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Testing the relationships between energy consumption and income in G7 countries with nonlinear causality tests

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Abstract

Knowing the real causal links between energy consumption and national income is crucial for policy decision making. In this article, we address this issue for the G7 countries by using two nonlinear causality tests in the sense of Hiemstra and Jones (1994), and Kyrstou and Labys (2006). Our results reveal some new, but mixed results. Hiemstra-Jones test indicates unidirectional causality running from energy consumption to GDP for the United Kingdom, while a bidirectional causality between energy consumption and GDP is found for Canada, France, Japan and United States. On the other hand, Kyrstou-Labys test shows that unidirectional causality runs from energy consumption to GDP for France and the United States, and from GDP to energy consumption for Germany. Overall, our findings suggest that policy implications of the energy-GDP links should be interpreted with caution, given the test-dependent and country-specific results.

Keywords:
energy consumption; GDP; nonlinear causality

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1. Introduction

There has been now a long debate on the dynamic interactions between economic dynamics and energy sector. The majority of previous studies focus particularly on three important causal relationships: oil-macroeconomy nexus, oil-stock market nexus, and energy-growth nexus. A consesus arising from the past literature is that oil prices significantly affect economic growth, stock markets and exchange rates through different channels and with different degrees depending on the energy profile of individual countries and markets under consideration (e.g., Hamilton, 1983; Mork, 1989; Hooker, 1996; Cologni and Manera, 2008; Jammazi and Aloui, 2010; Aloui et al., 2012). Moreover, the effects of oil prices can be asymmetric, nonlinear and sensitive to market phases (e.g., Balke et al., 2002; Zhang, 2008; Lardic and Mignon, 2008; Cologni and Manera, 2009). For example, Hamilton (1983) shows that rising oil prices are responsible for nine out of ten of the U.S. recessions since the Second World War. Zhang (2008) employs a nonlinear model to investigate the relationship between oil-price shock and economic growth in Japan, and shows the existence of nonlinearities and asymmetric linkages between the two variables studied. Lardic and Mignon (2008) reach the same conclusion for other developed economies from an asymmetric cointegration approach. On the other hand, past studies have found that stock market activities are significantly affected by oil price movements at both the market and sectoral levels (Jones and Kaul, 1996; Sadorsky, 2001; Park and Ratti, 2008; Arouri and Nguyen, 2010; Fayyad and Daly, 2011). The oil's impact is however sensitively different across economic sectors (e.g., oil versus non-oil industries) and across countries (e.g., net oil-exporting versus net oil-importing ones).

As far as the causal relationship between energy consumption and economic growth is concerned, the recent literature survey by Ozturk (2010) shows that no consensus neither on the existence nor on the direction of causality between the two variables of interest emerge from the past literature. While some studies find some evidence of unidirectional causality running from energy consumption to growth (Stern, 2000; Oh and Lee, 2004; Wolde-Rufael, 2004; Ho and Siu, 2007), the others conclude on the unidirectional causalitity from growth to energy consumption (Zamani, 2007; Mehrara, 2007; Ang, 2008; Zhang and Cheng, 2009) or even no causality between these variables (Halicioglu, 2009; Payne, 2009). There is also evidence to support the bidirectional causality between energy consumption and growth (Glasure, 2002; Erdal et al., 2008; Belloumi, 2009). Mixed rerults are found in Soytas and Sari (2003), Lee (2006), Francis et al. (2007), Akinlo (2008), and Chiou-Wei et al. (2008), among others. Overall, past empirical results appear to be country-specific and more often than not divergent across studies.

Even though the above-mentioned conflicting results can be attributed to the different dataset, countries' characteristics, variables used and different econometric methods, the accurate modeling of the underlying data stands out. It can be observed that most of previous studies rely on traditional linear Granger causality tests to examine the interactions between energy consumption and growth, while energy and economic variables are rather tied up by nonlinear links. The potential nonlinearity, which casts doubt on the results from linear framework, has been confirmed by several studies in energy economics (Hamilton, 2003; Lee and Chang, 2007; Chiou-Wei et al., 2008; Huang et al., 2008; Rahman and Serletis, 2010). In an earlier study, Hiemstra and Jones (1994) report that economic time series exhibit nonlinear dependence that has not always been addressed properly.

In this article, we investigate the causal relationship between energy consumption and national income by adopting a nonlinear approach. We indeed apply two nonlinear causality tests in the sense of Hiemstra and Jones (1994) and Kyrstou and Labys (2006) to the data of the most advanced countries (G7 countries). The most important feature of these tests is that they enable to detect nonlinear causal relationships while avoiding problems arising from model misspecification. Hiemstra and Jones (1994) show from a simulation study that the modified version of their test is robust to a number of model misspecifications. Moreover, unlike nonlinear error correction models may display stability problems (Saikkonen, 2005), these tests permit to gauge nonlinear causality without being concerned by the long-term dynamics reflecting the evolution of this causality. The "asymmetric" causality test of Kyrstou and Labys (2006) is advantageous in that it can reveal interesting information about the inherent dynamics of the underlying data-generating processes. According to Hristu-Varsakelis and Kyrtsou (2008), the detection of a causality relationship does not give information on whether shocks are positive or negative, and conversely the lack of an apparent causality relationship does not preclude the existence of causality when we condition certain features, such as a positive or negative sign.

