Energy Economics 32 (2010) 591–603

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

The causality between energy consumption and economic growth: A multi-sectoral analysis using non-stationary cointegrated panel data

Valeria Costantini [a,*], Chiara Martini [b]

[a] Department of Economics, University of Roma Tre, 77 Via Silvio D'Amico, 00145 Rome, Italy
[b] Italian National Agency for New Technologies, Energy and Environment (ENEA), Lungotevere Thaon di Revel, 76-00196 Rome, Italy

ARTICLE INFO

Article history:
Received 4 February 2009
Received in revised form 16 September 2009
Accepted 26 September 2009
Available online 6 October 2009

JEL classification:
C01
C32
C33
O13
Q43

Keywords:
Energy sector
Panel unit roots
Panel cointegration
Vector Error Correction Models
Granger causality

ABSTRACT

The increasing attention given to global energy issues and the international policies needed to reduce greenhouse gas emissions have given a renewed stimulus to research interest in the linkages between the energy sector and economic performance at country level. In this paper, we analyse the causal relationship between economy and energy by adopting a Vector Error Correction Model for non-stationary and cointegrated panel data with a large sample of developed and developing countries and four distinct energy sectors. The results show that alternative country samples hardly affect the causality relations, particularly in a multivariate multi-sector framework.

1. Introduction

The increasing attention given to global energy issues and the international policies needed to reduce greenhouse gas (GHG) emissions have given a renewed stimulus to research interest in the linkages between the energy sector and economic performance at country level. The empirical analyses and the adopted models for investigating these linkages highly depend on the development level and economic structure of the countries considered.

Toman and Jemelkova (2003) argue that most of the literature on energy and economic development discusses how development affects energy use rather than vice versa. This strand of literature considers economic growth as the main driver for energy demand and only advanced economies with a high degree of innovation capacity can decrease energy consumption without reducing economic growth.

Stern and Cleveland (2004), on the other hand, have stressed the importance of considering the effect of changes in energy supply on economic growth in both developed and developing countries. When energy supply is considered a homogenous input for the production function, economic development is harmed if policy constraints affect energy supply. When energy services are differentiated, emphasizing the existence of higher and lower-quality forms of energy, society should make a choice in terms of an optimal energy mix, considering that higher-quality energy services could produce increasing returns to scale. This means that energy regulation policies could provide impulse to economic growth rather than be detrimental to the development process, since they support the shift from lower-quality (typically less efficient and more polluting) to higher-quality energy services.

If we consider energy consumption as a function of economic output, regulation and technical innovation, a suitable representation is the formalization provided in Medlock and Soligo (2001) as expressed in Eq. (1):

$$EC_{tj} = f(Y_{tj}, p_{tj}, \tau(Y_{tj}, p_{tj})) \tag{1}$$

where energy consumption (EC) at time t for each j-th end-use sector is a function of economic output (Y), energy prices (p) and technology (τ). In this specification, public regulation in the energy sector is modelled through energy prices, whereas endogenous technical change (τ) is expressed as a function of output level and energy prices.

* Corresponding author. Tel.: +39 06 5733 5749; fax: +39 06 5733 5771.
E-mail addresses: v.costantini@uniroma3.it (V. Costantini), chiara.martini@enea.it (C. Martini).

0140-9883/$ – see front matter
doi:10.1016/j.eneco.2009.09.013

The opposite relation is adapted from Lee and Chang (2008) and Stern (2000a,b), as expressed in Eq. (2):

$$Y_{tj} = f(K_{tj}, L_{tj}, EC_{tj}(p_{tj})) \quad (2)$$

where economic output (Y) is a function of the capital stock (K), labour (L) and energy inputs (EC), here modelled as being strictly dependent on energy prices (p).[1]

These alternative views have important policy implications concerning, for example, aspects such as the development level of the considered country or the distributive effects related to the introduction of stringent energy (and environmental) regulations.

If we consider highly industrialized countries, total energy use has increased, energy efficiency has improved and energy intensity has steadily fallen, especially in the industrial sector. Stabilization of greenhouse gas concentrations requires reductions in fossil fuel energy use which is a major essential input throughout all modern economies. If energy conservation and a switch from fossil fuels to alternative energy sources can be affected using new energy-efficient technologies, the trade-off between energy and growth becomes less severe.

Moreover, if the development process is in the deindustrialization phase, the increasing importance of value-added produced by the service sector could lead to a global reduction in energy consumption due to a minor weight represented by energy-intensive industrial sectors.

