectional dependence may occur due to spatial or spill-over effects, or may occur due to unobserved (or unobservable) common factors (Baltagi and Pesaran, 2007).

In the presence of any form of cross sectional correlation of errors, ignoring this cross sectional dependence may result in misleading inference due to misspecification. In order to test for cross sectional dependence, tests which are proposed by Breusch and Pagan (1980), Pesaran (2004), Pesaran, Ullah, and Yamagata (2008) have been extensively used in empirical studies. For detailed explanations and extensive literature review of cross sectional dependence tests see Chudik and Pesaran (2013), for size and power comparisons see Pesaran et al. (2008). Since Breusch and Pagan (1980) is valid only for relatively small N and sufficiently large T - which is not the case in this study, is not employed. On the other hand, both Pesaran (2004) and Pesaran et al. (2008) are applicable to a variety of panel data models, including stationary and unit root dynamic heterogeneous panels with short T and large N. These cross sectional dependence tests perform well for small samples, consistent under structural breaks.

Pesaran (2004) considers the following heterogeneous panel data model:

$$y_{it} = \alpha_i + b_i' x_{i,t} + u_{it} \qquad (1)$$

Where i represent the cross section dimension, t represents the time dimension, $x_{i,t}$ is the vector of independent variables, α_i and $b_i'$are respectively the individual intercepts.After making some assumptions, in order to test null hypothesis of cross sectional independence Pesaran (2004) proposes the following test statistic (CD_{LM}). $CD_{LM}$is based on the pair-wise correlation coefficients rather than their squares used in the Breusch and Pagan (1980)'s LM test:

$$CD_{LM} = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{J=i+1}^{N} (\hat{\rho}_{ij}) \qquad (2)$$

Where $\hat{\rho}_{ij}$ is the estimated pair-wise correlations of theresiduals which are obtained from the ordinary least squares estimation of Eq. (1)for each i. Yet, Pesaran (2004) test is subject to decreasing power when population average pair-wise correlations are zero, but underlying individual population pair-wise correlations are non-zero (Pesaran et al., 2008). Besides when the factor loadings have zero mean in the cross sectional dimension, Pesaran (2004) test fails to reject the null hypothesis. To overcome these problems Pesaran et al. (2008) presents bias adjusted LM test. Pesaran et al., (2008) obtain LM_{adj} statistic by using the exact mean and variance of the LM statistic. The bias-adjusted LM test is,

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

Where μ_{Tij} and ϑ_{Tij}^2 are respectively the exact mean and variance of $(T-k)\hat{\rho}_{ij}^2$, that are provided in Pesaran et al. (2008). The test hypotheses are H_0: $u_{it}=\sigma_i\varepsilon_{it}$,ε_{it}~iid N(0,1) for all i and t against the H1: $u_{it}\neq\sigma_i\varepsilon_{it}$, ε_{it}~iid N(0,1) at least for one i and t.

The other important issue to test is whether or not the slope coefficients are homogenous.Assumption of homogenous slope coefficient for the whole panel might be restrictive and not realistic in many contexts. Likewise, imposing homogeneity of slope coefficients assumption in causality tests for whole panel is strong null hypothesis (Granger, 2003). Besides, the homogeneity assumption for the slope parameters is not able to capture heterogeneity due to cross sectional characteristics (Breitung, 2005). In order to test slope homogeneity Pesaran and Yamagata (2008) proposed a modified version of Swamy (1970) test, which is known as $\tilde{\Delta}$ test. Pesaran ve Yamagata (2008) tests the null hypothesis of H_0: $\beta_1= \beta_2= \beta_3=\ldots=\beta_N$ for all β against the hypothesis of H_1: $\beta_1= \beta_2= \beta_3= \ldots \neq\beta_N$ for at least one β. As long as the error terms are normally distributed,$\tilde{\Delta}$ test is valid for any combination of(N,T). In the Pesaran and Yamagata (2008)'s test; the first step is to obtain the following modified version of Swamy's test statistic:

