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Frauke Dobnik[1]

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Abstract

This paper examines the causal relationship between real GDP and energy consumption for 23 OECD countries from 1971 to 2009. Using recently developed panel econometric techniques the present paper takes into account structural breaks and cross-section dependence when analysing the energy consumption-growth nexus. The empirical results of this study indicate that there exists a long-run equilibrium relationship between real GDP and energy consumption, and the impact of real GDP on energy consumption is larger than vice versa. Furthermore, the empirical evidence of a dynamic panel error-correction model reveals a bidirectional causal relationship between economic growth and energy consumption in both the short and long run.

JEL Classification: C33, C23, Q43

Keywords: Energy consumption; panel unit roots and cointegration; structural breaks; cross-section dependence; panel error-correction model; Granger causality

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1 Introduction

The question of whether or not energy conservation policies affect economic activity has attracted a lot of attention in previous and current research. The direction of causation between energy consumption and economic growth is of crucial importance in the international debate on global warming and the reduction of greenhouse gas emissions. Furthermore, since the world's leading economies agreed on the Kyoto Protocol in 2005 to limit their greenhouse gas emissions relative to the amounts emitted in 1990, the information of this causal relation has become increasingly important. Hence, the developed countries require a suitable basis of decision-making to formulate sensible energy policies that account for any affect of reducing energy consumption to lower dioxide emissions on economic growth. For instance, if causality runs from energy consumption to economic growth, energy conservation policies may have a negative impact on an economy's growth.

The literature on the energy consumption-GDP growth nexus proposes four testable hypotheses regarding the possible outcomes of causality. The growth hypothesis suggests that energy consumption is a crucial component in growth, directly or indirectly as a complement to capital and labour as input factors of production. Hence, a decrease in energy consumption causes a decrease in real GDP. In this case, the economy is called 'energy dependent' and energy conservation policies may be implemented with adverse effects on real GDP. By contrast, the conservation hypothesis claims that policies directed towards lower energy consumption may have little or no adverse impact on real GDP. This hypothesis is based on a uni-directional causal relationship running from real GDP to energy consumption. Bi-directional causality corresponds with the feedback hypothesis, which argues that energy consumption and real GDP affect each other simultaneously. In this case, policy makers should take into account the feedback effect of real GDP on energy consumption by implementing regulations to reduce energy use. Finally, the neutrality hypothesis, which is confirmed by the absence of any causal relation, indicates that reducing energy consumption does not affect economic growth or vice versa. Hence, energy conservation policies would not have any impact on real GDP.

It should be noted, however, that the exclusive investigation of the direction of causation between energy consumption and economic growth may not provide unambiguous policy implications. Energy conservation policies cannot sensibly be constituted without the consideration of economic or environmental factors such as energy supply infrastructure, energy efficiency considerations or institutional constraints (Mahadevan and Asafu-Adjaye, 2007). For instance, energy conservation policies that effect a reduction in energy consumption due to improved energy efficiency may raise the productivity of energy consumption, which in turn may stimulate economic growth. Thus, a shift from less efficient energy sources to more efficient and less polluting options may establish a stimulus rather than an obstacle to economic growth (Costantini and Martini, 2010). Alternatively, poor energy supply infrastructure or other supply side disruptions that decrease energy consumption could indeed induce an adverse impact on economic growth. Furthermore, high substitutability between energy and other input factors on the production side can explain possible economic growth without a considerable increase in energy consumption.

The present study analyses the relationship between energy consumption and GDP of 23 developed countries covering the period from 1971 to 2009. The purpose of this paper is to overcome several shortcomings of previous and frequently used econometric methods to intervene convincingly in the discussion about the direction of causation between energy consumption and economic growth. Until now, most studies have analysed single countries on the basis of annual data and failed to reach a consensus on this causal relationship. As for many countries there are only annual data available, the span usually covers no more than 20-30 years. However, it is well-known that standard time series tests, such as the augmented Dickey-Fuller unit root test (Dickey and Fuller, 1979) and the Johansen (1991, 1995) cointegration test, have low statistical power, especially when the span of data is short, (Campbell and Perron, 1991). In response, recent studies have used panel data to extend the time series dimension by the cross-sectional dimension and, hence, exploit additional information. As panel-based tests rely on a broader information set, the power can substantially be increased and tests are more accurate and reliable. Studies using panel data, however, also provide ambiguous results.

One reason may be that almost all of them neglect the presence of structural breaks. It is well-known that inappropriately omitting breaks can lead to misleading inference in time series testing (Perron, 1989). That is also true for panel tests since panel data also include the time series dimension as mentioned by Lee and Chiu (2011). The importance of taking into account structural breaks when analysing energy consumption and GDP can be confirmed by several past events. First of all, the first oil crisis in 1973 occurred when the Arab oil embargo was proclaimed. The Iranian revolution followed in 1978, accompanied by exploding oil prices and a period of high inflation during the late 1970s. Furthermore, the global economic recession in the early 1980s may represent a potential structural break. Further critical events are: The 1986s oil glut caused by decreasing demand following the 1970s energy crisis, the stock market crash in the United States in 1987, the periods of moderate economic growth and low inflation in Western industrialised countries in the late 1980s and early 1990s, the oil price increase after Iraq's invasion of Kuwait 1990, and, finally, the 1997-1999 Asian financial crisis. Since all those mentioned events occurred within the period covered in this analysis, the consideration of structural breaks is strongly advisable. Hence, the present study makes a substantial contribution to the existing literature by doing so in a panel framework.

A second explanation for the failure to reach a consensus on the direction of causation between energy consumption and economic growth may be the neglect of dependence across the countries in a panel by using first generation panel unit root and cointegration tests. First generation panel tests are characterised by the assumption of independent cross-section members. This condition is unrealistic in view of the strong inter-economy linkages and therefore, is likely to be violated often, for instance, because of common oil price shocks. But most existing residual based tests use the assumption of cross-sectional independence to be able to get a convenient asymptotic distribution for the test statistic. The independence of the cross-section members allows for the use of standard asymptotic tools, such as the Central Limit Theorem. However, Banerjee et al. (2004) showed by means of simulations experiments that inappropriately assuming cross-sectional independence in the presence of cross-member cointegration can have distortionary impacts on the panel inference. Thus, they argued that the conclusions of many empirical studies may be based upon misleading inference since the assumption of independent panel members is usually not valid (Urbain and Westerlund, 2006). Until recently, only few so-called second generation panel tests have been proposed that take into account the existence of cross-sectional dependency relations (see Breitung and Pesaran, 2008, for a recent survey). Hence, the innovative contribution of the present paper is the application of panel econometric techniques that consider *both* structural breaks *and* cross-sectional dependence to provide more accurate and reliable results.

The remainder of this paper is organised as follows. Section 2 reviews the literature related to the causal relationship between energy consumption and economic growth using panel data. Given that the panel econometric methods applied in the present study are recently developed and less used in the empirical literature, Section 3 provides additional details on these methods. The data is presented and analysed in Section 4, which reveals the empirical results. Finally, Section 5 provides conclusions and policy implications.

2 Literature review

The relationship between energy consumption and economic growth is a widely studied research topic, however, the empirical evidence is mixed and conflicting with respect to the direction of causation. In addition to the methodical weaknesses described in the Introduction, this discrepancy in results may also be due to country-specific heterogeneity in climate conditions, economic development and energy consumption patterns. The vast literature on single country analysis using time series econometrics draws on the initial work of Kraft and Kraft (1978). This study provides evidence in favour of causality running from income to energy consumption in the United States for the period 1947-1974. In recent years researchers have taken advantage of newly developed panel econometric techniques. Table 1 summarises the thereby existing panel data studies on the energy consumption-growth nexus.[1] Furthermore, there are also some panel data studies on the relationship between growth and specific components of total energy consumption such as coal (Apergis and Payne, 2010a,b), electricity (e.g., Acaravci and Ozturk, 2010; Apergis and Payne, 2011a; Chen et al., 2007; Narayan and Smyth, 2009), nuclear energy (Apergis and Payne, 2010d; Lee and Chiu, 2011), and renewable energy (see, e.g., Apergis and Payne, 2010e; Sadorsky, 2009).