Nonetheless, empirical analysis has shown that energy regulations and the shifting in production structure do not necessarily lead to a consistent reduction in global energy consumption. This evidence is explained as a “rebound effect”, postulated first by Brookes (1990) and Khazzoom (1980). In some cases, energy-saving technical innovations tend to introduce more energy-using appliances to households and industries causing even more energy consumption as the money saved is spent on other goods and services which require energy to be produced. A stronger implication of the rebound effect is related to a reduction in energy prices that occurs when energy efficiency leads to a reduction in the energy demand (Binswanger, 2001). An innovation that reduces the amount of energy required to produce a unit of energy services lowers the effective price of energy services, resulting in an increase in their demand. The lower price of energy also results in an income effect that increases demand for all goods in the economy and therefore the energy required to produce them (Lovins, 1988; Newell et al., 1999; Popp, 2002). Therefore, if delinking between economic growth and energy consumption is the aim of energy policies, policy makers should consider some form of energy regulation (taxes, price cap or other) that allows cost of energy services to remain unchanged provided that technological innovation lowers effective energy prices (Bentzen, 2004).

Not many empirical studies have analysed this phenomenon by considering different economic sectors: a large part of the literature has investigated energy efficiency only at a general level. This has important policy implications. One of the most accurate contributions is the analysis by Zachariadis (2007) for G-7 countries where energy–economy causality for four sectors (industry, service, residential and transport) is analysed, using alternative estimation methods for each country. If declining energy intensity is observed only for specific sectors and not for the whole economy, differentiated policy measures are required in order to obtain the best results in terms of decoupling economic growth from energy consumption.

There are many studies that investigate the strength of the structural linkage between energy and growth using time series analysis for single countries and, more recently, panel datasets, but at the best of our knowledge there are no contributions which adopt a panel approach for analysing energy–economic growth causality at the sectoral level. The purpose of this paper is to provide empirical evidence on the better performance of panel sectoral datasets in explaining the causal linkages between the economy and energy consumption. Moreover, by using energy prices for each specific sector, we can estimate the elasticity parameters related to energy demand changes induced by public regulation, expressed as energy taxes and empirically represented by energy prices.

This paper is different from previous contributions in several aspects. The sample adopted for the dataset is rather wider than other contributions based on the panel approach and includes 71 countries, thus allowing a number of considerations on different results emerging from alternative sub-samples consisting of developed and developing countries. The analysis is carried out on the whole economy and on four distinct end-use sectors, industry, service, transport and residential, allowing for specific considerations to be made for each sector divided into the sub-samples examined in this paper. Comparing results from different sectors reinforces the need for a multivariate model that accounts for structural peculiarities of both sectors and countries. A first attempt is provided by including specific energy prices for each end-use sector for OECD countries and the results offer strong advice in favour of multivariate multi-sector models.

The rest of the paper is structured as follows. Section 2 provides the methodological strategy for addressing Granger causality in the energy sector with particular emphasis on contributions dealing with non-stationary and cointegrated panel dataset, Section 3 gives a description of the data used in the empirical analysis, Section 4 describes the econometric strategy and presents the empirical results and Section 5 concludes with some policy implications.

2. Econometric models for an analysis of causality between energy and economic growth

To date, empirical findings on the causal relationship between energy consumption and economic growth have been mixed, depending on the functional form adopted, the econometric approach used, the time periods and the sample of countries analysed. Based on the methodology used, the literature on the relationship between energy use and economic growth can be divided into four generations. Interest in the subject dates back to a pioneering study by Kraft and Kraft (1978) that examined the energy use and economic growth relationship in the USA and found evidence of causality running from income to energy consumption. Several studies on the USA followed (for example, Akara and Long, 1980; Yu and Wang, 1984), and also on other developed countries (Yu and Choi, 1985). First-generation studies assumed that the time series examined were stationary and they were based on a traditional VAR methodology (Sims, 1972) and Granger causality testing (1969). Subsequent studies recognized the non-stationarity of the data series and they therefore performed cointegration analysis in order to investigate the energy use and economic growth relationship. Second-generation studies, based on the Granger's two-stage procedure (Granger, 1988), tested pairs of variables for cointegrating relationships and used estimated Error Correction Models (ECM) to test for Granger causality, concentrating their attention mainly on transition economies (Cheng and Lai, 1997) and developing countries (Nachane et al., 1988). Third-generation literature used multivariate estimators (Johansen, 1991), facilitating the estimation of systems where restrictions on cointegrating relations can be tested and, at the same time, the possibilities of short-run adjustment can be investigated. Johansen's approach also allows for more than two variables in the cointegrating relationship (see, among others, Masih and Masih, 1996; Stern, 2000a,b; Asafu-Adjaye, 2000; Oh and Lee, 2004). Fourth-generation studies

[1] This simple assumption is required if we consider that energy supply is often affected by exogenous elements such as international energy prices and public regulation, assuming that public regulation can be fully expressed by domestic energy prices. We are aware that this is a simplification but we also know that, in many cases, energy taxes in OECD countries constitute the largest part of energy prices.

employ recently developed panel methods to test for unit roots, cointegration and Granger causality (Al-Iriani, 2006; Lee and Chang, 2007, 2008; Mahadevan and Asafu-Adjaye, 2007).

