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Nuclear Energy Consumption-Economic Growth Nexus in OECD: A Bootstrap Causality Test

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Abstract

This paper investigates the causal relationship between nuclear energy consumption and economic growth for 15 OECD countries. To this aim, the bootstrap causality test developed by Hacker and Hatemi-J (2006) is used over the period 1980-2012 that differs for each country. The results reveal that the neutrality hypothesis does hold for 10 out of 15 OECD countries. In other words, there is no causal relationship between nuclear energy consumption and economic growth in any direction. For these ten countries, nuclear energy may be a relatively small component of overall output and has no impact on economic growth. However, for the other five countries, there appears a significant causality between growth and nuclear energy consumption.

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Keywords: nuclear energy; economic growth; neutrality hypothesis; causality

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1. Introduction

The high energy prices and fluctuations, especially after the oil crisis in the 1970s, have made energy policies to be investigated. In this respect, whether energy consumption has impacts on economic growth has turned to be a crucial issue for the authorities. Over time, there happened new developments, such as Kyoto Agreement, which authorities should consider when they are implementing their energy and growth policies. Along with the Kyoto Agreement, countries have started to implement policies to mitigate greenhouse gas emissions and to reduce fossil fuel consumption. But in this case, if energy consumption is essential factor for the production process, the economic growth and employment will be damaged; therefore, authorities should seek new solutions (Wolde-Rufael and Menyah, 2010). As such, determining the causal linkage between energy consumption and economic growth has important implications for developing sound energy policies (Nazlioglu et al., 2011).

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In the literature there are four hypotheses regarding the causality between economic growth and energy consumption: i) If there is a unidirectional causality from energy consumption to economic growth, energy consumption directly causes economic growth. According to this growth hypothesis, economic growth depends on energy consumption, implying that negative energy shocks and energy conservation policies may depress economic growth. ii) In contrast, if there is a unidirectional causality from economic growth to energy consumption, energy conservation policies have little adverse or no effect on economic growth. This case is known as the conservation hypothesis. iii) The feedback hypothesis implies the bidirectional causality between energy consumption and economic growth. In this case, energy consumption and economic growth are interrelated and serve as complements to each other. According to the feedback hypothesis, excessive energy protection and reduced energy consumption may lead to pressure on economic activity. iv) Finally, the non-causality between the energy consumption and economic growth supports the neutrality hypothesis. Evidence of the neutrality hypothesis implies that neither conservative nor expansive policies in relation to energy consumption have no effect on economic growth. Therefore, determining the direction of causality between energy usage and economic activity is crucial for selecting an appropriate energy strategy (Chu and Chang, 2012, Squalli, 2007).

There is no unanimous idea regarding the direction of causality due to countries' characteristics, different data sets, variables and econometric methodologies that used (Naser, 2014, p. 289). Meanwhile, the usage of aggregate energy consumption rather than disaggregated one may be another reason behind the lack of uniformity in empirical results since the importance of a certain energy resource for a country may change over time. Thus, the usage of disaggregated data rather than aggregate one may be more meaningful (Naser, 2014, p. 289). To this end, nuclear energy is typically used as a disaggregate energy measure in recent empirical studies. Also, due to volatile oil prices, rapid energy demand growth, scarcity of alternative resources and high dependence on foreign energy sources, the importance of nuclear energy has been accelerating. Moreover, nuclear energy development induces industry-wide technology spill-over effects, and enhances the productivity of capital and labor (Toth and Rogner, 2006; Yoo and Ku, 2009; Yoo and Jung, 2005). Besides, nuclear energy has a main role in electricity supply which in turn is important for a nation's industry (Yoo and Ku, 2009, p.1905). Nuclear energy consumption also reduces air pollution and greenhouse gas emissions (Toth and Rogner, 2006; Heo et al., 2011, p.111). As a result of these advantages, the demand for nuclear energy raises. To alleviate increase in demand and formulate appropriate nuclear energy policies, policy makers need information regarding the relationship between nuclear energy consumption and economic growth (Yoo and Ku, 2009).