Following the seminal work of Kraft and Kraft (1978), a number of studies have examined the causal relationships between energy consumption and economic growth using data from the G7 countries. Table 1 shows that the empirical results of this strand of literature are also country-specific and often mixed.[1] Our article thus contributes to the related literature by adding new evidence from more robust nonlinear causality tests. The results from Hiemstra-Jones test show unidirectional causality from energy consumption to GDP for the United Kingdom, while a bidirectional causality between energy consumption and GDP is found for Canada, France, Japan and the United States. On the other hand, Kyrstou-Labys test provides evidence of unidirectional causality from energy consumption to GDP for France and the United States, and from GDP to energy consumption for Germany. These new mixed findings imply that policy interpretations of the energy-GDP links from the results of both previous studies and ours should be done with caution and that a country-specific approach is better than a panel data one as the latter may induce compensation effects across different countries.

The remainder of the article is organized as follows. Section 2 will discuss some explanations for the use of nonlinear causality tests and introduces two nonlinear Granger causality tests proposed by Hiemstra and Jones (1994), and Krystou and Labys (2006). Section 3 reports and discusses the empirical results. Section 5 provides some concluding remarks.

2. Nonlinearities and nonlinear Granger causality tests

Granger (1969) defines causality between two variables E and Y in terms of predictability.[2] Accordingly, a variable E is said to cause another variable Y with respect to the universe or information set including $E(t) = E_t, E_{t-1}, ...$ and $Y(t) = Y_t, Y_{t-1}, ...$ if Y_{t+1} can be better predicted by using the information in $E(t)$ than by not doing so, all other relevant information (including the present and the past of Y) being used in either case. Specifically, the traditional approach for testing Granger causality compares the prediction errors obtained by a model that relates Y to past and current values of both E and Y. This approach is naturally attractive because the test simply requires to determine whether the regression model coefficients, associated to past and current values of E are significant.

However, it is now common that the traditional Granger framework is exposed to two main drawbacks. First, parametric tests require several mod-

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[1] See Ozturk (2010) for the detailed literature survey.

[2] In our study, E and Y denote energy consumption and income, respectively.

Table 1: Summary of literature on energy consumption - economic growth nexus for G7 countries.

Country	Author(s)	Causality	Country	Author(s)	Causality
USA	Kraft and Kraft (1978)	Y → E	UK	Yu and Choi (1985)	Y − E
	Akarca and Long (1980)	Y − E		Erol and Yu (1987)	Y − E
	Yu and Hwang (1984)	Y − E		Lee (2006)	Y − E
	Yu and Choi (1985)	Y − E		Soytas and Sari (2006)	Y ↔ E
	Abosedra and Baghestani (1989)	Y → E			
	Yu and Jin (1992)	Y − E	France	Erol and Yu (1987)	Y − E
	Stern (1993)	E → Y		Soytas and Sari (2003)	E → Y
	Cheng (1995)	Y − E		Lee (2006)	Y → E
	Stern (2000)	E → Y		Soytas and Sari (2006)	E → Y
	Soytas and Sari (2003)	Y − E			
	Lee (2006)	Y ↔ E	Canada	Erol and Yu (1987)	E → Y
	Soytas and Sari (2006)	E → Y		Ghali and El-Sakka (2004)	Y ↔ E
	Chiou-Wei et al. (2008)	Y − E		Lee (2006)	E → Y
	Bowden and Payne (2009)	E → Y		Soytas and Sari (2006)	Y ↔ E
	Payne (2009)	Y − E	Italy	Erol and Yu (1987)	Y → E
				Soytas and Sari (2003)	Y → E
Japan	Erol and Yu (1987)	Y ↔ E		Lee (2006)	Y ↔ E
	Cheng (1998)	Y → E			
	Soytas and Sari (2003)	E → Y	Germany	Erol and Yu (1987)	Y → E
	Lee (2006)	Y → E		Soytas and Sari (2003)	E → Y
	Soytas and Sari (2006)	Y ↔ E		Lee (2006)	Y → E
				Soytas and Sari (2006)	Y → E

Note: Y = GDP, E = energy consumption. →, ↔, − represent unidirectional causality, bidirectional causality and no causality, respectively.

eling assumptions among which the most important is the linearity of the regression structure, while the nonlinearity of macroeconomic and financial series is becoming increasingly recognized by economists. Nonlinear models are thus more appropriate for modeling dependencies among economic variables. Second, the prediction errors from linear Granger causality tests are ultimately sensitive to the causality in the mean. Higher order structure, such as conditional heteroscedasticity, is often ignored. In this article, we address the first drawback by making use of two nonlinear Granger causality tests. The first, that of Hiemstra and Jones (1994), is nonparametrically conceived and based on correlation integrals, while the second, that of Krystou and Labys (2006), is based on a parametric model.