Panel datasets increase the sample size considerably, allowing for higher degrees of freedom and more accurate and reliable statistical tests; they also reduce multicollinearity between regressors. Another advantage of using panel cointegration is that it allows for heterogeneity between countries. Furthermore, the number of observations available when testing the stationarity of the residual series in a level regression is greatly increased in a panel framework and this can substantially increase the power of the cointegration tests especially when annual data are considered (Rapach and Wohar, 2004).

Very broadly speaking, the test for causal relationship between energy consumption and economic growth in a panel context is usually conducted in three steps. First, the order of integration in the economic and energy time series variables is tested. Second, after having established the order of integration in the series, panel cointegration tests are used to examine the long-run relationships between the variables in question. Granger (1981) showed that when the series are integrated of order one (they become stationary after first differencing), linear combinations might exist by virtue of which the series become stationary without differencing. Such series are called cointegrated. If integration of order one is found, the next step is to use cointegration analysis to investigate the existence of a long-run relationship between the set of integrated variables in question. When cointegration is found, the problems of differencing, represented by the loss of information on any long-run relationships between variables, can be avoided: a Vector Autoregression model (VAR) can be used to check whether a stationary linear combination of non-stationary variables exists implying that a long-run equilibrium relationship holds between the variables. Then, the last phase is represented by employing dynamic panel causality tests in order to evaluate the short-run and log-run direction of causality between the variables examined.

2.1. Unit root tests for panel data

One of the primary reasons for the utilization of a panel of cross section units for unit root tests is to increase statistical power of their univariate counterparts. The traditional augmented Dickey–Fuller test (ADF) (Dickey and Fuller, 1979) of unit root is characterized by having a low power in rejecting the null of no stationarity of the series, especially for short-spanned data. Recent developments in the literature suggest that panel based unit root tests have higher power than unit root tests based on individual time series. Panel data techniques could also be preferable because of their weak restrictions; indeed, they capture country-specific effects and heterogeneity in the direction and magnitude of the parameters across the panel. In addition, these techniques allow the model to be selected with a high degree of flexibility, proposing a relatively wide range of alternative specifications, from models with constant and deterministic trend up to models with no constant and no trend; within each model, there is the possibility of testing for common time effects.

Nonetheless, testing the unit root hypothesis with panel data is not without some additional complications. Panel data are generally characterized by unobserved heterogeneity with parameters that are cross section specific, whereas in some cases it is not appropriate to consider independent cross section units (it is the case for real exchange rates as mentioned in Breitung and Pesaran, 2008). Finally, the test outcomes are difficult to interpret because the rejection of the null of no unit root means that a significant fraction of cross section units is stationary but there is no explicit mention of the size of this fraction.

Recent developments in the panel unit root tests include Levin et al. (2002) (herein referred to as LLC), Im et al. (2003) (herein referred to as IPS), Breitung (2000) (herein referred to as BRT), Maddala and Wu (1999), Choi (2001) and Hadri (2000a,b). The basic autoregressive model can be expressed as follows:

$$y_{it} = \rho_i y_{it-1} + \delta_i X_{it} + \varepsilon_{it} \tag{3}$$

where $i=1, 2, \ldots, N$ represent countries observed over periods $t=1, 2, \ldots, T$, X_{it} are exogenous variables in the model including any fixed effects or individual trend, ρ_i are the autoregressive coefficients, and ε_{it} is a stationary process. If $\rho_i<1$, y_i is said to be weakly trend-stationary. On the other hand, if $\rho_i=1$, then y_i contains a unit root. LLC, BRT, and Hadri tests assume that the ε_{it} are IID $(0, \sigma_e^2)$ and $\rho_i=\rho$ for all i; this implies that the coefficient of y_{it-1} is homogeneous across all cross section units of the panel and that individual processes are cross-sectionally independent.

LLC and IPS seem to be the most popular tests, where LLC assumes homogeneity in the dynamics of the autoregressive coefficients for all panel members, whereas IPS allows for heterogeneity in these dynamics (namely, it allows for a heterogeneous coefficient of y_{it-1}).[2] Moreover, IPS proposes averaging the augmented Dickey–Fuller (ADF) tests, that is $\varepsilon_{it}=\sum_{j=1}^{pi}\phi_{ij}\varepsilon_{it-j}+u_{it}$, allowing for different orders of serial correlation.