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

Where $\hat{\beta}_i$denotes the pooled OLS estimator,$\tilde{\beta}_{WFE}$ denotes the weighted fixed effect pooled estimator, M_τ denotes an identity matrix, $\tilde{\sigma}_i^2$denotes the estimator of σ_i^2. Afterwards,the standardized dispersion statistic $\tilde{\Delta}$ is derived as follows:

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

As long as the error terms are normally distributed and (N, T) → ∞ and $\sqrt{N}/T \to \infty$, the $\tilde{\Delta}$ test has asymptotic standard normal distribution. In order to improve small sample properties, bias adjusted version of $\tilde{\Delta}$ is developed as follows:

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

If the presence of cross sectional dependence and heterogeneity is identified in this stage, then a panel causality test which can control for cross sectional dependence and heterogeneity should have employed. Otherwise misleading results would be obtained. Emirmahmutoglu and Kose (2011) panel causality approach, which can control both cross sectional dependence and heterogeneity, is employed in this study. The causality test suggested by Emirmahmutoglu and Kose (2011) is an extended version of Toda and Yamamoto (1995)'s lag augmented approach for panel data applications andis based on the meta-analysis of Fisher (1932). More clearly, this approach modifies probability values of Toda and Yamamoto (1995) by using Fisher's meta-analysis. This method considers a level VAR model with(k_i+ d max_i) lags in heterogeneous mixed panels:

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

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

where i (i = 1…N) isthe individual cross-sectional units and t (t=1,…T) is the time periods, μ_i^x and μ_i^y are fixed effects vectors, $u_{i,t}^x$ and $u_{i,t}^x$are column vectors of error terms, k_i is the lag structure, anddmax$_i$ is the maximal order of integration for each cross section in the system. $k_i$is assumed to be known or estimated by any model selection criteria and may vary across the cross sections (Lutkepohl, 2005). Emirmahmutoglu and Kose (2011) bootstrap procedure for testing causality form x to y is summarized in the following 5 steps:

Step I. Determine the maximal order of integration of variables in the system for each i by employing any appropriate unit root test, such as the Augmented Dickey Fuller (ADF) unit root test. Then select the lag orders via information criteria (AIC or SBC) by estimating the regression Eq. (8) using the OLS method.

Step II. By using k_i and d max_i from step I, re-estimate Eq. (8) by OLS under the non-causality hypothesis ($H_0 = A_{21,i1} = \cdots = A_{21,ik_i} = 0$) and obtain the residuals for each individual like follows:

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

Step III: Center the residuals as suggested by Stine (1987) ,

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

Where$\hat{u}_t = (\hat{u}_{1t}, \hat{u}_{2t}, \dots, \hat{u}_{Nt})'$, K=max($k_i$) ve l=max(d max_i)'dir. Next develop ($[\hat{u}_{i,t}]_{NxT}$) from these residuals. Select randomly a full column with replacement from the matrix at a time to preserve the cross covariance structure of the errors and denote the bootstrap residuals as $\hat{u}_{i,t}^*$ where t=1,2,…,T.

Step IV: Generate the bootstrap sample of y under the above given null hypothesis:

$$y_{i,t}^{*} = \mu_i^{y} + \sum_{j=1}^{k_i+dmax_i} A_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i+dmax_i} A_{22,ij}\, y_{i,t-j}^{*} + \tilde{u}_{i,t}^{*} \qquad (11)$$

Step V: Then substitute $y_{i,t}^{*}$ for $y_{i,t}$ in Eq. (8) and estimate the VAR model without imposing any restrictions on the equation and calculate individual Wald statistics. Then by using calculated Wald statistics have an asymptotic chi-square distribution with k_i degrees of freedom and compute individual p-values. At last, obtain the Fisher test statistic as in Eq. (12).

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

Repeat steps III-V 10,000 times for the bootstrap empirical distribution of the Fisher test statistics and specify the bootstrap critical values by selecting the appropriate percentiles of these sampling distributions. For causality from y to x, same procedure should be applied. For a similar bootstrap approach, see Kónya (2006).