2.1. Hiemestra-Jones test

Baek and Brock (1992) offer a nonparametric statistical method to detect nonlinear causal relations. This method basically relies on the assumption that the variables are mutually independent and identically distributed. However, this assumption seems to be quite restrictive as it eliminates the time dependence of variables and does not consider the nature and range of the dependence. Hiemstra and Jones (1994) modify the Baek and Brock (1992)'s test to allow the testing variables to exhibit short-term temporal dependence.

By defining the m-length lead vector of Y_t by Y_t^m, and the Ly-length and Le-length lag vectors of Y_t and E_t, respectively, by Y_{t-Ly}^{Ly} and E_{t-Le}^{Le}, we obtain the following representations (Hiemstra and Jones, 1994)

$$\begin{aligned} Y_t^m &= (Y_t, Y_{t+1}, ..., Y_{t+m-1}); m = 1, 2, ...; t = 1, 2, ... \\ Y_{t-Ly}^{Ly} &= (Y_{t-Ly}, Y_{t-Ly+1}, ..., Y_{t-1}); Ly = 1, 2, ...; t = Ly + 1, Ly + 2, ... \\ E_{t-Le}^{Le} &= (E_{t-Le}, E_{t-Le+1}, ..., E_{t-1}); Le = 1, 2, ...; t = Le + 1, Le + 2, ... \end{aligned} \quad (1)$$

The definition of nonlinear Granger noncausality is then given by

$$\begin{aligned} Pr(\|Y_t^m - Y_s^m\| < \epsilon | \|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\| < \epsilon, \|E_{t-Le}^{Le} - E_{s-Le}^{Le}\| < \epsilon) \\ = Pr(\|Y_t^m - Y_s^m\| < \epsilon | \|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\| < \epsilon), \quad (2) \end{aligned}$$

where $Pr\{.\}$ is probability and $\|\|$ is the maximum norm. If Eq. (2) holds for given values of m, Ly and $Le \geq 1$ and for $\epsilon > 0$, then $\{E_t\}$ does not strictly Granger cause $\{Y_t\}$. Eq. (2) states that the conditional probability that two arbitrary m-length lead vectors of $\{Y_t\}$ are within distance ϵ, given that the corresponding lagged L_y-length lag vectors of $\{Y_t\}$ are ϵ-close, is the same when the L_e-length lag vectors of E_t is ϵ-close. It should be noted that for a bivariate observable series (Y_t, X_t), $t1, ..., T$, the Hiemstra-Jones test consists of choosing a value of ϵ whose typical values are between 0.5 and 1.5 after normalizing the series to obtain unit variance, and to test subsequently Eq. (2) by estimating the conditional probabilities as ratios of unconditional probabilities.

Hiemstra and Jones (1994) show that under the Granger noncausality null hypothesis formulated by Eq. (2), the following statistic follows an asymptotic normal distribution as

$$\sqrt{n}(\frac{C1(m+Ly, Le, \epsilon, n)}{C2(m+Ly, \epsilon, n)} - \frac{C3(m+Ly, \epsilon, n)}{C4(Ly, \epsilon, n)}) \sim AN(0, \sigma^2(m, Ly, Le, \epsilon)), \tag{3}$$

where $n = T + 1 - m - \max(Ly, le)$, $C1(m + Ly, Le, \epsilon, n)$, $C2(m + Ly, \epsilon, n)$, $C3(m + Ly, \epsilon, n)$, and $C4(Ly, \epsilon, n)$ are correlation-integral estimators of the point probabilities corresponding to the left hand side and right hand side of Eq. (2). It has been shown that this test has a very good power against a variety of nonlinear Granger causal and noncausal relations (Hiemstra and Jones, 1994; Ma and Kanas, 2000). The asymptotic variance $\sigma^2(m, Ly, Le, \epsilon)$ is estimated using the theory of U-statistic for weakly dependent processes (Denker and Keller, 1983).[3] The test statistic in Eq. (3) is applied to the estimated residual series from the bivariate VAR model. The null hypothesis is that E_t does not nonlinearly strictly Granger cause Y_t, and Eq. (3) holds for all m, Ly, $Le \geq 1$ and $\epsilon > 0$. By removing a linear predictive power form a linear VAR model, any remaining incremental predictive power of one residual series for another can be considered as nonlinear predictive power (Baek and Brock, 1992).