If this expression is transformed into the Eq. (3), the IPS test specifies a separate ADF regression for each cross-section as expressed in Eq. (4):

$$y_{it} = \rho_i y_{it-1} + \textstyle\sum_{j=1}^{p_i}\phi_{ij}\varepsilon_{it-j} + \delta_i X_{it} + u_{it} \tag{4}$$

where p_i is the number of lags in the ADF regression and the error terms u_{it} are assumed to be independently and normally distributed random variables for all i and t with zero means and finite heterogeneous variances σ_i^2. Both p_i and the lag order ϕ in [4] are allowed to vary among cross-sections. The null hypothesis is that each series in the panel contains a unit root ($\rho_i=1$ for all i) whereas the alternative hypothesis is that at least one of the individual series in the panel is stationary ($\rho_i<1$ for at least one i). The test statistic is normally distributed under H_0 and the critical values for given values of N and T are provided in Im et al. (2003).[3]

In our study we have considered several alternative unit root tests such as LLC, IPS and BRT whereas a robustness check has been carried out both on single cross section units and on the whole panel dataset to investigate the existence of structural breaks. We have therefore checked for non-stationarity in single time series with structural breaks by using Zivot and Andrews (1992) and Kwiatkowski et al. (1992) tests, finding that most of cross section units are characterized by I(1) series and very few of them result I(0) in levels when structural breaks are considered. We have also performed an LM panel unit root tests with two endogenously determined structural breaks, obtaining stable results with series integrated of order one.

2.2. Panel cointegration

The panel cointegration technique developed by Pedroni (1999, 2000) significantly improves the conventional cointegration analysis applied on single country series allowing for cross-sectional interdependence with different individual effects in the intercepts and slopes

[2] This assumption is particularly reasonable since imposing uniform lag length among different countries is likely to be inappropriate: slope heterogeneity appears to be more reasonable when cross-country data are used and where heterogeneity could arise from different economic conditions and levels of development in each country.

[3] With regard to the stationarity tests, it could be appropriate to account for structural breaks in the data series. As shown by Perron (1989), allowing for a structural break when testing for a unit root is extremely important: in fact, a structural break can be mistaken for a non-stationarity process. Carrion-i-Silvestre et al. (2005) developed a method which is able to test the null hypothesis of panel stationarity while allowing for multiple structural breaks. Panel members may have a varying number of structural breaks and these may have different effects on each individual time series.

of the cointegrating equation, so that data are pooled to determine the common long-run relationship and, at the same time, the cointegrating vectors are allowed to vary across the panel units.

Pedroni (1999, 2000) suggests two types of residual-based tests for the test of the null of no cointegration in heterogeneous panels. As for the first type, four tests are based on pooling the residuals of the regression along the within-dimension of the panel (panel tests); as for the second type, three tests are based on pooling the residuals of the regression along the between-dimension of the panel (group tests). In both cases, the hypothesized cointegrating relationship is estimated separately for each panel member and the resulting residuals are then pooled in order to conduct the panel tests.

Other residual-based panel cointegration tests include the contributions by Westerlund (2005), based on variance ratio statistics and not requiring corrections for the residual serial correlations, Persyn and Westerlund (2008), with an error correction based cointegration test and Westerlund and Edgerton (2008), which take into account the existence of structural breaks within the panel.[4]

In our empirical estimations we have adopted Pedroni cointegration tests and Westerlund (2005) test for a robustness check because they perform well in heterogeneous panels in which both N and T are of moderately large dimension.

2.3. Testing Granger causality for non-stationary cointegrated panels

Whilst acknowledging the problems associated with small samples, panel data are increasingly used to test for causality between variables: using panel data allows us to obtain more observations by pooling the time series data across sections leading to higher power for the Granger causality tests. Johansen's VAR procedure (Johansen, 1988) and Pedroni's heterogeneous panel cointegration tests are only able to indicate whether or not the variables are cointegrated and if a long-run relationship exists between them. Since they do not indicate the direction of causality when the variables are cointegrated, causality is tested by the two-step Engle–Granger causality procedure (Engle and Granger, 1987) using a Vector Error Correction Model (VECM).

Having established a cointegrating relationship, the next step is to estimate the long-run equilibrium relationship given by the Error Correction Term (ECT henceforth), which is a measure of the extent by which the observed values in time $t-1$ deviate from the long-run equilibrium relationship. Since the variables are cointegrated, any such deviation at time $t-1$ should induce changes in the values of the variables in the next time point, in an attempt to force the variables back to the long-run equilibrium relationship.