Table 1: Overview of panel data studies on the energy consumption-economic growth nexus

Authors	Period	Countries	Causality
Lee (2005)	1975-2001	18 developing countries	Energy → Growth
Al-Iriani (2006)	1971-2002	GCC countries	Growth → Energy
Lee and Chang (2007)	1965-2002	22 developed countries	Energy ↔ Growth
	1971-2002	18 developing countries	Growth → Energy
Mahadevan and	1971-2002	10 net energy exporters 10	Growth → Energy
Asafu-Adjaye (2007)		10 net energy importers	Energy → Growth
Mehrara (2007)	1971-2002	11 oil exporting countries	Growth → Energy
Huang et al. (2008)	1971-2002	26 high income countries	Growth → Energy
		15 upper middle income countries	Growth → Energy
		22 lower middle income countries	Growth → Energy
		19 low income countries	Energy ∼ Growth
Lee et al. (2008)	1960-2001	22 OECD countries	Energy ↔ Growth
Lee and Chang (2008)	1971-2002	16 Asian countries	Energy → Growth
Narayan and Smyth (2008)	1972-2002	G-7 countries	Energy → Growth
Apergis and Payne (2009a)	1991-2005	11 countries within the	
		Commonwealth of Independent States	Energy ↔ Growth
Apergis and Payne (2009b)	1980-2004	6 Central American countries	Energy → Growth
Mishra et al. (2009)	1980-2005	9 Pacific Island countries	Energy ↔ Growth
Sinha (2009)	1975-2003	88 countries	Energy ↔ Growth
Apergis and Payne (2010c)	1980-2005	9 South American countries	Energy → Growth
Costantini and Martini (2010)	1960-2005	26 OECD countries	Energy ↔ Growth
	1970-2005	45 non-OECD countries	Energy ↔ Growth
Lee and Lee (2010)	1978-2004	25 OECD countries	Energy ↔ Growth
Ozturk et al. (2010)	1971-2005	13 upper middle income countries	Energy ↔ Growth
		24 lower middle income countries	Energy ↔ Growth
		14 low income countries	Growth → Energy
Apergis and Payne (2011b)	1990-2007	80 countries	Energy ↔ Growth
Belke et al. (2011)	1981-2007	25 OECD countries	Energy ↔ Growth
Kahsai et al. (2011)	1980-2007	40 Sub-Saharan African countries	Energy ↔ Growth
Niu et al. (2011)	1971-2005	4 developed Asia-Pacific countries	Energy ↔ Growth
		4 developing Asia-Pacific countries	Growth → Energy

Notes: X → Y means variable X Granger-causes variable Y. X ∼ Y means that there no Granger-causality exists.

The first panel data study on the relationship between energy consumption and growth by

[1]For a detailed literature overview including time series studies on the causal relationship between energy consumption and economic growth, see the recent surveys by Ozturk (2010) and Payne (2010)

Lee (2005) examined 18 developing countries over the period 1975-2001. He found uni-directional causality running from energy consumption to growth. This finding suggests that energy conservation may harm economic growth in developing countries. In contrast, Al-Iriani (2006) found uni-directional causality running from growth to energy consumption for six member countries of the Gulf Cooperation Council (GCC) covering the period 1971-2002. Thus, energy conservation policies may be adopted by the GCC without any adverse effects on economic growth. Correspondingly, the panel data studies listed in Table 1 in general provide ambiguous empirical results on the energy consumption-growth nexus similar to that found in time series studies. Even the distinction between developed and developing countries leads to no clear evidence for either group of countries. Similar to Lee (2005) and Al-Iriani (2006), most panel data analyses have applied the panel unit root tests proposed by Hadri (2000), Levin et al. (2002) (LLC) and/or Im et al. (2003) (IPS), the Pedroni (1999, 2004) panel cointegration test and the panel generalised method of moments (GMM) estimator proposed by Arellano and Bond (1991) to test for panel Granger causality. Furthermore, the listed studies also often use the Breitung (2000), and the Fisher-type ADF and PP tests (see Choi, 2001; Maddala and Wu, 1999) to test for unit roots. In addition, the long-run relationship between energy consumption and GDP, which is commonly confirmed by means of the already mentioned Pedroni (1999, 2004) test, is almost always estimated with fully modified OLS (FMOLS) as suggested in Pedroni (2000). In view of the repeated application of the same methods that continue to provide conflicting evidence, even for panels of similar countries, further methodological improvements seem to be necessary.

One reasonable issue is the consideration of structural breaks as illustrated in the Introduction. Another important point to note is that all panel unit root and cointegration tests mentioned above are so-called first generation panel tests, meaning that they restrictively assume independence across panel members. However, there are only a few panel data studies that apply appropriate methods to tackle these issues. Firstly, Chen and Lee (2007) re-investigate the stationarity of energy consumption per capita for seven regional panel sets covering the 1971-2002 period in the presence of potential structural breaks. Consequently, they used the panel unit root test proposed by Carrion-i-Silvestre et al. (2005) (CBL) which allows for multiple level shifts including bootstrap methods to consider general forms of cross-sectional dependence as well. Their results suggest evidence in favour of stationary energy consumption. Narayan and Smyth (2008) also applied the CBL test to the G-7 countries over the period 1972 to 2002, but without a structural break. However, they used the panel cointegration technique with multiple structural breaks of Westerlund (2006). Their main finding is that the Pedroni (1999) cointegration test failed to find evidence for a long-run relationship whereas cointegration can be detected when structural breaks are incorporated. As a robustness check of their stationarity results, Costantini and Martini (2010) performed the LM panel unit root test proposed by Im et al. (2005) which considers the presence of a single break. The evidence in favour of non-stationarity mostly remains the same. A study which does not account for structural breaks but cross-section dependence resulting from unobserved common factors is proposed by Belke et al. (2011). They applied the Bai and Ng (2004) PANIC procedure and the cointegration test approach suggested by Gengenbach et al. (2006) to test idiosyncratic and common components separately for unit roots and cointegration relations.

Moreover, there are no further panel data studies on the relationship between total energy consumption and growth dealing with structural breaks and/or cross-sectional dependence. However, in the analysis of the relation between electricity consumption and GDP of six Middle Eastern countries for the sample 1974-2002, Narayan and Smyth (2009) applied once again the Westerlund (2006) test to take into account structural breaks. Apergis and Payne (2010b) examined the integration property of coal consumption of 25 OECD countries over the period 1980-2005 by means of several panel unit root tests with structural breaks: Carrion-i-Silvestre et al. (2005), Im et al. (2005), and Westerlund (2005). The latter test examines the case in which multiple endogenous breaks are allowed in the level of the series. The empirical results suggest, even in the presence of structural breaks, integration of order one for coal consumption. Furthermore, they applied the Larsson et al. (2001) panel coinetgration test (LLL) that allows for cross-sectional dependence through the effects of the dynamics of the short run. Finally, Lee and Chiu (2011) analysed nuclear energy consumption over the period 1971 to 2006 for six developed countries also using Westerlund

(2006)'s panel cointegration test. In their study the corresponding estimated break dates are presented but not the results referring to the existence of cointegration.

Even though all these studies provide evidence in favour of the presence of a single or multiple structural breaks none of them consequently consider that issue in both the unit root and cointegration tests. Furthermore, except for the CBL test and the cointegration test approach of Gengenbach et al. (2006), all applied methods on total energy consumption neglect the existence of dependence across panel members. Consequently, this study take into account both structural breaks and cross-section dependence when testing for unit roots and cointegration, respectively.

3 Methodology

Since the pioneering work of Perron (1989) it is well known that it is critical to allow for structural breaks when testing time series for unit roots. The failure to take into account the potential presence of structural breaks may lead to misleading inference regarding the order of integration. For instance, a stationary time series with a broken trend could be mistaken for a non-stationary process if the unit root test neglects the presence of structural breaks (Perron, 1989). Furthermore, Breitung and Pesaran (2008) proposed that in many empirical analyses using panel data it is inappropriate to assume that cross-section members are independent. Indeed, the assumption of independence is usually not valid, in particular in the analysis of macroeconomic or financial data that have strong inter-economy linkages (Urbain and Westerlund, 2006).

Consequently, this paper uses recently developed panel techniques that accommodate both structural breaks and cross-sectional dependence simultaneously rather than neglecting both or tackling only one of these issues at a time. Since these econometric methods have yet been rarely applied in the empirical literature, this section discusses the techniques that are used in this study to analyse the energy consumption-growth nexus. First, the test for cross-sectional independence proposed by Pesaran (2004) is briefly presented. Second, this study describes the panel unit root test developed by Bai and Carrion-i-Silvestre (2009) which allows for structural breaks and cross-sectional dependence. Third, the panel cointegration test suggested by Westerlund and Edgerton (2008), which also considers structural breaks and dependence across countries, is introduced. Fourth, Sub-section 3.4 discusses Pesaran (2006)'s common correlated effects (CCE) estimators that are used to estimate the long-run relationship between energy consumption and GDP. Finally, the pooled mean group estimator for non-stationary heterogeneous panels suggested by Pesaran et al. (1999) to establish dynamic panel causality is briefly presented.