2.2. Kyrstou-Labys test

Kyrstou and Labys (2006) adopt a different perspective to address the concept of nonlinear Granger causality by introducing the bivariate noisy Mackey-Glass (hereafter "M-G") model defined as follows

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[3] For a complete and detailed derivation of the variance, see the appendix in Hiemstra and Jones (1994).

$$\begin{aligned} Y_t &= \alpha_{11}\tfrac{Y_{t-\tau_1}}{1+Y^{c1}_{t-\tau_1}} - \gamma_{11}Y_{t-1} + \alpha_{12}\tfrac{E_{t-\tau_2}}{1+E^{c2}_{t-\tau_2}} - \gamma_{12}E_{t-1} + \epsilon_t, \\ E_t &= \alpha_{21}\tfrac{Y_{t-\tau_1}}{1+Y^{c1}_{t-\tau_1}} - \gamma_{21}Y_{t-1} - \alpha_{22}\tfrac{E_{t-\tau_2}}{1+E^{c2}_{t-\tau_2}} - \gamma_{22}E_{t-1} + \eta_t, \end{aligned} \tag{4}$$

where ϵ_t and $\eta_t \sim N(0,1)$, $t = \tau, ..., N$, $\tau = max(\tau_1, \tau_2)$ and $Y_0, ..., Y_{\tau-1}$, $E_0, ..., E_{\tau-1}$ are given. The α_{ij}, and γ_{ij} are parameters to be estimated, τ_i are integer delays, and c_i are constants which can be chosen via prior selection. In this respect, the best delays, τ_1 and τ_2, are selected on the basis of likelihood ratio tests and the Schwarz criterion. The model (4) is more appropriate than a simple VAR in case where dependency structures of time series are more complicated and cannot be taken into account by vector autoregressions. The M-G-based causality test is similar to the linear Granger causality test, except that the models fitted to the series are M-G processes. This test is performed by estimating the M-G model parameters under no constraint with ordinary least squares. To examine whether E causes Y, another M-G model is estimated under the constraint $\alpha_{12} = 0$ that reflects our null hypothesis. Such a constraint arises from the fact that when E has a significant nonlinear effect on the current value of Y in the model M-G, α_{12} must be significantly different from zero. Let $\hat{\vartheta}$ and $\hat{\nu}$ the residuals obtained respectively by the unconstrained and constrained best-fit M-G models. Thus, the corresponding sums of residuals squares can be defined as $S_u = \sum_{t=1}^{T} \hat{\vartheta}^2$ and $S_c = \sum_{t=1}^{T} \hat{\nu}^2$. Recall that $n_u = 4$ is the number of free parameters in the M-G model and on the other side $n_c = 1$ is the number of parameters required to be zero when estimating the restricted model. Obviously, the test statistic follows a Fisher distribution as

$$S_F = \frac{(S_c - S_u)/n_c}{S_u/(T - n_u - 1)} \sim F_(n_c, T - n_u - 1), \tag{5}$$

where S_F is the test statistic.

What we have just presented is called the Kyrtsou-Labys "symmetric" version of the causality between E and Y. The "asymmetric" version of Kyrtsou-Labys test can be implemented by conditioning for positive or negative values of the causing series. To keep the matters tractable, suppose that we test, in model (4), whether nonnegative returns in the series E cause the series Y. In this case, an observation (E_t, Y_t) is included in the regression model only if $E_{t-\tau_2} \geq 0$. The same restricted set of observations is used to compute the model corresponding to the null hypothesis, i.e., $\alpha_{12} = 0$. The procedure is then repeated with the order of the series reversed. That is, one can test whether positive returns in Y cause E and again with the subset of nonnegative returns. Note that conditioning in terms of causing series sign is not the only way to carry out an asymmetric causality. The sign conditioning is frequently chosen because it offers many advantages in practical relevance. Moreover, the nonpositivity, or respectively nonnegativity is not the only possible conditioning way as one can consider other events such as start/end of the week, price movement thresholds.

3. Data and empiricals results

3.1. Data

We use per capita GDP data, expressed in constant 2000 U.S. dollars, and per capita energy consumption data, expressed in terms of kg oil equivalent for the G7 countries. The data for Germany cover the period 1970–2010, while those for the remaining G7 countries span the period from 1960 to 2010. All the data are at annual frequency and obtained from the Word Development Indicators. Accordingly, we see important differences in energy consumption and GDP levels across the G7 countries. The average per capital energy consumption ranges from 2315.59 kg oil equivalent (Italy) to 7471.94 kg oil equivalent (United States). The average per capital GDP is comprised between US$ 14070.35 (Italy) to US$ 26823.79 (Japan). A close look at these series shows that per capital GDP generally increases with the per capital energy consumption, thus suggesting potential of causal interactions between these two variables.

Next, we check the stationarity of the variables by using two autoregressive unit root tests: the Augmented Dickey-Fuller (ADF) test, and the Phillips-Perron (PP) test. The results of unit root tests are reported in Table 3. The ADF and PP tests indicate that our variables are integrated of order one, but their first differences are stationary. However, since the ADF and PP unit root tests are known to suffer potentially severe finite sample power and size problems[4], we also use three more efficient unit root tests to check the robustness of the ADF and PP results: the Elliott-Rothenberg-Stock

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[4] De Jong et al. (1992) show that these tests have low power against the alternative hypothesis that the series is stationary with a large autoregressive root. Schwert (1989) documents severe size distortion in the direction of over-rejecting the null hypothesis of unit root when the time series has a large negative moving average root.