The long-run equilibrium coefficients can be estimated by using single equation estimators such as the fully modified OLS procedures (FMOLS) developed by Pedroni (2000), the dynamic OLS (DOLS) estimator from Saikkonen (1991), the pooled mean group estimator (PMG) proposed in Pesaran et al. (1999) or by using system estimators as panel VARs estimated with Generalized Method of Moments (GMM) or Quasi Maximum Likelihood (QML). Single equation approaches assume there is homogeneity between cross section units for the long-run relationship whereas short-run dynamics are allowed to be cross section specific. While this restriction may seem too severe for some variables, on the other hand, allowing all parameters to be panel-specific would considerably reduce the appeal of a panel data approach (Breitung and Pesaran, 2008).[5]

In our study, we have performed a single equation estimator in the form of the FMOLS developed by Pedroni (2000) for the estimation of the residuals which will be included in the panel VECM as the error correction terms (ECTs). The FMOLS estimator has been applied to as many single equations as the number of the variables included in the VECM that are I(1) and cointegrated. For bivariate models, we have therefore estimated ECTs as the residuals (ε_{it} and η_{it} respectively) from the two following equations:

$$\begin{aligned} Y_{i,t} &= \alpha_i + \delta_i t + \beta_i EN_{i,t} + \varepsilon_{it} \\ EN_{i,t} &= \alpha_i + \delta_i t + \beta_i Y_{i,t} + \eta_{it} \end{aligned} \tag{5}$$

On the other hand, for multivariate models with prices, we have estimated ECTs (ε_{it}, η_{it}, ϕ_{it} respectively) from the following three separate equations:

$$\begin{aligned} Y_{it} &= \alpha_i + \delta_i t + \beta_i EN_{it} + \gamma_i P_{it} + \varepsilon_{it} \\ EN_{it} &= \alpha_i + \delta_i t + \beta_i Y_{it} + \gamma_i P_{it} + \eta_{it} \\ P_{it} &= \alpha_i + \delta_i t + \beta_i Y_{it} + \gamma_i EN_{it} + \varphi_{it} \end{aligned} \tag{6}$$

The second step for building a Granger causality model with a dynamic error correction term based on Holtz-Eakin et al. (1998) is to incorporate the residuals from the first step into a panel VECM. Generally, the GMM technique developed by Arellano and Bond (1991) can be adapted to estimate the panel VARs, using lags of the endogenous variables as instruments in order to arrive at unbiased and consistent estimates of the coefficients.

This specification implies that the error terms are orthogonal to the fixed and time effects as well as the lag values of the endogenous variables. The lagged dependent variables are correlated with the error terms, including the fixed effects. Hence, OLS estimates of the above model will be biased: this is resolved by removing the fixed effects by differencing. However, differencing introduces a simultaneity problem because lagged endogenous variables on the right-hand side are correlated with the differenced error term. In addition, heteroskedasticity is expected to be present because heterogeneous errors might exist with different panel members in the panel data. To deal with these problems, once the fixed effects have been removed by differencing, an instrumental variable procedure is adopted to estimate the model using predetermined lags of the system variables as instruments in order to produce consistent estimates of the parameters. A widely used estimator for a system of this type is the panel generalized method of moments (GMM) estimator proposed by Arellano and Bond (1991). The final dynamic error correction model can be specified as follows:

$$\begin{aligned} \Delta Y_{i,t} &= \alpha_j^y + \beta_i^y ECT_{i,t-1}^y + \sum_{k=1}^{m} \delta_{i,k}^y \Delta Y_{i,t-k} + \sum_{s=1}^{q} \gamma_{i,s}^y \Delta EN_{i,t-s} + u_{i,t} \\ \Delta EN_{i,t} &= \alpha_j^e + \beta_i^e ECT_{i,t-1}^e + \sum_{k=1}^{m} \delta_{i,k}^e \Delta Y_{i,t-k} + \sum_{s=1}^{q} \gamma_{i,s}^e \Delta EN_{i,t-s} + v_{i,t} \end{aligned} \tag{7}$$

where $ECT_{i,t-1}^{y,e}$ are the lagged residuals derived from the long-run cointegrating relationship in Eq. (5), $\delta_i^{y,e}$ and $\gamma_i^{y,e}$ are the short-run adjustment coefficients and $u_{i,t}$ and $v_{i,t}$ are disturbance terms assumed to be uncorrelated with mean zero. In these models, the optimal lag length for the two variables (m and q respectively) can be determined by the Akaike or the Schwarz Information Criteria and an instrumental variable estimator must be used because of the correlation between the error term and the lagged dependent variables.