In contrast to aggregate energy consumption, there have been few studies specifically addressing the causal relationship between nuclear energy consumption and economic growth (Yoo and Ku, 2009). Some of them employ panel data models while others apply time series analysis. For instance, Naser (2014) examines the relationship between oil consumption, nuclear energy consumption and economic growth in four emerging economies (Russia, China, South Korea, and India) by using Granger non-causality and Toda-Yamamoto tests over the period from 1965 to 2010. The results propose that nuclear energy stimulates economic growth in both South Korea and India. In another panel data analysis, Chu and Chang (2012) searched whether energy consumption promotes economic growth by using specifically oil and nuclear energy consumption data for G-6 countries over the period of 1971-2010. The results indicate that nuclear energy consumption causes economic growth in Japan, UK, and the US; economic growth causes nuclear energy consumption in the US; nuclear consumption and economic growth have no causal relation in Canada, France and Germany.

Applying a panel causality test which allows for both cross-sectional dependency and heterogeneity, Nazlioglu et al. (2011) analyzed the relationship between nuclear energy consumption and economic growth for 14 OECD countries during the period 1980-2007.

The results indicate that there is no causality between nuclear energy consumption and economic growth in 11 countries, supporting the neutrality hypothesis. Focusing on a group of 19 developed and developing countries for the period 1984–2007, Apergis et al. (2010) used a panel error correction model and their findings support the unidirectional causality running from nuclear energy consumption to economic growth in the short-run while bi-directional causality in the long-run. In contrast to Apergis et al. (2010), Apergis and Payne (2010) found evidence of the bidirectional causality between nuclear energy consumption and economic growth in the short-run and of the unidirectional causality running from nuclear energy consumption to economic growth in the long-run. In another study, Lee and Chiu (2011) examined the short-run dynamics and long-run equilibrium for developed countries for 1971–2006. The panel causality results find evidence of the unidirectional causality running from oil prices and economic growth to nuclear energy consumption in the long-run, while there is no causality between nuclear energy consumption and economic growth in the short run.

Second research strand includes time series studies. For instance, Yoo and Jung (2005) find unidirectional causality running from nuclear energy consumption to economic growth in Korea. In line with Yoo and Jung (2005), Wolde-Rufael (2010), analyzing the nuclear energy consumption and economic growth relationship for India, has obtained evidence of the unidirectional causality running from nuclear energy consumption to economic growth which supports the growth hypothesis. Yoo and Ku (2009) investigate the relationship between nuclear energy consumption and economic growth for 6 countries (i.e., Argentina, France, Germany, Korea, Pakistan, and Switzerland). They find that the causal relationship between nuclear energy consumption and economic growth is not uniform across countries. Similarly, Wold-Rufael and Menyah (2010) obtained different results across 6 industrialized countries. Their results imply that there is no causality between nuclear energy consumption and real GDP for the USA and France, whereas bidirectional relationship is obtained for France, Spain, UK and the USA; unidirectional causality running from nuclear energy consumption to economic growth is found in Japan, Netherlands and Switzerland. In addition, a one-way causality running from economic growth to nuclear energy consumption is obtained in Canada and Sweden.

The purpose of this article is to investigate the causality between nuclear energy consumption and economic growth, and to obtain policy implications from the results. To this end, we apply the bootstrap causality test developed by Hacker and Hatemi-J (2006) for 15 OECD countries over the period 1980-2012 that differs for each country. This study will contribute to the literature since the empirical literature investigating direction of the causality between nuclear energy use and economic growth produced conflicting results. Moreover, Hacker and Hatemi-J (2006) extended the MWALD test, developed by Toda and Yamamoto (1995) in order to obtain more robust results. This causality test performs better in small samples and considers the autoregressive conditional heteroscedasticity (ARCH) condition.

The remainder of the paper is organized as follows. In Section 2, data and methodology are explained. In Section 3, empirical results are provided, and conclusion and policy implications are presented in Section 4.

2. Data and Methodology

2.1. Data

Our sample of countries consists of the following 15 OECD countries: Belgium, Canada, France, Germany, Netherlands, Spain, Sweden, UK, US, Japan, Switzerland, Finland, South Korea, Czech Republic, and Mexico. The selection of time period differs over the period 1970 to 2012 for each country based on data availability. Besides, all variables were measured in their natural logarithms to reduce the heterogeneity of data. In Table 1, we presented the countries under study with their time periods.