(ERS) test of Elliot et al. (1996), the Dickey-Fuller test with GLS detrending procedure of Ng and Perron (2001), and the modified Phillips-Perron test of Perron and Ng (1996). We find evidence of nonstationarity for the variables in levels and stationarity for the variables in first differences.

Table 2: Summary of basic statistics.

	Energy consumption				GDP			
	Mean		SD		Mean		SD	
Countries	Level	Difference	Level	Difference	Level	Difference	Level	Difference
Canada	7124.19	64.610	1144.95	201.11	17935.30	324.00	4983.07	386.48
France	3422.80	47.442	776.30	120.98	16443.13	307.49	4855.71	267.66
Germany	4241.76	4.8213	216.08	121.83	19015.73	335.27	4160.73	389.29
Italy	2315.59	40.374	623.87	82.682	14070.35	262.69	4581.36	308.72
Japan	3025.48	60.182	967.00	115.99	26823.79	631.30	10135.51	729.11
UK	3557.72	4.9807	224.97	102.73	18229.95	359.47	6073.53	446.39
USA	7471.94	31.661	680.19	201.13	25894.63	475.59	7709.26	548.36

Notes: this table presents the main statistics of our sample data. The per capita GDP and per capita energy consumption data are expressed in constant 2000 U.S. dollars and in terms of kg oil equivalent, respectively. All the data are at annual frequency and obtained from the Word Development Indicators.

In the next subsection, we apply the nonlinear causality tests to the variables in first differences in order to detect the causal relationships between energy consumption and GDP.

3.2. Results from the Hiemstra-Jones test

Table 4 presents the empirical results from the Hiemstra-Jones nonlinear Granger causality test, based on the residuals of a VAR model. Similar to Hiemstra and Jones (1994), we fix the values for the head length $m = 1$, the common lag lengths of 1 to 8 lags and a common scale parameter of $e = 1.5$. We find evidence of a significant unidirectional nonlinear Granger causality running from energy consumption to GDP for the UK. The *growth hypothesis* investigated by the previous literature is thus supported by our data for the UK, meaning that the level of energy consumption, through affecting both directly and indirectly the industrial production, plays a crucial role in economic growth. In this scheme of things, a negative energy supply shock (i.e., sudden supply decreases) will adversely cause the economic growth to decline. Compared to previous studies, our result contrasts those of Yu and

Table 3: Results of unit root tests

	Canada	France	Germany	Italy	Japan	UK	USA
Unit root results for energy consumption							
ADF							
Level	-1.749	-1.309	-2.714	-2.46	-1.024	-1.734	-2.393
First difference	-4.347**	-7.447**	-5.601**	-3.285*	-5.013**	-4.242**	-4.549**
PP							
Level	-1.125	-1.269	-2.699	-3.654	-1.177	-1.59	-1.789
First difference	-4.283**	-7.456**	-5.573 **	-5.955 **	-5.069 **	-6.733**	-4.501**
ERS							
Level	28.8537	32.8002	22.0803	99.2125	25.7197	24.5401	26.9517
First difference	1.2112**	3.764**	1.2904**	2.1358*	2.8298*	1.7419**	1.2668**
DF-GLS detrending							
Level	-1.0516	-1.0052	-1.9725	0.0422	-1.2323	-1.283	-1.371
First difference	-4.3871**	-7.3092**	-4.1445**	-2.8393**	-2.3233*	-3.3753**	-4.5602**
Modified PP							
Level	-0.9276	-0.7813	-1.5445	0.3212	-1.0838	-1.0611	-1.1728
First difference	-3.1577**	-3.4717**	-3.1809**	-2.4607*	-2.0657*	-2.7483**	-3.1973**
Unit root results for GDP							
ADF							
Level	-0.9249	-1.288	-2.823	-0.9105	-0.5441	-2.162	-1.987
First difference	-4.521**	-5.163**	-5.915**	-5.556**	-5.2**	-4.737**	-5.3**
PP							
Level	-0.8119	-0.8152	-2.817	-2.394	-0.6491	-1.862	-2.315
First difference	-5.008**	-5.082**	-5.931**	-5.483**	-5.126**	-4.262**	-5.205**
ERS							
Level	84.4324	15.2086	7.6973	30.9447	28.2833	25.4143	12.2371
First difference	1.2489**	3.9822**	1.4919**	3.7469**	1.194**	2.3397*	4.0492*
DF-GLS detrending							
Level	0.803	-1.4518	0.4133	-0.327	-1.1374	-1.2139	-2.0253
First difference	-4.9143**	-5.1694**	-5.9157**	-5.6664**	-5.199**	-2.4208*	-5.208**
Modified PP							
Level	1.0274	-1.4599	-2.3866	-0.2496	-0.7696	-1.3844	-1.8648
First difference	-3.2859**	-3.3501*	-3.0398**	-3.4264**	-3.3267**	-2.2956*	-3.3509*

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

Choi (1985), Erol and Yu (1987), and Lee (2006), who find no causality between energy consumption and economic growth for the UK. Differently, Soytas and Sari (2006) find evidence of bidirectional causality for the UK from multivariate cointegration, error correction models and generalized variance decompositions, and.