The source of causation can be identified by testing the significance of the coefficients of the independent variables in Eq. (7). First, for weak

[4] Several other panel cointegration tests have been developed very recently but a comprehensive examination of this topic is beyond the scope of this paper. For a high-quality review, see Breitung and Pesaran (2008).

[5] The FMOLS estimator is preferred to the DOLS because in the latter the covariates are included in first differences and not in levels. Moreover, according to Pedroni (2001) and Breitung and Pesaran (2008), FMOLS and DOLS estimators have the same asymptotic distribution and they can perform poorly if the number of time periods is smaller than 20. In our case the OECD sample covers 45 years whereas the full sample and the non-OECD samples rely on 35 years. FMOLS is therefore a suitable estimator.

Granger causality, we test H_0: $\delta_i^{y,e} = 0$ and $\gamma_i^{y,e} = 0$, $\forall i$ in Eq. (7).[6] Masih and Masih (1996) and Asafu-Adjaye (2000) interpreted the weak Granger causality as a short-run causality in the sense that the dependent variable responds only to short term shocks to the stochastic environment. Next, the presence (or absence) of long-run causality can be reviewed by examining the significance of the speed of adjustment $\beta_i^{y,e}$ (namely, the coefficients of $ECT_{i,t-1}^{y,e}$ which represents how fast deviations from the long-run equilibrium are eliminated following changes in each variable). The significance of $\beta_i^{y,e}$ determines the long-run relationship in the cointegrating process and movements along this path can therefore be considered permanent. Finally, it is also desirable to check whether the two sources of causation are jointly significant: a joint test on the error correction term and respective interactive terms (namely, the lagged variables of each VECM variable) can then be performed to investigate strong causality (Oh and Lee, 2004). This kind of causality shows which variables bear the burden of a short-run adjustment so that a long-run equilibrium following a shock to the system is established (Asafu-Adjaye, 2000): if there is no causality in either direction, the "neutrality hypothesis" holds, otherwise, unidirectional or bi-directional causality exists. Since all the variables are entered into the model in stationary form, a standard Wald *Chi-sq* statistic can be used to test the null hypothesis of no causality (or weak exogeneity of the dependent variable).[7]

If we consider a third variable related to energy prices in a multivariate context, the panel VECM results as follows:

$$\begin{aligned}
\Delta Y_{i,t} &= \alpha_j^y + \beta_i^y ECT_{i,t-1}^y + \sum_{k=1}^{m} \delta_{i,k}^y \Delta Y_{i,t-k} + \sum_{s=1}^{q} \gamma_{i,s}^y \Delta EN_{i,t-s} \\
&\quad + \sum_{v=1}^{r} \lambda_{i,v}^y \Delta P_{i,t-v} + u_{i,t} \\
\Delta EN_{i,t} &= \alpha_j^e + \beta_i^e ECT_{i,t-1}^e + \sum_{k=1}^{m} \delta_{i,k}^e \Delta Y_{i,t-k} + \sum_{s=1}^{q} \gamma_{i,s}^e \Delta EN_{i,t-s} \\
&\quad + \sum_{v=1}^{r} \lambda_{i,v}^e \Delta P_{i,t-v} + \nu_{i,t} \\
\Delta P_{i,t} &= \alpha_j^p + \beta_i^p ECT_{i,t-1}^p + \sum_{k=1}^{m} \delta_{i,k}^p \Delta Y_{i,t-k} + \sum_{s=1}^{q} \gamma_{i,s}^p \Delta EN_{i,t-s} \\
&\quad + \sum_{v=1}^{r} \lambda_{i,v}^p \Delta P_{i,t-v} + \eta_{i,t}
\end{aligned} \tag{8}$$

3. Dataset analysis

As we have seen in the literature review, there are many recent contributions addressing causal relationships between the energy sector and economic performance. Most of them analyse the question from a country level perspective comparing the results of VAR models for different countries, mainly divided into homogeneous groups on the basis of development level, geographical areas or other common characteristics. A single country analysis is rarely followed by a panel framework (as in Al-Iriani, 2006; Al-Rabbaie and Hunt, 2006; Chen and Lee, 2007; Lee, 2005, 2006; Lee and Chang, 2007, 2008; Mahadevan and Asafu-Adjaye, 2007; Mehrara, 2007), and the panel datasets account for a small number of countries. In our work, we have collected information on 71 countries, divided into two groups: OECD, with 26 countries, and non-OECD, with 45 countries, as listed in Table A1 in the Appendix. The countries included in the OECD group are quite homogeneous whereas in the non-OECD group, countries are quite heterogeneous, both with regard to development level and policy settings. A future research task could be a more detailed investigation of group-specific effects by analysing the same relationships inside different sub-groups.