We use real gross fixed capital formation and labor force as control variables since nuclear energy alone might not be strong enough to spur economic growth and avoid omitted variable bias (Wolde-Rufael and Menyah, 2010). Also, in an empirical analysis, exclusion of relevant variables could cause biased and inconsistent estimations and no-causality results in a bivariate system (Lutkepohl, 1982). Regarding the capital variable, we are in line with many researchers (see Apergis and Payne, 2010; Lee et al., 2008; Narayan and Smyth, 2008; Soytas et al., 2007; Soytas and Sari, 2007, 2009; Wolde-Rufael, 2010, 2012) and use real gross fixed capital formation (2005 US dollar) as a proxy for the stock of physical capital due to the absence of capital stock. In addition, we use real GDP (2005 US dollar) instead of GNP as a proxy for economic growth given that nuclear energy consumption depends upon goods and services produced within the country, not outside the country (Yoo and Ku, 2009). Nuclear energy consumption is measured in terms of tera-Watt hours (TWh), while total labor force is measured in thousands. The real GDP and real gross fixed capital formation data are from the World Bank Development Indicators (2014) while nuclear energy consumption and labor force data are from the British Petroleum Statistical Review of World Energy (2013) and the Conference Board and Groningen Growth and Development Centre (2013), respectively.

Table 1: Countries and their time periods

Belgium (1980-2012)	Spain(1980-2012)	Switzerland(1980-2012)
Canada (1980-2012)	Sweden(1980-2012)	Finland(1980-2012)
France(1980-2012)	UK(1980-2012)	South Korea(1980-2012)
Germany(1970-2012)	USA(1980-2012)	Czech Rep. (1990-2012)
Netherlands(1980-2012)	Japan(1970-2012)	Mexico(1990-2012)

Notes: The numbers in parentheses denote time periods for each country.

2.2. Methodology

2.2.1. Information Criteria

Our estimation procedure has three steps. First, we employed the augmented Dickey-Fuller (ADF hereafter, 1979) and Phillips and Perron (PP hereafter, 1988) unit root tests to define the maximum integration order of variables since Toda and Yamamoto (TY hereafter, 1995) use this maximum integration order as an additional lag number to augment VAR model. The ADF and PP unit root tests are generally employed in the empirical studies, thus, we don’t explain their methodologies.

The second step is the selection of the optimal lag order (p) for VAR model. There are many information criteria in the literature; however, as asserted by Hatemi-J (2003), the simulations results indicate that Schwarz (SBC, 1978) Bayesian information criterion and the Hannan and Quinn (HQC, 1979) information criterion appear to perform best. The SBC criterion is defined as

$$SBC = \ln(\det \hat{\Omega}_j) + j\frac{n^2 \ln T}{T}, \qquad j = 0,........,K \tag{1}$$

where is the maximum likelihood estimation of the variance-covariance matrix when the lag order used in estimation is . is the sample size. The objective is to choose the largest order for the time series by the that minimizes the SBC criterion. Additionally, Hannan and Quinn (1979) developed the following information criterion as an alternative to SCB.

$$HQC = \ln(\det \hat{\Omega}_i) + j\frac{2n^2 \ln(\ln T)}{T}, \qquad J = 0,......,k \tag{2}$$

However, the earlier studies revealed that each of these two criteria can perform better than the other based on the properties of the true VAR model, but the true model is not known in empirical studies. Thus, Hatemi-J (2003) developed the following information criterion (HJC) by combining these two criteria in order to obtain maximal probability to choose the optimal lag order.

$$HJC = \ln(\det \hat{\Omega}_J) + j\left(\frac{n^2 \ln T + 2n^2 \ln(\ln T)}{2T}\right) \qquad J = 0,......,k \tag{3}$$

2.2.2. Hacker and Hatemi-J (2006) Causality Test

In the third step in our estimation procedure, we run causality test. Especially, Granger non-causality (Granger, 1969) test is one of the most applied methods in applied research and originally based on asymptotic distribution theory. It based on a vector autoregressive model of the order p, i.e. VAR (p).

$$y_t = \upsilon + A_1 y_{t-1} + ... + A_p y_{t-p} + \varepsilon_t \tag{4}$$

where y_t is the 4x1 vector of the variables, υ is the 4x1 vector of intercepts, and ε_t is a 4x1 vector of error terms, A_r is 4x4 matrix of parameters for lag r ($r = 1, \ldots\ldots\ldots, p$).