3. *Empirical Findings*

As per the methodology section, at first cross sectional dependence is investigated. The null hypothesis of cross sectional independence is tested by employing Pesaran (2004) and Pesaran et al. (2008); findings are summarized in Table 1. Both tests strongly reject the null at 1% level of significance for all of the income groups. This finding implies that a shock originating in one country may spill over to the countries within the panel.

Table 1: Cross sectional independence test results

Country Group	CD_{LM}	LM_{adj}
High Income Countries	54.001 (0.000)	107.540 (0.000)
Middle Income Countries	33.876 (0.000)	140.379 (0.000)
Low Income Countries	19.729 (0.000)	56.749 (0.000)

Under the null hypothesis of slope homogeneity, the presences of cross section specific characteristics are examined by so-called $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ tests of Pesaran and Yamagata (2008). The findings are presented in Table 2, as seen from the results both $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ tests strongly reject the null hypothesis at 1% significance level for all three of the country groups. This result implies that slope coefficients vary between countries over the analysis period. To avoid incorrect inference from causality test, this heterogeneity should have taken into account.

Table 2: Slope homogeneity test results

Country Group	$\tilde{\Delta}_{adj}$	$\tilde{\Delta}_{adj}$
High Income Countries	19.52 (0.000)	20.933 (0.000)
Middle Income Countries	24.366 (0.000)	26.129 (0.000)
Low Income Countries	22.436 (0.000)	24.060 (0.000)

Since it can control for cross sectional dependence and heterogeneity, Emirmahmutoglu and Kose (2011)'s bootstrap methodology has been applied. In the first step, by conducting ADF unit root test maximal order of integration of cross sections and lag orders are determined via SBC and the appropriate lag order is determined by Schwarz information criteria (SIC). For the sake of saving space ADF test results are not given, if requested results will be provided by the corresponding author. Afterwards, the bootstrap distribution of Fisher test statistics is estimated after 10,000 replications. The overall results for the panels reported in Table 3, for country-specific results see Appendix A.

Table 3: Panel causality test results

Country Group	Rceh to Emp non-causality hypothesis			Emp to Rceh non-causality hypothesis		
High Income Countries						
Fisher test statistic	100.648			87.354		
	1%	5%	10%	1%	5%	10%
Bootstrap Critical Values	147.389	119.364	108.434	144.354	119.197	108.634
Middle Income Countries						
Fisher test statistic	102.891			206.315*		
	1%	5%	10%	1%	5%	10%
Bootstrap Critical Values	180.200	134.92	122.343	161.999	132.635	120.672
Low Income Countries						
Fisher test statistic	25.456			46.602**		
	1%	5%	10%	1%	5%	10%
Bootstrap Critical Values	78.841	52.342	43.906	64.012	44.754	37.885

* Rejects the null hypothesis at 1 % significance level. ** Rejects the null hypothesis at 5 % significance level *** Rejects the null hypothesis at 10 % significance level

Test results indicate that there is no causal link between non-hydro renewable energy consumption and employment to population ratio for high income countries. This result is not surprising and is in line with the arguments presented in Chang et al. (2015), Menegaki (2011), Furchtgott-Roth (2012), The European Commission (2014) and Lesser (2010). This empirical evidence can be explained by many different factors. In the first place, these countries have already adopted non-hydro renewables on larger scales than other country groups examined in this study. Taking notice of that high income countries have already adopted non-hydro renewables on larger scales than other country groups, it can be said that non-hydro renewable energy's relatively high prices/costs are the main reason behind this neutrality evidence. Raising energy prices/costs eliminate energy intensive jobs or driven offshore. Strong cost and price effects neutralize the other job creator effects of non-hydro renewable energy deployment, like investment effect, operation and management effect… Second, this finding is can be seen as a direct consequence of increasing labor productivity over time in these developed countries as highlighted in The European Commission (2014). Third, the countries in this group are in an advanced stage of their developments and have not much to gain from adopting technologies compared to, for instance, the emerging countries.