The dataset we have constructed combines several sources. For the energy sectors, we have collected data from the IEA publications on OECD and non-OECD energy balances, containing annual data on energy final consumption for the whole economy and for the main sectors, as industry, commerce and public services, transport and residential sector, all expressed in terms of kg of oil equivalent. All information on economic performance in the different sectors is taken from the World Bank dataset on World Development Indicators (WDI). More specifically, we have considered the gross domestic product, the value added of industry and service, the household final consumption expenditures, all considered in terms of per capita constant 2000 US$. We chose to adopt household final consumption expenditure for modelling the residential sector because this comprises the data covering the largest country sample. An alternative variable is the final consumption expenditures (as proposed by Zachariadis, 2007) but it is strongly and positively correlated with household final consumption expenditure and would not provide additional information in our model.

For the transport sector, we have used the GDP to represent the economic dimension, which is a common choice in literature. In Table 1, all variables are defined and associated with the acronyms used in the econometric estimates where *i* stands for countries and *t* for time period (year).

Data for energy prices are provided by IEA statistics on energy prices and taxes (quarterly) for OECD countries only for the time period 1978–2005. We have collected data for the whole energy sector and the four specific end-use sectors we have included in our analysis. We have considered four different energy prices: total energy price, total industry price, total household price and total gasoline price (all expressed in terms of constant 2000 US$ per toe). We have decided to use the total industry price both for the industrial and the service sector even though many contributions affirm that the best price variable for service is the cost of electricity. In our dataset, the electricity price is often missing or not complete throughout the time period, thus consistently reducing the number of observations. We have performed a simple correlation analysis where the electricity price is highly correlated with all the other energy prices but mostly with total industry price.[8]

For bivariate models, data availability allows considering the period 1970–2005 for the full sample and the non-OECD sample whereas for OECD countries, the time series cover the period 1960–2005. For multivariate models including energy prices, we have a reduced sample with only OECD countries in the period 1978–2005. Considering the wide divergence among countries, both in the energy sectors and in economic performance, we have considered per capita levels and we have then transformed all data into natural logarithms because of the high variance in levels between developed and developing countries.

Figs. 1 and 2 report some trends in the energy sector for the period 1960–2005 in terms of total energy consumption. It is clear that only the industrial sector has experienced a drastic change after the first oil crisis in 1972–1973 with a consistent reduction in consumption path allowing for an almost non-increasing energy trend. On the contrary, the other sectors, especially transport, show rising consumption for the entire period, without significant changes. If the same distinction among sectors is applied to the sample of non-OECD economies, the

[6] A variable x_t is defined to be statistically weakly exogenous with respect to the variable y_t if it satisfies. $E(x_t|x_{t-1}, x_{t-2}, \ldots; y_{t-1}, y_{t-2}, \ldots) = E(x_t|x_{t-1}, x_{t-2}, \ldots)$ where E is the mathematical expectation operator and x_t and y_t are variables with $t = 1,\ldots,n$ time observations (Engle et al., 1983).

[7] Other approaches can be developed that reflect different methods of testing for Granger causality: an Autoregressive Distributed Lag (ARDL) model or a vector autoregressive (VAR) model with augmented lag order to allow for the implementation of the Dolado and Lütkepohl (1996) and Toda and Yamamoto (1995) methods. Altinay and Karagol (2004), Lee (2006), Wolde-Rufael (2006), and Zachariadis (2007) constitute examples of studies in which these methods have been employed. Nonetheless, we have adopted the panel VECM approach because of its extreme flexibility and, above all, because it allows heterogeneous panels to be used.

[8] We are aware that we could specify energy sectors with prices even for non-OECD countries by using the general Consumer Price Index as a proxy of energy price (as suggested in Zachariadis, 2007) but we have preferred to adopt sector-specific energy prices to obtain more accurate estimates of price elasticities, because CPI does not account homogenously for energy services in all countries.

Table 1
Definition of variables and acronyms.

Variable	Definition	Source
Energy consumption variables		
$ENTOT_{it}$	Natural logarithm of Total Energy final consumption (kg of oil equivalent per capita)	International Energy Agency (IEA), energy balances
$ENIND_{it}$	Natural logarithm of Total Energy final consumption for industry sector (kg of oil equivalent per capita)	
$ENSER_{it}$	Natural logarithm of Total Energy final consumption for commerce and public services (kg of oil equivalent per capita)	
$ENTRA_{it}$	Natural logarithm of Total Energy final consumption for transport sector (kg of oil equivalent per capita)	
$ENRES_{it}$	Natural logarithm of Total Energy final consumption for residential sector (kg of oil equivalent per capita)	
Energy price variables		
$ENPR_{it}$	Total energy price (constant 2000 US$/ton of oil equivalent)	International Energy Agency (IEA), energy prices and taxes
$INDPR_{it}$	Total industry price (constant 2000 US$/ton of oil equivalent)	
$RESPR_{it}$	Total household price (constant 2000 US$/ton of oil equivalent)	
$GASPRS_{it}$	Total gasoline price (constant 2000 US$/ton of oil equivalent)	
Economic sectors variables		
GDP_{it}	Natural logarithm of per capita GDP (constant 2000 US$ per capita)	World Bank WDI and OECD statistics
IND_{it}	Natural logarithm of per capita industry value added (constant 2000 US$ per capita)	
SER_{it}	Natural logarithm of per capita service value added (constant 2000 US$ per capita)	
$HFCEX_{it}$	Natural logarithm of per capita household final consumption expenditure (constant 2000 US$ per capita)	