Next, our results reveal significant bidirectional nonlinear causality between energy consumption and economic growth in four countries: Canada, France, Japan, and the USA. These causal feedback linkages are all positive and indicative of the fact that energy consumption and income are jointly determined. As a result, policymakers should have to pay close attention to any shocks to energy supply and economic growth. The empirical evidence is particularly strong in the case of France as the null hypotheses under consideration are rejected at the conventional levels for two lags (2 and 6) regarding the causality from energy to income, and for four lags (2, 4, 6, and 7) regarding the causality from income to energy. While the bidirectional energy-growth nexus was found for Canada (Ghali and El-Sakka, 2004; Soytas and Sari, 2006), for Japan (Erol and Yu, 1987; Soytas and Sari, 2006), and for the USA (Lee, 2006), our finding for France is new. Indeed, previous studies rather show evidence of unidirectional causality running from income to energy consumption (Lee, 2006), unidirectional causality running from energy consumption to GDP (Soytas and Sari, 2003, 2006) and no causality (Erol and Yu, 1987).

For the remaining countries (Germany and Italy), no causal relationships are found between energy consumption and income. The validity of the *neutrality hypothesis* implies that for these countries, neither conservative nor expansive energy consumption policies will affect their economic growth. In addition, the fact that the economic growth is not linked to energy gives the said countries some degree of flexibility in planning the ecnomic development strategies.

3.3. Results for the Kyrstou-Labys tests

Table 5 shows the results for the parameter-prior selection in the M-G-based Kyrstou-Labys tests. The first two columns indicate that the nonlinear effects between energy consumption and income can date at least from one year ago. For example, a 10-year lagged value of the US income can affect the current value of energy consumption, while a 2-year lagged value of the US energy consumption may still have significant effects on income. As to the causality from energy consumption to income, the relatively large values of the delay variable (τ_2) signify that an active and efficient energy management strategy is needed in order to promote economic growth.

The Kyrstou-Labys tests are then performed for each sample countries, based on the predetermined parameters in Table 5. We firstly carry out the symmetric version of the test and report the results in Table 6. Recall that this test allows to detect the nonlinear causality between the variables of interest (i.e., energy consumption and GDP in their first differences) without distinguishing the signs of their changes. Our findings show that there is no causality in both directions for three countries (Canada, Japan and the UK) at the conventional levels of confidence. Our results for Canada and Japan are thus not in line with those of Evol and Yu (1987) and Lee (2006), among others. In the United States, energy consumption is found to cause economic growth at the 5% level, but the causality from the opposite direction is not significant. Earlier studies including Stern (1993, 2000), Soytas and Sari (2006), and Bowden and Payne (2009) find similar results. The same pattern of unidirectional causality is observed for France, but with stronger statistical association. These results imply that the French and US economies