3.1 Cross-section dependence

The cross-section dependence (CD) test proposed by Pesaran (2004) tests the null hypothesis of zero dependence across the panel members and is applicable to a variety of panel data models such as stationary and unit root dynamic heterogeneous panels with structural breaks, with small T and large N (Pesaran, 2004). The CD test is based upon an average of all pair-wise correlations of the ordinary least squares (OLS) residuals from the individual regressions in the panel data model

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it}, \tag{1}$$

where $i = 1, ..., N$ represents the cross-section member, $t = 1, ..., T$ refers to the time period, and x_{it} is a $(k\times1)$ vector of observed regressors. The intercepts, α_i, and the slope coefficients, β_i, are allowed to vary across the panel members.
The CD test statistic is defined as

$$\mathrm{CD} = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \to \mathrm{N}(0,1), \tag{2}$$

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the OLS residuals, $\hat{u}_{it}$, associated with Equation (1)

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T}\hat{u}_{it}\hat{u}_{jt}}{\left(\sum_{t=1}^{T}\hat{u}_{it}^2\right)^{1/2}\left(\sum_{t=1}^{T}\hat{u}_{jt}^2\right)^{1/2}}. \tag{3}$$

3.2 Panel unit root test

Bai and Carrion-i-Silvestre (2009) developed panel unit root statistics which pool modified Sargan and Bhargava (1983) (MSB) tests for individual time series, taking into account both multiple structural breaks and cross-section dependence through a common factors model proposed by Bai and Ng (2004). They allow for structural breaks in the level, slope or both at different dates for different countries and may have different magnitudes of shift. Additionally each series can have a different number of breaks and within each series the number of breaks in the level and the slope can also be different. Hence, the test approach proposed by Bai and Carrion-i-Silvestre (2009) takes into account a high degree of heterogeneity across countries. Furthermore, the common factors may be stationary, non-stationary or a combination of both. The common factor approach allows the common shocks to affect countries differently via heterogeneous factor loadings. Bai and Carrion-i-Silvestre (2009) modified the Bai and Ng (2004) PANIC procedure to achieve a robust decomposition into common and idiosyncratic components in the presence of structural breaks. They developed an iterative estimation procedure that is appropriate to deal with heterogeneous breaks in the deterministic components.

In summary, their overall procedure consists of the following steps:

1. Difference the variables and estimate the number and locations of structural breaks for each time series.

2. Given the locations of the structural breaks, estimate the common factors, factor loadings, and the magnitudes of changes via the iteration procedure mentioned above.

3. Calculate the residuals for each time series based on the estimated quantities in step 2 and then obtain the cumulative sum of residuals as described in Bai and Ng (2004).

4. Determine the modified univariate MSB test for each residual series.[2]

5. Construct the panel MSB test by pooling the individual ones.

[2]The univariate MSB test for unit root was originally introduced by Stock (1999), who generalised the procedure of Sargan and Bhargava (1983) to non-i.i.d. and non-normal errors.

These steps are based on the following general panel data model:

$$
\begin{aligned}
X_{i,t} &= D_{i,t} + F_t'\pi_i + e_{i,t} && (4)\\
(I - L)F_t &= C(L)u_t && (5)\\
(1 - \rho_i L)e_{i,t} &= H - i(L)\varepsilon_{i,t}, && (6)
\end{aligned}
$$

where the index $i = 1, ..., N$ represents panel members and $t = 1, ..., T$ denotes the time period. $C(L) = \sum_{j=0}^{\infty} C_j L^j$ and $H_i(L) = \sum_{j=0}^{\infty} H_{i,j} L^j$, where L is the lag operator and ρ_i is the autoregressive parameter. The component $D_{i,t}$ represents the deterministic part of the model, F_t is a $(r \times 1)$ vector of common factors, and $e_{i,t}$ denotes the idiosyncratic disturbance term. Despite the operator $(1 - L)$ in Equation 6, F_t need not to be $I(1)$. The integration property of the F_t depends on the rank of $C(1)$. If $C(1) = 0$, the F_t is $I(0)$. If $C(1)$ is of full rank, then each component of F_t is $I(1)$. If $C(1) = 0$ but not full rank, then some components of F_t are $I(1)$ and some are $I(0)$.[3]

With regard to the deterministic component $D_{i,t}$, Bai and Carrion-i-Silvestre (2009) propose the following two models:

$$
\begin{aligned}
\text{Model 1:} \quad D_{i,t} &= \mu_i + \sum_{j=1}^{l_i} \theta_{i,j} DU_{i,j,t} && (7)\\
\text{Model 2:} \quad D_{i,t} &= \mu_i + \beta_i t + \sum_{j=1}^{l_i} \theta_{i,j} DU_{i,j,t} + \sum_{k=1}^{m_i} \gamma_{i,k} DT_{i,k,t}, && (8)
\end{aligned}
$$

where l_i and m_i denote the structural breaks affecting the mean and the trend of a series, respectively, which are not necessarily equal. The dummy variables are defined as $DU_{i,j,t} = 1$ for $t > T^i_{a,j}$ and 0 otherwise, and $DT_{i,k,t} = (t - T^i_{b,k})$ for $t > T^i_{b,k}$ and 0 otherwise. $T^i_{a,j}$ and $T^i_{b,k}$ represent the jth and kth dates of the breaks in the level and trend, respectively, for the ith individual with $j = 1, ..., l_i$ and $k = 1, ..., m_i$.

The introduced common factors capture the co-movement of the time series as well as cross-section correlation. Since those factors are unobserved, they need to be consistently estimated. Following Bai and Ng (2004), Bai and Carrion-i-Silvestre (2009) estimate these un-

[3]For a detailed description of the underlying set of assumptions, see Bai and Carrion-i-Silvestre (2009)

observed common factors by applying the principal components analysis to the differenced-detrended model. They provide separate analyses for the two deterministic models as the limiting distribution of the MSB statistic depends on the specification.[4]

Bai and Carrion-i-Silvestre (2009) pool the individual MSB test statistics to increase the statistical power. The standard approach to pooling described in Levin et al. (2002) requires cross-sectionally independent panel members, a condition that is not fulfilled in this framework. However, the combination of individual MSB test statistics is appropriate since the $e_{i,t}$ are independent across the panel units. This follows from the fact that the limiting distributions are free from the common factors. Bai and Carrion-i-Silvestre (2009) provide two approaches for pooling the individual test statistics so as to test the null hypothesis H_0: $\rho_i = 1$ for all $i = 1, ..., N$ against the alternative H_1: $|\rho_i| < 1$ for some i. The first approach is to use the average of individual statistics:

$$Z = \sqrt{N}\frac{\overline{\text{MSB}(\lambda)} - \bar{\xi}}{\bar{\zeta}} \rightarrow \text{N}(0, 1), \tag{9}$$

with $\overline{\text{MSB}(\lambda)} = N^{-1}\sum_{i=1}^{N}\text{MSB}_i(\lambda_i)$, $\bar{\xi} = N^{-1}\sum_{i=1}^{N}\xi_i$, and $\zeta^2 = N^{-1}\sum_{i=1}^{N}\zeta_i^2$, where ξ_i and ζ_i^2 denote the mean and the variance of the individual modified $\text{MSB}_i(\lambda_i)$ statistic, respectively, and $\lambda_i = T_i^b/T$ represents the break fraction parameter.[5] The individual MSB statistics are asymptotically invariant to mean breaks, but not to breaks in the linear trend. Hence, Bai and Carrion-i-Silvestre (2009) introduced a second approach based on simplified test statistics which are invariant to both mean and trend breaks:

$$Z^* = \sqrt{N}\frac{\overline{\text{MSB}^*(\lambda)} - \bar{\xi}^*}{\bar{\zeta}^*} \rightarrow \text{N}(0, 1), \tag{10}$$

with $\overline{\text{MSB}^*(\lambda)} = N^{-1}\sum_{i=1}^{N}\text{MSB}_i^*(\lambda_i)$, $\bar{\xi}^* = N^{-1}\sum_{i=1}^{N}\xi_i^*$, and $\zeta^{*2} = N^{-1}\sum_{i=1}^{N}\zeta_i^{*2}$, where ξ_i^* and ζ_i^{*2} denote the mean and the variance of the individual modified $\text{MSB}_i^*(\lambda_i)$ statistic, respectively, and $\lambda_i = T_i^b/T$ represents the break fraction parameter.[6]

[4] See Bai and Carrion-i-Silvestre (2009) for details.
[5] See Bai and Carrion-i-Silvestre (2009) for a description of the individual MSB statistics.
[6] See Bai and Carrion-i-Silvestre (2009) for a description of the individual simplified MSB statistics.