However, Granger and Newbold (1974) indicated that the regression analysis which depends on the asymptotic distribution theory does not work well if the integration orders of variables are not zero (i.e. nonstationary) by using Monte Carlo simulations. In this case, spurious results may be obtained. Besides, Sims et al. (1990) asserted that asymptotic distribution theory cannot be employed to test for the causality among non-stationary variables in level form using the vector autoregressive (VAR) model. In this case, TY (1995) developed a modified Wald (MWALD) test that asymptotically has a chi-square distribution regardless of the order of integration or cointegration properties of the variables in the model. However, Hacker and Hatemi-J (2006) denoted that MWALD test does not perform well in the case of non-normally distributed data with autoregressive conditional heteroscedasticity (ARCH) effects. Therefore, they developed a leveraged bootstrap causality test that provides consistent results under both non-normality and heteroscedasticity.

Hacker and Hatemi-J (2006) improved the size properties of the MWALD test through bootstrap resampling. Their results indicated that the bootstrapped empirical size for the modified Wald test is close to the correct size in the different cases when the extra lags are greater than or equal to the integration order of both variables, and it is generally closer to the correct size than the asymptotic distribution empirical size. Furthermore, Hacker and Hatemi-J (2006) found that ARCH error process usually results in greater size distortions especially in the case of the asymptotic distribution. However, they employed the bootstrap method with leverage adjustments against the presence of ARCH effects and non-normality in residuals, and found that size distortions due to ARCH effect do not appear significant in the case of the bootstrap distribution.

Based on the TY (1995) causality test, the following augmented $VAR(p+d)$ model is employed in causality test.

$$y_t = \upsilon + A_1 y_{t-1} + \ldots\ldots\ldots\ldots\ldots\ldots + A_p y_{t-p} + \ldots\ldots\ldots\ldots\ldots\ldots + A_{p+d} y_{t-p-d} + \varepsilon_t$$

(5)

It is assumed that the order p of the process is known and d is equal to the maximum order of integration of the variables. The $VAR(p+d)$ in Eq. (5) could be written compactly as

$$Y = DZ + \delta$$

(6)

where

$Y := (y_1, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots, y_T)$ (nxT) matrix:

$D := (\upsilon, A_1, \ldots\ldots, A_p, \ldots\ldots\ldots, A_{p+d})$ $(nx(1+n(p+d)))$ matrix,

$$Z := \begin{bmatrix} 1 \\ y_t \\ y_{t-1} \\ \vdots \\ y_{t-p-d+1} \end{bmatrix} \quad ((1+n(p+d))x1) \text{ matrix, for } t = 1, \ldots\ldots\ldots, T$$

$Z := (Z_0, \ldots\ldots\ldots\ldots, Z_{T-1})$ $((1+n(p+d))xT)$ matrix, and

$\delta = (\varepsilon_1, \ldots\ldots\ldots\ldots, \varepsilon_T)$ (nxT) matrix.

For testing the null hypothesis of non-Granger causality__ H_0: $C\beta = 0$ __ MWALD test statistic, developed by

Toda and Yamamoto (1995), is formulated as follows:

$$MWALD = (C\hat{\beta})'[C((Z'Z)^{-1} \oplus S_U)C']^{-1}(C\hat{\beta}) \tag{7}$$

where $\oplus$ is the Kronecker product, $\beta = vec(D)$, where vec refers to column–stacking operator, C is a $pxn(1+n(p+d)$ indicator matrix. The elements in each row of C take a value of one if the related parameters in β is zero whereas they take a value of zero if there is no such restriction under the null hypothesis. S_U is the variance-covariance matrix of the unrestricted VAR model in Eq. (6). When the assumption of normality is viable, the MWALD test statistic is asymptotically χ^2 distributed with the number of degrees of freedom equal to the number of restrictions to be tested (i.e., p).

To carry out the bootstrap simulations, Eq. (6) first is estimated with restrictions implied by the null hypothesis of Granger non-causality. Second, the bootstrap data, y_t^*, is generated by using the estimated coefficients from the regression $\hat{\upsilon}$, $\hat{A}_1,\ldots,\hat{A}_p$; the original data $y_{t-1},\ldots,y_{t-p}$; and the bootstrap residuals, $\hat{\varepsilon}_t$. The mean of the resulting set of drawn modified residuals is subtracted from each of the modified residuals in that set. Through the use of leverages, the modified residuals, which are the regression's raw residuals, have constant variance. To compute the bootstrap critical values, we carried out bootstrap simulations 100,000 times with the MWALD test statistic produced each time. Therefore, the generation of the empirical distribution for the Wald test statistic is provided. The last step is to compute the MWALD statistic using the original data.