Table 4: Hiemstra-Jones's nonlinear causality test

Canada						France					
H_0: E do not cause GDP			H_0: GDP do not cause E			H_0: E do not cause GDP			H_0: GDP do not cause E		
Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL
1	-2.0789	-13.311	1	-0.3073	-1.9681	1	-0.7459	-4.7762	1	-0.9234	-5.9132
2	0.6477	4.1476*	2	-0.9016	-5.773	2	4.5825	29.3429**	2	0.3531	2.2613*
3	0.1255	0.8040	3	-0.9988	-6.3957	3	-0.1367	-0.8759	3	0.0361	0.2311
4	0.0000	0.0000	4	-0.8978	-5.7489	4	-0.1431	-0.9162	4	0.8627	5.5240**
5	0.0000	0.0000	5	-0.6147	-3.9366	5	-1.0541	-6.7497	5	-1.2536	-8.0274
6	0.0000	0.0000	6	9.6464	61.767**	6	0.80602	5.1610**	6	0.9586	6.1380**
7	-0.6173	-3.9527	7	2.0512	13.134**	7	0.0000	0.0000	7	0.3467	2.2202*
8	-1.2216	-7.8222	8	0.0000	0.0000	8	0.0000	0.0000	8	0.0056	0.0364
Germany						Italy					
H_0: E do not cause GDP			H_0: GDP do not cause E			H_0: E do not cause GDP			H_0: GDP do not cause E		
Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL
1	-0.3489	-1.9427	1	-0.7990	-4.4487	1	-0.8785	-5.6257	1	-0.6193	-3.9657
2	-2.4369	-13.568	2	-3.3417	-18.606	2	-0.5687	-3.6417	2	-0.6183	-3.9594
3	-0.2959	-1.6480	3	-0.0009	-0.0052	3	-0.6246	-3.999	3	0.14534	0.9306
4	-0.5667	-3.1553	4	-0.0972	-0.5413	4	-0.6345	-4.0628	4	-0.2004	-1.2833
5	-0.4532	-2.5236	5	-0.1555	-0.86611	5	-0.7049	-4.5136	5	-0.2249	-1.4404
6	-0.5367	-2.9885	6	-0.3005	-1.6731	6	-0.9914	-6.3484	6	-0.32462	-2.0786
7	-0.7673	-4.2724	7	-0.4296	-2.3919	7	-1.0279	-6.5823	7	-0.3763	-2.4099
8	-0.8204	-4.5682	8	-0.25	-1.3919	8	-1.6119	-10.321	8	-0.7786	-4.9855
Japan						UK					
H_0: E do not cause GDP			H_0: GDP do not cause E			H_0: E do not cause GDP			H_0: GDP do not cause E		
Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL
1	0.1895	1.2139	1	-1.2792	-8.1914	1	-0.6290	-4.0276	1	-0.6730	-4.3098
2	-0.1466	-0.9391	2	-0.2648	-1.6958	2	-0.0755	-0.4838	2	-3.8681	-24.768
3	0.2658	1.7019*	3	0.3608	2.3107*	3	-0.9426	-6.0360	3	-0.8590	-5.5003
4	0.0000	0.0000	4	-0.1068	-0.6843	4	1.1401	7.3006**	4	-0.2615	-1.6749
5	0.0000	0.0000	5	-0.1196	-0.7663	5	0.6667	4.2695*	5	-0.4577	-2.9311
6	0.0000	0.0000	6	0.0000	0.0000	6	0.5515	3.5313*	6	-0.5398	-3.4564
7	0.0000	0.0000	7	0.0000	0.0000	7	0.0549	0.3518	7	-0.3652	-2.3385
8	0.0000	0.0000	8	0.0000	0.0000	8	0.0796	0.5101	8	-0.5401	-3.4589
USA											
H_0: E do not cause GDP			H_0: GDP do not cause E								
Lags	CS	TVAL	Lags	CS	TVAL						
1	-0.4946	-3.1670	1	-0.6047	-3.8723						
2	-0.8363	-5.3550	2	-0.1519	-0.9729						
3	-94.832	-607.226	3	3 15.54	99.524**						
4	0.3765	2.4111*	4	-0.0407	-0.2606						
5	-1.5380	-9.8483	5	-0.7683	-4.9196						
6	0.1768	1.1326	6	0.0000	0.0000						
7	0.0788	0.5050	7	0.0000	0.0000						
8	0.07311	0.4681	8	-0.5440	-3.4837						

Notes: E and Y indicate energy consumption and GDP, respectively. CS and TVAL are respectively the difference between the two conditional probabilities, and the standardized test statistic. "lags" denotes the number of lags in the residual series used in the test. ** and * indicate significance at the 1% and 5% levels, respectively.

depend, to a large extent, on energy and that energy consumption is likely to invigorate income. For Germany, we observe a weak causality relation running from income to energy consumption, indicating that this country has a less energy-dependent economy. This finding contrasts with that of Soytas and Sari (2003), but supports that of Erol and Yu (1987), Lee (2006), and Soytas and Sari (2006).

Whether the direction of changes in the studied series has a significant effect on their causal relationships can be examined by the asymmetric version of the Kyrstou-Labys test. We report the results in Tables 7 and 8. The exponent p (respectively, n) indicate that only positive (respectively,

Table 5: Parameter-prior selection in the M-G model

	τ_1	τ_2	c_1	c_2
USA	10	2	1	2
UK	1	10	3	4
Germany	10	7	10	4
Japan	2	10	2	10
France	9	10	5	1
Italy	10	1	1	10
Canada	10	6	10	2

Notes: This table reports the results for the parameter-prior selection. τ_1 and τ_2 are the optimal integrer delay variables for the causality from income to energy consumption, and for the causality from energy consumption to income, respectively. c_1 and c_2 are the power of the lagged values of income and energy consumption, respectively.

Table 6: Kyrstou-Labys nonlinear causality test (symmetric case)

Relation ($A \to B$)	F-statistic	Probability
$E_{USA} \to Y_{USA}$	6.7902	0.0150
$Y_{USA} \to E_{USA}$	0.9053	0.3501
$E_{UK} \to Y_{UK}$	0.2608	0.6139
$Y_{UK} \to E_{UK}$	0.5628	0.4599
$E_{Germany} \to Y_{Germany}$	0.0693	0.7957
$Y_{Germany} \to E_{Germany}$	3.2855	0.0887
$E_{Japan} \to Y_{Japan}$	0.0572	0.8129
$Y_{Japan} \to E_{Japan}$	0	1
$E_{France} \to Y_{France}$	15.8266	0.0005
$Y_{France} \to E_{France}$	1.1388	0.2957
$E_{Italy} \to Y_{Italy}$	4.1357	0.0523
$Y_{Italy} \to E_{Italy}$	0	1
$E_{Canada} \to Y_{Canada}$	0.4854	0.4922
$Y_{Canada} \to E_{Canada}$	2.3932	0.1339

Notes: we consider the null hypothesis that A does not cause B.