On the other hand, non-hydro renewable energy is still growing and is being promoted in high income countries. So this reality can be associated with high income per capita levels (so income/budget effect) and environmental awareness of these societies. Individual results show that there is a unidirectional Granger causality from non-hydro renewable energy consumption to employment to population ratio for Singapore, Venezuela, Germany and Greece. This result implies that promotion of non-hydro renewable energy in these countries contributes to employment levels. Also non-hydro renewable energy related conservation policies may have adverse effects on employment unless some measures are taken for domestic production and export of renewable technology. On the other hand, for Russia and Canada a unidirectional Granger causality is found to running from employment to population ratio to non-hydro renewable energy consumption. Both Russia and Canada are fossil fuel rich countries, they already have cheap energy. Therefore, it can be argued that relatively expensive non-hydro renewable energy has very little to contribute the employment for these countries but very much to environment. As a matter of fact, promotion of renewable energy is a matter of environmental awareness and the detected unidirectional causality supports this view. Result revealed that the income/budget effect plays an important role in the adoption process of renewable energy adoption for Russia and Canada.

Bootstrap causality test results for middle income countries suggest that the null of no Granger causality from employment to population ratio to non-hydro renewable energy consumption can be rejected at 1% level of significance. Expected job creation effect of renewable energy is not observed, possibly due to cost/price effect. Also in middle income countries operation and management effect might not work properly depending on the shortage of skilled workers for green jobs. It might be said that in middle countries income/budget effect is important. With the exception of China, being dependent on foreign suppliers technologically is another problem for middle income countries examined.

For China test results indicate that there is bidirectional causality between non-hydro renewable energy and employment to population ratio. As argued in Furchtgott-Roth (2012) and Fang (2011) China is one of the most benefited countries from renewables as a top technology supplier. In contrast to overall panel, for El Salvador and for Paraguay there is a causality link running from non-hydro renewable energy consumption to employment to population ratio. This result is closely associated to labor market structure, renewable energy regulations, development stage of states and implies that positive effects of renewable energy outmatch the negative employment effects.

As for middle income countries, the overall results for the low income countries panel suggest that there is a unidirectional causality from employment to non-hydro renewable energy consumption at 5 % level of significance. Therefore, similar inferences can be drawn for low income countries. Briefly, the key concepts are domestic renewable energy industry and relatively high renewable energy prices. Additionally, the unidirectional causality link also shows that cost/price effect has been overwhelming the positive employment effects. Hence solving employment problems first would mitigate the negative cost/price effects and would increase energy consumption capacity of the society.

All in all, causality test results cannot reject the null hypothesis of non-causality from non-hydro renewable energy consumption to employment for any of the panels. These findings suggest that, in contrast to general belief, renewable energy has not significantly contributed to employment over the analysis period. Moreover this finding remains valid for all of the income groups.

4. Conclusion

Given the ongoing renewable energy boom and the high expectations regarding its potential economic benefits, it is important to gain a better understanding of growth and employment impacts of renewables. Though employment factor based green job estimations promise greatly expanded and well-paid employment, there is no consensus view on the net employment impacts or on the causality relationship. The direction of causality is of particular importance for long term development of energy industries and economies. This article contributes to the discussion on the dynamic nexus of renewable energy and employment by implementing a bootstrap panel causality approach.