To yield satisfactory results when pooling, Bai and Carrion-i-Silvestre (2009) consider the second approach proposed by Maddala and Wu (1999) and Choi (2001) that pools the p-values of the individual tests:

$$P = -2 \sum_{i=1}^{N} \ln p_i \rightarrow \chi^2_{2N} \tag{11}$$

$$P_m = \frac{-2 \sum_{i=1}^{N} \ln p_i - 2N}{\sqrt{4N}} \rightarrow \mathrm{N}(0,1), \tag{12}$$

where p_i, $i = 1, ..., N$, is the individual p-value. Bai and Carrion-i-Silvestre (2009) denote the corresponding P and P_m statistic that are computed by means of the p-values of the simplified MSB statistic as P^* and P^*_m, respectively.

3.3 Panel cointegration test

A panel cointegration test that considers both structural breaks and cross-section dependence was developed by Westerlund and Edgerton (2008). Apart from cross-sectional dependence and unknown structural breaks in both the intercept and slope, their test allows for heteroskedastic and serially correlated errors, as well as cross unit-specific time trends. Moreover, the structural breaks may be located at different dates for different panel members. Westerlund and Edgerton (2008) propose two versions to test for the null hypothesis of no cointegration which can be used under those general conditions. Their test is derived from the Lagrange multiplier (LM)-based unit-root tests developed by Schmidt and Phillips (1992), Ahn (1993), and Amsler and Lee (1995). The model under consideration is

$$y_{it} = \alpha_i + \eta_i t + \delta_i D_{it} + x'_{it}\beta_i + (D_{it}x_{it})'\gamma_i + z_{it}, \tag{13}$$

$$x_{it} = x_{it-1} + w_{it}, \tag{14}$$

where the indices $i = 1, ..., N$ and $t = 1, ..., T$ denote panel members and the time period, respectively. The k-dimensional vector x_{it} contains the regressors and is specified as a random walk. The variable D_{it} is a scalar break dummy such that $D_{it} = 1$ if $t > T_i$ and zero otherwise. Hence, α_i and β_i represent the cross unit-specific intercept and slope coefficient before the break, while δ_i and γ_i represent the change in these parameters after the break. w_{it} is an error term with mean zero and independent across i.[7] The disturbance term z_{it} is generated by the following model that allows cross-sectional dependence through unobserved common factors

$$\begin{aligned} z_{it} &= \lambda_i' F_t + \upsilon_{it} && (15) \\ F_{jt} &= \rho_j F_{jt-1} + u_{jt} && (16) \\ \phi_i(L)\Delta\upsilon_{it} &= \phi_i \upsilon_{it-1} + e_{it}, && (17) \end{aligned}$$

where $\phi_i(L) := 1 - \sum_{j=1}^{p_i} \phi_{ij} L^j$ is a scalar polynomial in the lag operator L, F_t is a r-dimensional vector of unobservable common factors F_{jt} with $j = 1, ..., r$, and λ_i is the corresponding vector of factor loading parameters. The error term u_t is independent of e_{it} and w_{it} for all i and t, and e_{it} is mean zero and independent across both i and t. Under the assumption that $\rho_j < 1$ for all j, it is assured that F_t is stationary involving that the order of integration of the composite regression error z_{it} depends only on the degree of integration of the idiosyncratic disturbance term υ_{it}. Hence, the relationship in Equation (13) is cointegrated if $\phi_i < 0$ and spurious if $\phi_i = 0$.[8]

Westerlund and Edgerton (2008) test the null hypothesis that all N cross-section units are spurious ($\mathrm{H}_0 : N_1 = 0$ with $N_0 := N - N_1$) against the alternative that the first N_1 cross-section units are cointegrated while the remaining $N_0 := N - N_1$ units are spurious ($\mathrm{H}_1 : N_1 > 0$).[9] For testing purposes the LM principle is used that the score vector has zero mean when evaluated at the vector of true parameters under the null. Westerlund and Edgerton (2008) therefore consider the following pooled log-likelihood function

$$\log(L) = \text{constant} - \frac{1}{2} \sum_{i=1}^{N} \left(T \log(\sigma_i^2) - \frac{1}{\sigma_i^2} \sum_{t=1}^{T} e_{it}^2 \right). \qquad (18)$$

[7]For notational simplicity, the model is restricted to allow for only one break.

[8]Further assumptions that are made to develop the test can be found in Westerlund and Edgerton (2008).

[9]Westerlund and Edgerton (2008) argue that the assumption that the cointegrated units lie first is only for notational simplicity, and is by no means restrictive.

Their test can be derived by first concentrating the log-likelihood function with respect to σ_i^2 and then evaluating the resulting score at the restricted maximum likelihood estimates. Let $\hat{\sigma}_i^2 := 1/T \sum_{t=1}^{T} e_{it}^2$, then the score contribution for unit i is given by

$$\frac{\partial \log L}{\partial \phi_i} = \frac{1}{\hat{\sigma}_i^2} \sum_{t=2}^{T} (\Delta \hat{S}_{it} - \Delta \hat{S}_i)(\hat{S}_{it} - \hat{S}_i), \tag{19}$$

where $\hat{S}_{it}$ is a certain residual defined below, while $\Delta \hat{S}_i$ and $\hat{S}_i$ are the mean values of $\Delta \hat{S}_{it}$ and $\hat{S}_{it}$, respectively. The score vector is proportional to the numerator of the least squares estimate of ϕ_i in the regression

$$\Delta \hat{S}_{it} = \text{constant} + \phi_i \hat{S}_{it-1} + \text{error}. \tag{20}$$

It follows that a test of the null of no cointegration for cross-section unit i can be formulated equivalently as a zero-slope restriction in Equation (20), which can be tested by means of either the least squares estimate of ϕ_i or its t-ratio. Hence, by considering the form of the log-likelihood function, a panel test of H_0 vs. H_1 can be constructed by using the cross-sectional sum of these statistics for each i.

In the presence of cross-sectional dependence, the variable $\hat{S}_{it}$ can be computed as

$$\hat{S}_{it} := y_{it} - \hat{\alpha}_{it} - \hat{\eta}_i t - \hat{\delta}_i D_{it} - x_{it}' \hat{\beta}_i - (D_{it} x_{it})' \hat{\gamma}_i - \hat{\lambda}_i' \hat{F}_t, \tag{21}$$

where the common factor $\hat{F}_t$ is the accumulated sum of the principal component estimates $\Delta \hat{F}$ of ΔF. This defactoring makes the test robust to cross-sectional dependence generated by common factors, while the test regression can additionally be augmented to also make it robust to serial correlation

$$\Delta \hat{S}_{it} = \text{constant} + \phi_i \hat{S}_{it-1} + \sum_{j=1}^{p_i} \phi_{ij} \Delta \hat{S}_{it-j} + \text{error}. \tag{22}$$

To obtain the new panel test, Westerlund and Edgerton (2008) define

$$\mathrm{LM}_{\phi}(i) := T\hat{\phi}_i\left(\frac{\hat{\omega}_i}{\hat{\sigma}_i}\right), \tag{23}$$

where $\hat{\phi}_i$ is the least squares estimate of ϕ_i in Equation (22) with $\hat{\sigma}_i$ as the estimated standard error from the same regression, and $\hat{\omega}_i^2$ is the estimated long-run variance of $\Delta\upsilon_{it}$ based on $\hat{S}_{it}$. To obtain the second test statistic, Westerlund and Edgerton (2008) introduce the t-ratio of $\hat{\phi}_i$ given by

$$\mathrm{LM}_{\tau}(i) := \frac{\hat{\phi}_i}{\mathrm{SE}(\hat{\phi}_i)}, \tag{24}$$

where $\mathrm{SE}(\hat{\phi}_i)$ is the estimated standard error of $\hat{\phi}_i$. Based on $\mathrm{LM}_{\phi}(i)$ and $\mathrm{LM}_{\tau}(i)$ Westerlund and Edgerton (2008) propose the two panel LM-based test statistics for the null of no cointegration as

$$\overline{\mathrm{LM}}_{\phi}(N) := \frac{1}{N}\sum_{i=1}^{N}\mathrm{LM}_{\phi}(i), \quad \text{and} \quad \overline{\mathrm{LM}}_{\tau}(N) := \frac{1}{N}\sum_{i=1}^{N}\mathrm{LM}_{\tau}(i). \tag{25}$$