Table 7: Kyrstou-Labys nonlinear causality test (asymmetric case for positive changes in the causing variables)

Relation ($A \rightarrow B$)	F-statistic	Probability
$E^p_{USA} \rightarrow Y_{USA}$	11.8988	0.0014
$Y^p_{USA} \rightarrow E_{USA}$	0.0131	0.9094
$E^p_{UK} \rightarrow Y_{UK}$	1.5821	0.2165
$Y^p_{UK} \rightarrow E_{UK}$	0.8513	0.3623
$E^p_{Germany} \rightarrow Y_{Germany}$	1.3129	0.2623
$Y^p_{Germany} \rightarrow E_{Germany}$	0.0029	0.9576
$E^p_{Japan} \rightarrow Y_{Japan}$	6.9564	0.0123
$Y^p_{Japan} \rightarrow E_{Japan}$	0	1
$E^p_{France} \rightarrow Y_{France}$	34.4100	0
$Y^p_{France} \rightarrow E_{France}$	0.9631	0.3330
$E^p_{Italy} \rightarrow Y_{Italy}$	7.5184	0.0095
$Y^p_{Italy} \rightarrow E_{Italy}$	0	1
$E^p_{Canada} \rightarrow Y_{Canada}$	0.1038	0.7491
$Y^p_{Canada} \rightarrow E_{Canada}$	0.3701	0.5468

Notes: we consider the null hypothesis that A does not cause B.

Table 8: Kyrstou-Labys nonlinear causality test (asymmetric case for negative changes in the causing variables)

Relation ($A \rightarrow B$)	F-statistic	Probability
$E^n_{USA} \rightarrow Y_{USA}$	4.1866	0.0481
$Y^n_{USA} \rightarrow E_{USA}$	0.0720	0.7900
$E^n_{UK} \rightarrow Y_{UK}$	4.0388	0.0520
$Y^n_{UK} \rightarrow E_{UK}$	0.5498	0.4632
$E^n_{Germany} \rightarrow Y_{Germany}$	0.2831	0.5992
$Y^n_{Germany} \rightarrow E_{Germany}$	217.7047	0
$E^n_{Japan} \rightarrow Y_{Japan}$	1.2392	0.2730
$Y^n_{Japan} \rightarrow E_{Japan}$	0	1
$E^n_{France} \rightarrow Y_{France}$	0.0795	0.7796
$Y^n_{France} \rightarrow E_{France}$	0	1
$E^n_{Italy} \rightarrow Y_{Italy}$	0.0097	0.9222
$Y^n_{Italy} \rightarrow E_{Italy}$	0	1
$E^n_{Canada} \rightarrow Y_{Canada}$	7.0055	0.0120
$Y^n_{Canada} \rightarrow E_{Canada}$	111.0337	0

Notes: we consider the null hypothesis that A does not cause B.

negative) values of the causing series were selected. Table 7 shows that there is a significant unidirectional causality at the 1% and 5% levels, running from positive changes in energy consumption to changes in GDP (France, Italy, Japan, and the USA). On the other hand, energy consumption reductions significantly cause GDP changes in Canada and the USA (at the 5% level), and in the UK (at the 10% level). By contrast, the causality from GDP reductions to changes in energy consumption is significant for Canada and Germany. Taken together, negative changes in either GDP or energy consumption provoke adjustments in the value of the other variable.

4. Conclusion

In this paper, we investigated the causal relationships between energy consumption and income for the G7 countries. Our approach differs from the majority of previous studies in that we focus on the nonlinear patterns of the possible underlying interactions between the two variables of interest. More specifically, we draw the empirical evidence from two powerful nonlinear Granger causality tests, proposed by Hiemstra and Jones (1994), and Kyrstou and Labys (2006). Using per capita GDP and energy consumption data, our results appear to be very country-specific, and sometimes mixed between the two nonlinear tests we consider. For example, while the nonparametric Hiemstra-Jones test shows evidence of a bidirectional relationship between energy consumption and income for France, the symmetric Kyrstou-Labys test concludes on the existence of a unidirectional causality from energy consumption to income. The results for Germany are also conflicting as the Hiemstra-Jones test and the symmetric Kyrstou-Labys test detect, respectively, no causality and a unidirectional causality from income to energy consumption. It is important to note that the presence of bidirectional nonlinear relationships we found for France was never evidenced in previous studies. Finally, we show that the directions of changes in the energy consumption and income matter for their causal interactions and that they should be considered while making policy decisions to balance governments' expenditures and revenues.

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