3. Empirical Results

3.1. Results of Unit Root Tests

As a first step, ADF and PP unit root tests were employed to determine maximum integration order of the variables. Also, because Hacker and Hatemi-J (2006) argued that having more extra lags than the integration order results in less size distortion than having less extra lags than the integration order, maximum integration order is used among different unit root tests and models (See Yildirim et al., 2012).

As presented in Table 2, for Belgium, Canada, Germany, UK, South Korea, and Mexico, maximum integration order of the variables are one, I(1). However, for the other countries, i.e. France, Netherlands, Spain, Sweden, USA, Japan, Switzerland, Finland, and Czech Republic, maximum integration order are two, I(2).

Table 2: Unit Root Test Results

ADF				PP	
Belgium	Variables	Intercept -Trend	Intercept	Intercept- Trend	Intercept
	Growth	I(1)	I(1)	I(1)	I(1)
	Capital	I(1)	I(1)	I(1)	I(1)
	Labor	I(0)	I(1)	I(0)	I(1)
	Nuclear	I(1)	I(0)	I(1)	I(0)
Canada	Growth	I(1)	I(1)	I(1)	I(1)
	Capital	I(1)	I(1)	I(1)	I(1)
	Labor	I(0)	I(1)	I(0)	I(1)
	Nuclear	I(1)	I(0)	I(1)	I(0)
France	Growth	I(1)	I(1)	I(1)	I(1)
	Capital	I(0)	I(1)	I(2)	I(1)
	Labor	I(1)	I(1)	I(2)	I(2)
	Nuclear	I(0)	I(0)	I(0)	I(0)
Germany	Growth	I(1)	I(1)	I(1)	I(0)
	Capital	I(1)	I(0)	I(1)	I(1)
	Labor	I(0)	I(1)	I(1)	I(1)
	Nuclear	I(1)	I(0)	I(0)	I(0)
Netherlands	Growth	I(1)	I(1)	I(1)	I(1)
	Capital	I(1)	I(1)	I(1)	I(1)
	Labor	I(1)	I(1)	I(2)	I(2)
	Nuclear	I(0)	I(0)	I(0)	I(0)
Spain	Growth	I(2)	I(2)	I(2)	I(2)
	Capital	I(2)	I(2)	I(2)	I(2)
	Labor	I(2)	I(2)	I(2)	I(2)
	Nuclear	I(1)	I(0)	I(0)	I(0)
Sweden	Growth	I(1)	I(1)	I(1)	I(1)
	Capital	I(1)	I(1)	I(1)	I(1)
	Labor	I(1)	I(1)	I(2)	I(2)
	Nuclear	I(0)	I(0)	I(0)	I(0)
UK	Growth	I(1)	I(1)	I(1)	I(1)
	Capital	I(1)	I(1)	I(1)	I(1)
	Labor	I(0)	I(1)	I(0)	I(1)
	Nuclear	I(1)	I(1)	I(1)	I(1)
US	Growth	I(1)	I(1)	I(1)	I(1)
	Capital	I(1)	I(1)	I(2)	I(1)
	Labor	I(1)	I(0)	I(2)	I(1)
	Nuclear	I(1)	I(0)	I(1)	I(0)

Japan	Growth	I(1)	I(0)	I(1)	I(0)
	Capital	I(1)	I(1)	I(1)	I(1)
	Labor	I(1)	I(1)	I(1)	I(1)
	Nuclear	I(2)	I(2)	I(2)	I(2)
Switzerland	Growth	I(1)	I(1)	I(1)	I(1)
	Capital	I(1)	I(1)	I(1)	I(1)
	Labor	I(2)	I(1)	I(2)	I(1)
	Nuclear	I(1)	I(0)	I(1)	I(0)
Finland	Growth	I(1)	I(0)	I(1)	I(1)
	Capital	I(0)	I(1)	I(2)	I(1)
	Labor	I(2)	I(0)	I(2)	I(2)
	Nuclear	I(2)	I(0)	I(0)	I(0)
South Korea	Growth	I(1)	I(0)	I(1)	I(0)
	Capital	I(1)	I(0)	I(1)	I(1)
	Labor	I(1)	I(1)	I(1)	I(1)
	Nuclear	I(1)	I(0)	I(1)	I(0)
Czech Rep.	Growth	I(1)	I(1)	I(0)	I(1)
	Capital	I(2)	I(1)	I(1)	I(1)
	Labor	I(1)	I(1)	I(1)	I(1)
	Nuclear	I(2)	I(1)	I(2)	I(1)
Mexico	Growth	I(1)	I(1)	I(1)	I(1)
	Capital	I(0)	I(1)	I(1)	I(1)
	Labor	I(1)	I(1)	I(1)	I(1)
	Nuclear	I(1)	I(0)	I(1)	I(0)