Finally, in consideration of the asymptotic properties of $\mathrm{LM}_{\phi}(i)$ and $\mathrm{LM}_{\tau}(i)$, Westerlund and Edgerton (2008) obtain the following normalised test statistics[10]

$$Z_{\phi}(N) = \sqrt{N}(\overline{\mathrm{LM}}_{\phi}(N) - E(B_{\phi})), \tag{26}$$

$$Z_{\tau}(N) = \sqrt{N}(\overline{\mathrm{LM}}_{\tau}(N) - E(B_{\tau})). \tag{27}$$

3.3.1 Estimation of breaks

Westerlund and Edgerton (2008) follow the strategy of Bai and Perron (1998) to determine the location of structural breaks. The approach developed by Bai and Perron (1998) allows for general forms of serial correlation and heteroskedasticity in the errors, lagged dependent variables, trending regressors, as well as different distributions for the errors and the regressors across the segments that are separated by the breaks. Moreover, they consider the case of a partial structural change model meaning that not all parameters are necessarily subject

[10]The complete analysis of the asymptotic properties of the newly developed tests and the explicit derivation of $Z_{\phi}(N)$ and $Z_{\tau}(N)$ are explained in Westerlund and Edgerton (2008).

to shifts. In line with this approach Westerlund and Edgerton (2008) individually estimate the break point(s) for each panel member i by minimising the sum of squared residuals from the regression in Equation 13 in first differences. The break point estimator is defined as

$$\hat{\tau}_i = \underset{0<\tau_i<1}{\arg\min} \frac{1}{T-1} \sum_{t=2}^{T} (\Delta \hat{z}_{it})^2. \tag{28}$$

3.4 Long-run estimators

Pesaran (2006) proposed common correlated effects (CCE) estimators to estimate heterogeneous panel data models with a multifactor error structure. The basic idea is to filter the cross-unit specific regressors by means of cross-section averages of the dependent variable and the observed regressors. Thus, cross-sectional dependence can be eliminated since the unobserved common factors can be well approximated by those cross-section averages. Therefore, the number of the stationary factors need not to be estimated. The CCE procedure can be computed by running standard panel regressions where the observed regressors are augmented with cross-sectional averages of the dependent variable and the cross unit-specific regressors. Pesaran (2006) developed two CCE estimators, the pooled and mean group CCE estimator, to consider two different but related estimation and inference problems: one that concerns the coefficients of the cross unit-specific regressors and the other that focuses on the means of the individual coefficients. Kapetanios et al. (2011) extend the work of Pesaran (2006) to the case where the unobserved common factors are non-stationary. They show that the CCE estimators are consistent even in the presence of unit roots in the unobserved common factors and are also robust to structural breaks in the mean of those unobserved factors.

Pesaran (2006) assumed the heterogeneous panel data model with y_{it} as the observation on the i-th panel member at time t for $i = 1, ..., N$ and $t = 1, ..., T$

$$y_{it} = \alpha_i' d_t + \beta_i' x_{it} + e_{it}, \tag{29}$$

where d_t represents a $(n \times 1)$ vector of observed common effects including, on the one hand, deterministic components such as intercepts or seasonal dummies and, on the other hand, non-stationary observed common effects such as the oil price. The observed cross unit-specific regressors are denoted by the $(k \times 1)$ vector x_{it}, while the error term e_{it} is specified by a multifactor structure

$$e_{it} = \gamma_i' f_t + \varepsilon_{it}, \tag{30}$$

where f_t denotes the $(m \times 1)$ vector of unobserved common factors and ε_{it} are the cross unit-specific (idiosyncratic) disturbance terms, which are assumed to be independently distributed of $(d_t,\ x_{it})$. Since the unobserved factors f_t could be correlated with $(d_t,\ x_{it})$, a general specification of the cross unit-specific regressors is adopted

$$x_{it} = A_i' d_t + \Gamma_i' f_t + v_{it}, \tag{31}$$

where A_i and Γ_i denote $(n \times k)$ and $(m \times k)$ factor loading matrices with fixed components, and v_{it} are the specific components of x_{it} distributed independently of the common effects and across i, but assumed to follow general covariance stationary processes.

Combining Equations (29)-(31) yields the system

$$\underset{((k+1)\times 1)}{z_{it}} = \begin{pmatrix} y_{it} \\ x_{it} \end{pmatrix} = \underset{((k+1)\times n)}{B_i'} \underset{(n\times 1)}{d_t} + \underset{((k+1)\times m)}{C_i'} \underset{(m\times 1)}{f_t} + \underset{((k+1)\times 1)}{u_{it}}, \tag{32}$$

where

$$u_{it} = \begin{pmatrix} \varepsilon_{it} + \beta_i' v_{it} \\ v_{it} \end{pmatrix} = \begin{pmatrix} 1 & \beta_i' \\ 0 & I_k \end{pmatrix} \begin{pmatrix} \varepsilon_{it} \\ v_{it} \end{pmatrix}, \ B_i = \begin{pmatrix} \alpha_i & A_i \end{pmatrix} \begin{pmatrix} 1 & 0 \\ \beta_i & I_k \end{pmatrix}, \ C_i = \begin{pmatrix} \gamma_i & \Gamma_i \end{pmatrix} \begin{pmatrix} 1 & 0 \\ \beta_i & I_k \end{pmatrix}, \tag{33}$$

with I_k as the identity matrix of order k. The rank of C_i is determined by the rank of the $(m \times (k+1))$ matrix of the unobserved factor loadings $\tilde{\Gamma}_i = \begin{pmatrix} \gamma_i & \Gamma_i \end{pmatrix}$.[11]

Pesaran (2006) suggested the use of cross-section averages of the dependent variable, y_{it}, and the regressors, x_{it}, as proxies for the unobserved common factors. For illustration pur-

[11] See Pesaran (2006) for details on the underlying assumptions.

poses of the elimination of those factors, consider the simple cross-section averages of the Equations in (32)[12]

$$\bar{z}_t = \bar{B}'d + \bar{C}'f_t + \bar{u}_t, \tag{34}$$

where $\bar{z}_t = 1/N \sum_{i=1}^{N} z_{it}$, $\bar{v}_t = 1/N \sum_{i=1}^{N} u_{it}$, $\bar{B} = 1/N \sum_{i=1}^{N} B_i$ and $\bar{C} = 1/N \sum_{i=1}^{N} C_i$. Suppose that $\text{Rank}(\bar{C}) = m \leq k+1$ for all N, so that $f_t = (\bar{C}\bar{C}')^{-1}\bar{C}(\bar{z}_t - \bar{B}'d_t - \bar{u}_t)$. If $u_t \to 0$ and $\bar{C} \xrightarrow{p} C$ as $N \to \infty$ then

$$f_t - (CC')^{-1}C(\bar{z}_t - \bar{d}) \xrightarrow{p} 0, \text{ as } N \to \infty. \tag{35}$$

This suggests that it is valid to use $\bar{h}_t = (d_t', \bar{z}_t')$ as observable proxies for the unobservable common factors f_t, and justified the basic idea of the common correlated effects (CCE) estimators proposed by Pesaran (2006).

Pesaran (2006) presents two estimators of the means of the cross unit-specific slope coefficients. One is the mean group (MG) estimator developed in Pesaran and Smith (1995) and the other is a generalisation of the fixed effects (FE) estimator that considers potential cross-sectional dependence. First, the common correlated effects mean group (CCEMG) estimator is a simple average of the individual CCE estimators, $\hat{b}_i$ of β_i, defined as

$$\hat{b}_{CCEMG} = \frac{1}{N}\sum_{i=1}^{N}\hat{b}_i, \tag{36}$$

$$\hat{b}_i = (X_i'\bar{M}X_i)^{-1}X_i'\bar{M}y_i, \tag{37}$$

where $X_i = (x_{i1}, ..., x_{iT})'$, $y_i = (y_{i1}, ..., y_{iT})$, and $\bar{M} = I_T - \bar{H}(\bar{H}'\bar{H})^{-1}\bar{H}'$ with $\bar{H} = (D, \bar{Z})$, where D and $\bar{Z}$ denote the $(T \times n)$ and $(T \times (k+1))$ matrices of observations on d_t and $\bar{z}_t$, respectively.