After testing for cross sectional dependency and slope homogeneity, this paper applies a panel Granger causality methodology that takes account of possible cross-sectional dependence and heterogeneity in the data, to test the existence and direction of a causal relationship between non-hydro renewable energy and employment for a sample of 80 countries. Countries are examined in three different groups based on gross national income per capita levels- low income countries, middle income countries, and high income countries. For high income countries causality test results show that there is no causal link between employment and non-hydro renewable energy consumption. On the other hand, for middle income and low income countries test results indicate that there is a unidirectional causality running from employment to population ratio to non-hydro renewable energy consumption. Given these results the most obvious finding is that any significant employment gains have not occurred over the analysis period. But some of the country specific results, as of Germany and China, suggest the opposite. These contradictions would enlighten the issue a lot. Greening the economy may enhance energy security, environmental protection, and economic growth, but it doesn’t guarantee increased employment. In other words, employment gains from renewable energy is not corollary, is just a consequence of well-designed country specific mix of policies and investment decisions. Required policy and decisions should be differing according to countries development stage, unemployment rate, labor market structure, mix of domestic energy sources, current account balance, foreign energy dependency rate, environmental constraints etc. Still, it might be said that policies promoting manufacturing and exporting green technologies, building and upgrading new worker skills, innovations are necessary for ensuring positive employment impacts of non-hydro renewable energy.

The other very important determinant of renewables employment impact is the cost competitiveness of renewable energy technologies. Simply the more cost-competitive energy prices, the more employment. On the other hand, test results also reveal that for low and middle income economies employment is the Granger cause of non-hydro renewable energy consumption. Since increased employment to population ratios means increased wages, more prosperity, and more access to energy, resolving employment problems would contribute to adoption of non-hydro renewables. But same doesn’t go for the high income countries, according to test results for high income countries employment to population ratio doesn’t cause non-hydro renewable energy consumption.

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Appendix A

Appendix A Table 1. Panel causality test results for high income countries

	Rceh to Emp no causality hypothesis			Emp to Rceh no causality hypothesis		
Country	K i	Wi	Pi	K i	Wi	Pi
Argentina	1	0.205	0.651	1	0.038	0.846
E. Guinea	1	0.821	0.365	1	0.219	0.640
Russian Federation	3	3.168	0.366	3	8.598	0.035*
Singapore	1	4.780	0.029*	1	0.391	0.532
Venezuela	1	5.474	0.019*	1	0.600	0.438
Australia	3	7.769	0.051	3	6.842	0.077
Austria	1	2.357	0.125	1	0.029	0.864
Belgium	3	0.353	0.950	3	1.628	0.653
Canada	1	0.277	0.598	1	3.847	0.05*
Chile	1	0.179	0.672	1	0.807	0.369
Denmark	1	0.376	0.540	1	0.176	0.675
Finland	2	0.684	0.710	2	5.581	0.061
France	1	2.575	0.109	1	1.580	0.209
Germany	2	8.395	0.015*	2	8.200	0.017
Greece	3	10.637	0.014*	3	4.018	0.260
Hungary	3	9.853	0.02*	3	4.838	0.184
Iceland	1	3.541	0.060	1	4.946	0.026
Ireland	2	0.143	0.931	2	1.674	0.433
Israel	1	3.490	0.062	1	0.820	0.365
Italy	2	4.637	0.098	2	3.067	0.216
Japan	1	0.461	0.497	1	0.188	0.665
Korea	1	0.021	0.884	1	3.626	0.057
Luxembourg	1	1.000	0.317	1	1.056	0.304
Netherlands	3	1.772	0.621	3	4.942	0.176
New zeland	2	2.389	0.303	2	0.011	0.995
Norway	2	0.728	0.695	2	5.798	0.055
Poland	3	4.497	0.213	3	1.217	0.749
Portugal	2	3.848	0.146	2	0.587	0.746
Spain	2	0.146	0.930	2	1.796	0.407
Sweden	2	0.279	0.870	2	1.133	0.568
Switzerland	2	0.810	0.667	2	0.454	0.797
UK	3	5.063	0.167	3	2.727	0.436
USA	3	2.951	0.399	3	0.050	0.997
Fisher test statistic	100.648			87.354		
Bootstrap Critical Values	1%	5%	10%	1%	5%	10%
	147.389	119.364	108.434	144.354	119.197	108.634

* Rejects the null hypothesis at 5 % significance level.