3.2. Selection of Optimal Lag Order

Hatemi-J (2003) proved that HJC criterion can pick the true lag order in both stable and unstable VAR models. Therefore, we chose the optimal lag order based on the HJC information criterion. The results of lag length selection were tabulated in Table 3.

Table 3: Results of Lag Length Selection

Countries	AIC	SBC	HQC	HJC
Belgium	[1]	[1]	[2]	[2]
	-26.206	-19.587	-20.578	-20.006
Canada	[1]	[1]	[1]	[1]
	-24.228	-17.609	-18.244	-17.926
France	[1]	[2]	[2]	[2]
	-28.449	-22.047	-23.190	-22.619
Germany	[1]	[1]	[2]	[1]
	-24.478	-17.316	-17.893	-17.590
Netherlands	[1]	[1]	[2]	[2]
	-24.2091	-17.5902	-18.5559	-17.9841
Spain	[1]	[3]	[3]	[3]
	-24.868	-18.276	-19.928	-19.102
Sweden	[1]	[1]	[1]	[1]
	-22.497	-15.878	-16.514	-16.196
UK	[1]	[1]	[3]	[1]
	-23.403	-16.784	-17.792	-17.102
US	[1]	[2]	[2]	[2]
	-27.178	-21.325	-22.468	-21.897
Japan	[1]	[1]	[2]	[2]
	-22.572	-15.410	-16.250	-15.758
Switzerland	[1]	[1]	[3]	[1]
	-25.799	-19.180	-19.966	-19.497
Finland	[2]	[2]	[3]	[2]
	-23.7777	-18.0947	-19.4857	-18.6665
South Korea	[1]	[1]	[3]	[3]
	-21.987	-15.368	-16.873	-16.047
Czech Rep.	[1]	[1]	[2]	[2]
	-20.5109	-15.7144	-17.0978	-16.3968
Mexico	[1]	[2]	[2]	[2]
	-17.647	-14.402	-15.845	-15.1240

Notes: Akaike Information Criterion (AIC), Hannan–Quinn (HQ), Schwarz Bayesian Information Criterion (SBC), Hatemi-J Criterion (HJC). The numbers in brackets are the optimal lag lengths and min test statistics are in the parenthesis.

As seen in Table 3, for six countries, i.e. Canada, France, Spain, Sweden, US, and Mexico, three information criteria (SBC, HQC, and HJC) choose the same lag length. However, for the other nine countries, different lag lengths were selected based on information criteria.

3.3. Results of the Hacker-Hatemi-J Causality Test

Table 4: Causality test results based on HJC

Countries	TYp	NEC does not Granger cause Y				TYp	Y does not Granger cause NEC			
		MWALD	1%	5%	10%		MWALD	1%	5%	10%
Belgium	0.676	0.781	12.314	7.208	5.293	0.326	2.238	13.040	7.578	5.588
Canada	0.232	1.427	8.141	4.454	3.039	0.654	0.200	8.218	4.448	3.050
France	0.078^{c}	5.090	14.864	8.280	5.961	0.298	2.418	15.500	8.628	6.161
Germany	0.754	0.097	7.658	4.225	2.906	0.337	0.919	7.539	4.163	2.871
Netherlands	0.955	0.173	15.540	8.344	8.344	0.645	0.001	19.475	8.147	5.572
Spain	0.829	0.883	27.317	13.867	9.749	0.348	3.296	26.192	13.462	9.514
Sweden	0.816	0.054	8.717	4.651	3.152	0.199	1.644	8.939	4.671	3.132
UK	0.022^{b}	5.237^{b}	8.477	4.466	3.027	0.161	1.963	8.153	4.311	2.973
US	0.634	0.911	15.420	8.522	6.103	0.011^{b}	9.003^{c}	16.471	9.124	6.543
Japan	0.867	0.283	12.972	7.543	5.535	0.308	2.356	12.642	7.333	5.391
Switzerland	0.657	0.197	8.901	4.639	3.162	0.681	0.168	8.893	4.795	3.271
Finland	0.000^{a}	18.532^{a}	15.476	8.744	6.298	0.071^{c}	5.289	15.724	8.678	6.254
South Korea	0.716	1.354	19.156	10.395	7.622	0.057^{c}	7.498	18.154	10.665	7.947
Czech Rep.	0.521	1.301	246.117	45.555	21.304	0.000^{a}	48.330^{b}	226.476	43.688	21.095
Mexico	0.019^{b}	7.887^{c}	18.322	9.282	6.361	0.050^{c}	5.982	20.073	10.012	6.872