Second, if the individual slope coefficients, β_i, are the same, efficiency could be gained by pooling. Hence, Pesaran (2006) developed the common correlated effects pooled (CCEP)

[12] Pesaran (2006) applied more general weighted cross-section averages. To simplify the illustration, this study restricts the discussion about the CCE estimators to simple averages (see Kapetanios et al., 2011).

estimator given by

$$\hat{b}_{CCEP} = \left(\sum_{i=1}^{N} X_i' \bar{M} X_i \right)^{-1} \sum_{i=1}^{N} X_i' \bar{M} y_i. \tag{38}$$

3.5 Panel Causality

To examine the direction of causality between energy consumption and economic growth this study employs a dynamic panel error-correction specification

$$\Delta Y_{it} = \alpha_i^y + \sum_{k=1}^{h} \theta_{1i,k}^y \Delta Y_{i,t-k} + \sum_{k=0}^{h} \theta_{2i,k}^y \Delta E_{i,t-k} + \lambda_i^y \varepsilon_{i,t-1}^y + u_{it}^y \tag{39}$$

$$\Delta E_{it} = \alpha_i^e + \sum_{k=1}^{h} \theta_{1i,k}^e \Delta E_{i,t-k} + \sum_{k=0}^{h} \theta_{2i,k}^e \Delta Y_{i,t-k} + \lambda_i^e \varepsilon_{i,t-1}^e + u_{it}^e, \tag{40}$$

where $i = 1, ..., N$ represents the countries and $t = 1, ..., T$ denotes the time period while Y_{it} and E_{it} are economic growth and energy consumption in logarithms, respectively. Δ denotes the first-difference operator, α_i stands for the fixed effects, k denotes the lag length, $\varepsilon_{i,t-1}$ represents the one period lagged error-correction term, and u_{it} is the serially uncorrelated error term with mean zero. The coefficients $\theta_{1i,k}^j$ and $\theta_{2i,k}^j$, $j = y, e$, denote the short-run dynamics while λ_i^j, $j = y, e$, represents the speed of adjustment. The present paper applies the pooled mean group (PMG) estimator proposed by Pesaran et al. (1999) to estimate the Equations (39) and (40). While instrumental variable estimators such as the widely used Arellano and Bond (1991) GMM estimator require pooling of individuals and allow only the intercepts to differ across countries, the PMG estimator allows for the investigation of long-run homogeneity without making the less plausible assumption of identical short-run dynamics in each country. Furthermore, the mean group estimator (see Pesaran and Smith, 1995) that averages the coefficient of the country-specific regressions is a consistent but no good estimator when either N or T is small (Hsiao et al., 1999). In comparison, the PMG estimator relies on a combination of pooling and averaging of coefficients. The optimal lag length is selected by means of the Schwarz Information Criterion.

The direction of causality can be determined by testing for the significance of the coefficients of each dependent variable in Equations (39) and (40). First, this study considers short-run causality by testing the null hypotheses $H_0 : \theta^{y}_{2ik} = 0$ and $H_0 : \theta^{e}_{2ik} = 0, \forall ik$. The former checks whether causality runs from energy consumption to economic growth and the latter whether economic growth leads energy consumption. Second, long-run causality can be identified by testing the significance of the speed of adjustment, i.e. to test whether the coefficient of the respective error-correction term represented by λ^{j}_{i}, $j = y, e$, is equal to zero. Finally, this study tests for strong causality by applying joint tests including the coefficients of the respective explanatory variable and the respective error-correction term of each equation. Since all variables are represented in stationary form the various null hypotheses can be tested using standard Wald tests with a *chi-squared* distribution.

4 Empirical analysis

4.1 Data and empirical specification

This study uses annual data from 1971 to 2009 for 23 OECD countries. These are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Luxembourg, Mexico, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States. Data on real GDP per capita in constant 2000 U.S. dollars is used as a proxy for economic growth (Y) and energy consumption is represented by energy use in kilograms of oil equivalent per capita (E).[13] All variables are in natural logarithms and have been obtained from the World Bank's World Development Indicators.

To examine the energy consumption-growth nexus the present empirical analysis is based on the following panel regression model specifying the relationship between real GDP per capita, Y_{it}, and energy consumption per capita, E_{it},

$$Y_{it} = \alpha_i + \beta_i E_{it} + \varepsilon_{it}, \tag{41}$$

[13] This study uses per capita data because they are less sensitive to territorial changes and provide the variables in the same units for countries of different sizes (Lanne and Liski, 2004).

where $i = 1, ..., N$ represents each of the 23 OECD countries and $t = 1, ..., T$ denotes each year during the period 1971 to 2009.

4.2 Cross-section dependence tests

As a first step, this study applies the cross-section dependence (CD) test developed by Pesaran (2004) to verify the consideration of cross-section dependence in the analysis of the energy consumption-growth nexus. Thus, both real GDP per capita and energy consumption per capita are initially tested for dependence across the 23 OECD countries under investigation. The pair-wise correlations which are necessary to compute the CD statistics are obtained from the residuals of the regression of each variable on a constant, a linear trend and a lagged dependent variable for each country. The results of the CD tests based on these correlations indicate that GDP and energy consumption are highly dependent across countries. The null hypothesis of cross-section independence can be clearly rejected by a value of 43.80 for real GDP ($p = 0.45$) and 31.63 for energy consumption ($p = 0.34$).[14] This finding underlines the already mentioned importance of taking into account cross-section dependence when analysing the energy consumption-growth nexus.

4.3 Unit root tests

As a starting point of the integration analysis, this study applies the first generation panel unit root tests which neglect the presence of both structural breaks and cross-section dependence, but are commonly used in the panel data literature on the energy consumption-growth nexus. Specifically, the Levin et al. (2002) (LLC) test and the t-statistic proposed by Breitung (2000) which both tests for a common unit root process as well as the W-statistic suggested by Im et al. (2003) (IPS), the Fisher-type ADF and Fisher-type PP test (see Choi, 2001; Maddala and Wu, 1999) that assume individual unit root processes are applied. Without exception, all unit root tests assume non-stationarity under the null hypothesis. Since these tests are meanwhile widely used and previously described the present paper does not discuss further details of them. As displayed in Table 2, the results suggest that real GDP

[14]The CD test are performed using the Stata routine "xtcsd" proposed by De Hoyos and Sarafidis (2006).

per capita and energy consumption per capita are integrated of order one, $I(1)$.[15]

Table 2: Panel unit root test statistics without structural breaks and cross-section dependence

Variable	LLC	Breitung	IPS	ADF-Fisher	PP-Fisher
Y	3.15	10.53	1.19	47.14	24.39
ΔY	-7.07***	1.09	-12.05***	237.38***	192.67***
E	1.13	5.33	-0.00	51.85	48.41
ΔE	-18.59***	-8.80***	-21.84***	458.26***	465.91***

Notes: Probabilities for the Fisher-type tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality. The choice of lag levels for the Breitung, IPS and Fisher-ADF test are determined by empirical realisations of the Schwarz Information Criterion. The LLC and Fisher-PP tests were computed using the Bartlett kernel with automatic bandwidth selection. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

The failure of the first generation panel unit root tests to reject the null of non-stationarity for the levels of the variables may be due to the omission of structural breaks (Perron, 1989). Thus, the consideration of structural breaks and, additionally, cross-section dependence should provide more reliable results. Consequently, this study applies the second generation panel unit root test proposed by Bai and Carrion-i-Silvestre (2009) as a second step. This test allows for structural breaks in the level, slope or both, which can occur at different dates for different countries and may have different magnitudes of shift. Furthermore, the common factor approach enables the common shocks to affect countries differently via heterogeneous factor loadings.

The results of the test developed by Bai and Carrion-i-Silvestre (2009) are presented in Table 3 and confirm the finding of non-stationarity in the variables. The null hypothesis of a unit root cannot be rejected for all tests in the model without any break, with a break in the mean and with a break in the trend.

4.4 Cointegration tests

Once integration of order one is established, the next step is to determine whether a long-run relationship between GDP and energy consumption exists. To examine the existence of a

[15] The results of all noted first generation panel unit root tests are examined using EViews 6.0.