Appendix A Table 2. Panel causality test results for middle income countries

	Rceh to Emp no causality hypothesis			Emp to Rceh no causality hypothesis		
Country	K i	Wi	Pi	K i	Wi	Pi
Albania	3	3.812	0.283	3	22.766	0.000*
Algeria	1	0.026	0.873	1	0.544	0.461
Angola	2	1.242	0.537	2	1.245	0.537
Armenia	1	0.267	0.267	1	2.968	0.085
Azerbaijan	1	1.212	0.271	1	1.726	0.189
Bangladesh	1	2.365	0.124	1	0.208	0.648
Belarus	3	6.391	0.094	3	3.288	0.349
Bolivia	2	0.106	0.948	2	2.471	0.291
Bulgaria	3	5.624	0.131	3	4.776	0.189
China	3	14.539	0.002*	3	17.243	0.001*
Colombia	1	0.024	0.877	1	1.495	0.221
Costa Rica	1	2.089	0.148	1	2.298	0.130
Dominican Rep.	1	0.049	0.824	1	1.271	0.260
Egypt, Arab Rep.	1	0.892	0.345	1	0.021	0.885
El Salvador	1	6.581	0.010*	1	0.036	0.849
Gabon	3	1.112	0.774	3	61.251	0.000*
Georgia	1	0.762	0.383	1	5.005	0.025
Ghana	3	9.679	0.021**	3	13.295	0.004*
Honduras	1	1.327	0.249	1	0.623	0.430
Indonesia	1	0.059	0.809	1	1.131	0.287
Iran, Islamic Rep.	1	0.708	0.400	1	6.255	0.012**
Jamaica	2	0.084	0.959	2	0.737	0.692
Jordan	3	5.617	0.132	3	6.727	0.081
Kazakhstan	1	0.265	0.607	1	0.06	0.807
Kenya	2	3.75	0.153	2	1.367	0.505
Malaysia	1	0.504	0.478	1	0.137	0.711
Moldova	1	3.353	0.067	1	0.964	0.326
Namibia	1	0.032	0.857	1	0.002	0.965
Paraguay	1	5.184	0.023**	1	0.018	0.895
Philippines	1	0.071	0.789	1	4.624	0.032
Romania	2	3.034	0.219	2	0.069	0.966
Senegal	1	0.247	0.619	1	1.817	0.178
Thailand	3	0.106	0.991	3	2.374	0.499
Turkey	3	6.946	0.074	3	23.461	0.000*
Ukraine	1	1.058	0.304	1	3.827	0.050**
Uzbekistan	2	1.076	0.584	2	0.029	0.986
Zambia	1	0.125	0.723	1	1.613	0.204
Fisher test statistic	102.891			206.315*		
Bootstrap Critical Values	1%	5%	10%	1%	5%	10%
	180.200	134.92	122.343	161.999	132.635	120.672

* *Rejects the null hypothesis at 5 % significance level. *Rejects the null hypothesis at 1 % significance level.

Appendix A Table 3. Panel causality test results for low income countries

	Rceh to Emp no causality hypothesis			Emp to Rceh no causality hypothesis		
Country	K i	Wi	Pi	K i	Wi	Pi
Benin	3	5.742	0.125	3	2.859	0.414
Congo, Dem. Rep.	3	14.193	0.003*	3	0.952	0.813
Eritrea	3	2.292	0.514	3	3.030	0.387
Ethiopia	3	2.304	0.512	3	5.073	0.167
Haiti	2	1.331	0.514	2	33.280	0.000*
Mozambique	1	0.501	0.479	1	0.031	0.860
Nepal	1	0.056	0.813	1	1.738	0.187
Tanzania	1	0.880	0.348	1	0.007	0.935
Togo	2	0.135	0.598	2	1.311	0.519
Zimbabwe	3	2.252	0.935	3	1.193	0.755
Fisher test statistic	25.456			46.602**		
Bootstrap Critical Values	1%	5%	10%	1%	5%	10%
	78.841	52.342	43.906	64.012	44.754	37.885

* Rejects the null hypothesis at 1 % significance level. * *Rejects the null hypothesis at 5 % significance level.