Notes: a, b, and c denote statistical significance at 1%, 5%, and 10% levels, respectively. The leveraged bootstrap critical values were obtained through 100,000 bootstrap simulations; TYp refers to the probability values by the Toda- Yamamoto procedure for the MWALD statistics. NEC and Y denote nuclear energy consumption and real GDP.

The results of the bootstrap-corrected causality test based on the HJC information criterion were provided in Table 4. Besides, for the purpose of comparison, the TY causality test was also employed and its results were also tabulated in Table 4.

The null hypothesis of Granger non-causality is rejected if the Wald test statistic is greater than the bootstrap critical value. Thus, as shown in Table 4, there is one-way causality running from nuclear energy consumption to economic growth for UK, Finland and Mexico for different significance levels. For these three countries, the growth hypothesis is confirmed, and therefore energy conservation policies may have detrimental effects on economic growth rates of these three countries. However, for US and Czech Republic, one-way causality running from economic growth to nuclear energy consumption is supported, and the conservation hypothesis is confirmed. In this case, energy conservation policies may not have negative impacts on economic growth processes of US and Czech Republic. For the remaining ten countries, the neutrality hypothesis is confirmed as there is no causal relationship between nuclear energy consumption and economic growth in any direction. For these ten countries, nuclear energy may be a relatively small component of overall output and has no impact on economic growth.

To the aim of comparison, we also carried out the TY causality test, and reported its probability values in Table 4. In general, the results of the TY test are in line with those of the bootstrap causality test. For instance, the both tests confirmed the growth hypothesis for the UK, the conservation hypothesis for the US and Czech Republic, and the neutrality hypothesis for Belgium, Canada, Germany, Netherlands, Spain, Sweden, Japan, and Switzerland. However, they obtained different results for the remaining four countries. For instance, in the case of France, the TY causality test supported the growth hypothesis while the bootstrap causality test confirmed the neutrality hypothesis. Additionally, for Finland and Mexico, the TY causality test supported the feedback hypothesis whereas the bootstrap causality test confirmed the growth hypothesis. For South Korea, the neutrality hypothesis was confirmed by the bootstrap causality test while the conservation hypothesis was supported by the TY causality test.

4. Conclusion

In this study, we analyzed the relationship between nuclear energy consumption and economic growth for 15 OECD countries. To this aim, the bootstrap causality test developed by Hacker and Hatemi-J (2006) was employed along with TY causality test. The results from the bootstrap-corrected causality test based on the HJC information criterion revealed that the neutrality hypothesis is affirmed for 10 OECD countries while the TY causality test indicated that the neutrality hypothesis is supported for 8 OECD countries. In other words, the neutrality hypothesis was confirmed for most OECD countries under study. For these countries, there may be more influential factors than nuclear energy consumption on economic growth process. Nuclear energy consumption level is not high relative to other energy sources such as fossil-based or non-renewable energy kinds around the world. Countries that have nuclear energy power plants are limited because there are still doubts and risks surrounding the nuclear energy sector such as the risk of proliferation of nuclear material, the peril of terrorism, operational safety, and radioactive waste disposal (Apergis and Payne, 2010; Toth and Rogner, 2006; Vaillancourt et al., 2008). However, this situation does not indicate that nuclear energy is an unimportant energy source. In particular, the growing concerns over global warming, climate change, depletion of fossil-based sources, and high and volatile oil prices highlight the importance of nuclear energy sector. Besides, in the next future, countries will begin to invest more in their nuclear energy sectors and consume more nuclear energy, and thus the impact of nuclear energy demand on economic growth will increase as well.

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