Table 3: Panel unit root test statistics with structural breaks and cross-section dependence

Model	Test	Y	E
Constant and trend	Z	0.56	-0.53
	P	33.36	57.75
	P_m	-1.32	1.22
Mean shift	Z	0.34	-0.75
	P	38.35	38.51
	P_m	-0.80	-0.78
Trend shift	Z	-0.20	-1.06
	P	44.37	49.04
	P_m	-0.17	0.32
	Z^*	1.49	1.05
	P^*	35.91	45.89
	P_m^*	-1.05	-0.01

Notes: P^* and P_m^* denote the corresponding P and P_m statistics that are computed by means of the p-values of the simplified MSB statistics, respectively. The 1%, 5% and 10% critical values for the standard normal distributed Z and P_m statistics are 2.326, 1.645 and 1.282, while the critical values for the chi-squared distributed P statistic are 71.201, 62.830 and 58.641, respectively. The number of common factors are estimated using the panel Bayesian information criterion proposed by Bai and Ng (2002).

cointegration relationship this study repeats both types of tests, with and without structural breaks and cross-sectional dependence. Firstly, the first generation panel cointegration tests proposed by Kao (1999) and Pedroni (1999, 2004), and implemented in EViews 6.0, are applied. Kao (1999)'s test is a generalisation of the Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests in the context of panel data. Pedroni proposes seven test statistics that can be distinguished in two types of residual based tests. Four tests are based on pooling the residuals of the regression along the within-dimension of the panel (panel tests), while three are based on pooling the residuals along the between-dimension (group tests). Both Kao and Pedroni assume the null hypothesis of no cointegration and use the residuals determined by a panel regression to construct the test statistics and determine the asymptotically normal distribution.

Table 4 reports the empirical realisations of Kao's and Pedroni's panel cointegration tests. With the exception of the panel υ-statistic in the case with trend, none of the test statistics result in the rejection of the null hypothesis of no cointegration. Hence, the results of these first generation panel cointegration tests that neither allow for structural breaks nor cross-section dependence suggest no evidence for a long-run equilibrium relationship between energy consumption per capita and real GDP per capita.

Table 4: Panel cointegration test results without structural breaks and cross-section dependence

Pedroni's panel cointegration test results			
without trend		*with trend*	
Test statistics	Values	Test statistics	Values
Panel υ-Statistic	-2.60	Panel υ-Statistic	15.96***
Panel ρ-Statistic	2.24	Panel ρ-Statistic	2.55
Panel PP-Statistic	2.32	Panel PP-Statistic	2.05
Panel ADF-Statistic	2.25	Panel ADF-Statistic	2.03
Group ρ-Statistic	1.51	Group ρ-Statistic	2.38
Group PP-Statistic	2.05	Group PP-Statistic	1.71
Group ADF-Statistic	1.28	Group ADF-Statistic	1.11
Kao's panel cointegration test result			
ADF-statistic	-1.10		

Notes: The null hypothesis is that the variables are not cointegrated. Under the null hypothesis, all the statistics are distributed as standard normal distributions. The finite sample distribution for the seven statistics has been tabulated in Pedroni (2004). *, **, and *** indicate that the estimated parameters are significant at the 10%, 5%, and 1% levels, respectively.

Similar to the first generation unit root tests, the first generation panel cointegration tests may not be able to reject the null because of the missing consideration of structural breaks. Hence, in a second step, this study applies the LM-based tests proposed by Westerlund and Edgerton (2008) that simultaneously consider cross-section dependence and structural breaks, which may be located at different dates for different panel members. Additionally, this test allows for heteroskedastic and serially correlated errors, and cross unit-specific time trends.

Both test statistics $Z_\phi(N)$ and $Z_\tau(N)$ of Westerlund and Edgerton (2008) reveal evidence in favour of a long-run relationship between energy consumption per capita and real GDP per capita when allowing for breaks in the level and the slope of this relationship (see Table 5). Narayan and Smyth (2008) proposed the same finding that Pedroni's test statistics do not reject the null of no cointegration whereas once structural breaks are incorporated they found cointegration by means of the test suggested by Westerlund (2006).

Table 5: Panel cointegration test results with structural breaks and cross-section dependence

Model	$Z_\phi(N)$	$Z_\tau(N)$
No break	-5.33***	-1.68***
Mean shift	-2.27**	-1.48*
Regime shift	-2.41***	-1.75***

Notes: The LM-based test statistics $Z_\phi(N)$ and $Z_\tau(N)$ are normal distributed. The number of common factors is determined by means of the information criterion proposed by Bai and Ng (2004) and the maximum number is set to 5. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Furthermore, Table 6 reports the contemporaneously estimated breaks for each country. Applying the approach of Westerlund and Edgerton (2008) this study finds one structural break for each country in both specifications with mean shift and regime shift. Those can be associated with huge global shocks. Several countries share the common break dates 1974 in consequence of the first oil crisis in 1973, 1990 at the time of Iraq's invasion of Kuwait with the subsequent oil price increase, 2002 in the aftermath of the sharp oil price decreases in the 1997-1999 Asian crisis and in 2001/2002 around the September 11 attacks, and 2005 marking the large and continued rise in oil prices until 2008. Additionally, there are many occasional breaks in the late 1970s and during the 1980s reflecting the turbulence throughout this period including the 1978 Iranian revolution and the Iran-Iraq War, accompanied by exploding oil prices and a period of high inflation during the late 1970s, the global economic recession in the early 1980s, the fall in oil prices in 1986, the 1987 Wall Street stock market crash, and the periods of moderate economic growth and low inflation in Western industrialised countries in the late 1980s and early 1990s.

A comparison with previous studies reporting explicit estimated break dates in the cointegration relation between energy consumption and economic growth reveals that these findings can be roughly confirmed by Narayan and Smyth (2008) who found structural breaks of the energy consumption-growth nexus for the G7 countries during the 1980-1988 sub-period of the whole sample period 1972-2002, and Lee and Chiu (2011) who provide the occurrence of structural breaks for six developing countries during the periods 1976-1979, 1982-985, and 1991-1992 when analysing nuclear energy consumption from 1971-2006. Since the

Table 6: Estimates of breaks

Country	Mean shift	Regime shift
Australia	1982	1982
Austria	1976	2005
Belgium	1979	1979
Canada	1990	1990
Denmark	1974	2005
Finland	1979	1979
France	1992	1976
Germany	1990	2002
Greece	1986	1986
Hungary	1990	1990
Ireland	1978	1987
Italy	2002	2002
Japan	1984	1998
Luxembourg	1985	1985
Mexico	1999	1999
Netherlands	1998	2005
Norway	2002	1988
Portugal	1974	1974
Spain	1977	1986
Sweden	1992	2005
Switzerland	1974	1974
United Kingdom	1990	1990
United States	1990	1990

Notes: The break dates are selected by means of the test approach suggested in Westerlund and Edgerton (2008) which follows the strategy of Bai and Perron (1998) to determine the location of structural breaks.

present analysis includes three to four times more countries than the studies by Narayan and Smyth (2008) and Lee and Chiu (2011) over a larger sample period, this paper is able to more clearly determine structural breaks that are common to several countries due to global shocks such as the first oil crisis in 1973.

4.5 Long-run estimations

As a next step, the present paper explicitly estimates the long-run relationships between energy consumption per capita and real GDP per capita:

$$
\begin{aligned}
Y_{i,t} &= \alpha_i^y + \delta_i^y t + \beta_i^y E_{i,t} + \varepsilon_{i,t}^y \\
E_{i,t} &= \alpha_i^e + \delta_i^e t + \beta_i^e Y_{i,t} + \varepsilon_{i,t}^e
\end{aligned}
\tag{42}
$$

where $i = 1, ..., N$ refers to each country in the panel and $t = 1, ..., T$ denotes the time period, α_i and δ_i are country-specific fixed effects and time trends, respectively. For this purpose, this study uses not only the fixed effects (FE) and mean group (MG) estimator proposed by Pesaran and Smith (1995) but also Pesaran's (2006) common correlated effects (CCE) estimators to consider the presence of common factors which cause cross-section dependence. In addition to dependence across countries, the detected structural breaks can be taken into account by including country-specific dummy variables that are specified accordingly to the estimated break dates (see Table 6) as described in the robustness check below.

The results of the long-run estimates are reported in Table 7. The first two columns give the naive pooled fixed effects and mean group estimates. As the CD test statistics show, these exhibit considerable cross-section dependence. In contrast, the common correlated effects pooled (CCEP) and common correlated effects mean group (CCEMG) estimates in the other two columns have a purged and, hence, greatly reduced cross-section dependence. The estimated income elasticities of energy consumption, β^e, in the first row of Table 7 (0.50-0.71) are larger than the estimated long-run coefficients of energy consumption, β^y, affecting real GDP (0.26-0.41). This finding indicates, regardless of the yet to be determined direction of causation, that real GDP has a stronger impact on energy consumption in the long run than vice versa.

The same conclusion might be drawn from other empirical studies analysing the energy consumption-growth nexus for OECD countries that report estimated long-run elasticities. Lee et al. (2008) estimated a long-run coefficient of energy consumption of 0.25 and Narayan and Smyth (2008) reported the corresponding values 0.12, 0.16 and 0.39 whereas Lee and Lee (2010) estimated a larger value for the income elasticity of 0.52. However, as long as there are only a few studies reporting long-run elasticities no conclusion can be drawn. A comparison of these results with those of the present study reveals that they do not differ to an important degree. The reported values of previous studies are slightly smaller, if different at all, which might be due to the inclusion of either energy prices or capital as an additional explanatory variable.

Table 7: Results of long-run estimations

Dep.	FE		MG		CCEP		CCEMG	
Var.	β	CD	β	CD	β	CD	β	CD
Y_{it}	0.41 [7.95] (0.05)	12.95	0.40 [8.06] (0.05)	14.37	0.40 [4.81] (0.08)	-3.76	0.26 [3.65] (0.07)	-3.50
E_{it}	0.64 [5.75] (0.11)	22.61	0.71 [8.05] (0.09)	19.62	0.66 [4.21] (0.16)	-4.01	0.50 [3.91] (0.13)	-3.69

Notes: Numbers in parentheses are standard errors and numbers in brackets represent the t-statistics. CD denotes the cross-section dependence test proposed by Pesaran (2004) which assumes cross-section independence under the null hypothesis.

Furthermore, the present paper checks the robustness of its estimated long-run elasticities by the inclusion of country-specific dummy variables that are specified according to the detected breaks in the mean and/or trend as reported in Table 6 and oil prices as an observed common factor. The results do not qualitatively change and are available upon request from the author.

4.6 Dynamic panel causality

Finally, this section analyses the main objective of this study on the energy consumption-growth nexus: the direction of causation between energy consumption and economic growth. This is done by the application of the pooled mean group (PMG) estimator proposed by Pesaran et al. (1999) to the dynamic panel error-correction specification in Equations (39) and (40), and Wald *chi-squared* tests to evaluate the various Granger causality relationships.[16] Table 8 shows the corresponding results.

Table 8: Results of panel causality tests for the energy consumption-growth nexus in OECD countries - revisited

Dependent Variable	Sources of causation (independent variable)						
	Short-run				Long-run	Strong causality	
	ΔY		ΔE		ECT	ΔY, ECT	ΔE, ECT
ΔY	-		74.69***	(0.24)	-0.06***	-	154.46***
ΔE	235.87***	(0.80)	-		-0.11***	238.22***	-

Notes: Table 8 reports the empirical realisations of the Wald *chi-squared* test statistics for short-run and strong causality. The sum of the (lagged) coefficients for the respective short-run changes is denoted in parentheses. The lag length is two. ECT represents the coefficient of the error-correction terms ε^y and ε^e, respectively. ***, ** and * indicate that the null hypothesis of no causation is rejected at the 1%, 5% and 10% levels, respectively.

The empirical exercise reveals a bi-directional causal relationship between ΔY and ΔE in all three cases, short-run, long-run and strong causality. Hence, energy consumption per capita Granger-causes real GDP per capita and vice versa, implying that an increase in one leads to an increase in the other. Similar to the long-run estimation results, the examination of the sum of lagged coefficients on the respective variable indicates that real GDP (0.80) has also in the short run a greater impact on energy consumption than vice versa (0.24). Furthermore, the significance of the error correction terms (ECT) indicates that both variables readjust towards a long-run equilibrium relationship after a shock occurs. The estimated speed of adjustment of real GDP (-0.06) is slightly slower than the speed of adjustment of energy consumption (-0.11). With respect to the energy consumption-growth nexus these findings lend support for the feedback hypothesis which argues that energy consumption and real GDP affect each other simultaneously.

In the empirical literature on the energy consumption-growth nexus of OECD countries the

[16] This study uses the Stata routine "xtpmg" proposed by Blackburne and Frank (2007) to estimate the dynamic panel error-correction model by means of the pooled mean group estimator and test for significance.

same finding is also reported by the panel data analyses of Lee and Chang (2007), Lee et al. (2008), Costantini and Martini (2010), Lee and Lee (2010), and Belke et al. (2011). More precisely, Costantini and Martini (2010) and Lee and Lee (2010) report bi-directional short-run and strong causality whereas in the long run real GDP is found to be a driver for energy consumption indicating that energy policies have no adverse impact on economy's long-run growth. The smaller long-run and adjustment coefficients of energy consumption compared to real GDP estimated by the present study also give evidence in this direction. Compared with other previous panel data studies on OECD countries, the findings of bi-directional causal relationships contradict, on the one hand, those of Huang et al. (2008) who found a uni-directional causal relationship running from economic growth to energy consumption with a negative impact, and, on the other, those of the panel data analysis by Narayan and Smyth (2008) who inferred that energy consumption Granger-causes real GDP positively in the long run. Furthermore, the empirical results of this study also refute the neutrality hypothesis such as all other panel data studies on the energy consumption-growth nexus, except for the sub-analysis by Huang et al. (2008) of 19 low income countries.

5 Conclusion

This study has analysed the causal relationship between real GDP and energy consumption for a panel of 23 OECD countries covering the period 1971-2009. Recognising the lack consensus of the widely studied energy consumption-GDP growth nexus it is appropriate to take into special consideration important issues that were largely neglected by the empirical literature so far. These include most of all structural breaks and dependence across countries when using panel data. Their consideration is promising toward providing more suitable and reliable results since the occurrence of critical energy and economic events that likely may cause structural breaks and the existence of strong inter-economic linkages between OECD countries cannot plausibly be ignored. Consequently, the present paper has applied recently developed panel econometric techniques to tackle these issues.

Indeed, a long-run equilibrium relationship between real GDP and energy consumption can only be found when taking into account structural breaks and cross-section dependence. In addition, the thereby estimated breaks can be associated with well-known global shocks. The empirical evidence reveals that a 1% increase in energy consumption leads to an increase in real GDP of 0.26-0.41%. In turn, the estimated income elasticity of energy consumption turns out to be 0.50-0.71. Furthermore, panel causality tests indicate bi-directional causality between real GDP and energy consumption in the short and long run. Hence, no variable leads the other. This finding supports evidence for the feedback hypothesis which argues that real GDP and energy consumption affect each other simultaneously.

Strong policy implications emerge for governments with regard to the implementation of energy conservation policies. Initially, the empirical results suggest that energy consumption and real GDP are both endogenous and, hence, single equation forecasts of one of them might be misleading. Furthermore, energy conservation policies, on the one hand, are faced with the unpleasant situation of directly and adversely affecting economic growth when reducing energy consumption. On the other hand, there may also be an indirect feedback effect of economic growth on energy consumption. Interestingly, the empirical results suggest that in the short and long run, energy consumption has a smaller impact on economic growth than vice versa. Thus, the adverse affect of energy conservation policies on economic growth should not be overemphasized as compared to the larger impact of economic growth on energy consumption. However, policy makers may be worried about limiting economic growth even though the OECD countries have high potential for energy savings since their level of energy consumption per capita and CO_2 emissions per capita are far above the world averages. Hence, to ease the trade-off between energy consumption and economic growth such governments should implement energy policies that emphasise the use of alternative energy sources rather than exclusively try to reduce overall energy consumption in order to minimise dioxide emissions. Accordingly, they should make the necessary efforts to increase the investments in energy infrastructure and the restructuring of the energy sector to change the composition of energy consumption by substituting environmental friendly energy sources for fossil fuels (see Lee and Lee, 2010; Narayan and Smyth, 2008). To reduce greenhouse gas emissions OECD countries should also encourage their industries to invest in new technologies that make alternative energy sources more feasible.

However, the empirical finding that energy consumption causes economic growth does not necessarily imply that energy conservation will harm economic growth if energy-efficient production technologies are used. In fact, a reduction in energy consumption due to improvements in energy efficiency may raise productivity, which in turn may stimulate economic growth. Thus, a shift from less efficient and more polluting energy sources to more efficient energy options may establish a stimulus rather than an obstacle to economic development (Costantini and Martini, 2010).

Moreover, the empirical results of the present study indicate that there is cross-section dependence in real GDP, energy consumption and their long-run relationship, and that such a relation can only be detected when considering structural breaks. These findings suggest the importance for policy makers to base their decisions on studies of the long-run relationship and direction of causation that take into account relationships of dependency across countries and the impact of past exogenous shocks. Hence, this study motivates both researchers and politicians to follow this new direction of research to properly assess energy models, reliably predict future developments, and design sensible energy policies to restructure the energy sector and conserve energy. An interesting task for future research may be the analysis of supplementary energy sources and different sectoral patterns of energy consumption for a sensible implementation of specific energy policies.

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