picture changes radically and all the sectors have increasing trends in energy consumption. A short period of reduction in energy consumption was experienced only by the industry sector across 1994–2001, followed by a sharp and prolonged increase.

The energy trend for all the sectors in non-OECD countries is strongly affected by the sharp increase after the 1992–1994 period experienced by many countries caused by the inclusion of a specific energy source "Combustible Renewables and Waste" in the IEA Energy Balances which is highly consistent for countries such as China, Congo, India and Indonesia, thus producing a noticeable structural break, especially for the industrial and residential sectors. We have considered this shock in the energy variables by modelling a country-specific time dummy for that period.

Figs. 1 and 2 clearly show how drawing conclusions from aggregated data on the energy sector and on the whole economy could lead to distortive policy measures. Furthermore, disaggregated models for distinct sectors are useful for calculating specific income and price elasticities, thus comparing countries and regions with different development levels, and also for investigating the potential divergent effects of different policy settings.

The analysis of the dataset is started by testing the statistical properties of the time series. First, the stationarity of variables is investigated: we have performed the following unit root tests for panel data: IPS (Im et al., 2003), BRT (Breitung, 2000) and LLC (Levin et al., 2002). Tests have been computed under two different specifications, represented by the inclusion of individual effects or individual effects and trends, as reported in the Appendix Table A2.[9]

The unit root hypothesis cannot be rejected when the variables are taken in levels and any causal inference from the series in levels would therefore be invalid. However, when using the first differences, the null of unit roots is strongly rejected at the 1% significance level for all series. Therefore, it is concluded that all the series are non-stationary and integrated of order one. This finding is confirmed by all the tests employed in all the three alternative country samples examined, the full sample, the OECD and the non-OECD sample.

Energy prices–specified as total energy price, energy price for industry, energy price for households and gasoline price–are also I(1), since the series became stationary after first differencing (Appendix Table A3).

[9] As a standard procedure, before performing panel unit root tests we have computed poolability tests on each variable by using a Breusch–Pagan Lagrange multiplier (LM) test. The null hypothesis of random group effect model, that is the variances of groups are zero, has been rejected for all variables included in the analysis, so that the pooled regression model is not appropriate, and a panel approach should be adopted.

For a robustness check of the stationarity results, we have performed the LM panel unit root test with endogenously determined structural breaks as suggested in Im et al. (2005). Evidence for the existence of structural breaks in correspondence of the oil crises has been found but results do not strongly support the stationarity of the series, so that cointegration tests still remain necessary.

Having established that all the variables to be used in the estimation are I(1), we then proceeded to test whether a long-run relationship existed between them using Pedroni's heterogeneous panel cointegration tests. The Pedroni (1999) heterogeneous panel statistics reject the null of no cointegration when they have large negative values except for the panel-v test which rejects the null of cointegration when it has a large positive value. The results shown in Appendix Table A4, associated with bivariate models, suggest a rejection of the null hypothesis of no cointegration at least at the 5% significance level. Therefore, a long-run relationship exists between economic and energy variables, both for the whole economy and the different sectors examined, with some cautions on two specifications: the residential sector for non-OECD sample, and the transport sector for OECD countries.

An analysis of cointegration on multivariate models including energy prices for the OECD sample strongly supports the existence of a long-run relationship demonstrating that the inclusion of prices allows to reinforce the statistical robustness of the linkages between the variables examined here.

Tests conducted on the period 1960–2005 for bivariate models show cointegration only in a homogeneous panel setting whereas in the period 1978–2005, full heterogeneity is observed, as has already been found by Al-Rabbaie and Hunt (2006). On the other hand, the tests on multivariate models were computed on the period 1978–2005 with full heterogeneity (Appendix Table A5).

We have also performed the alternative Persyn and Westerlund panel cointegration test to check for robustness of the results obtained with the Pedroni tests. In this case, the null hypothesis is the absence of cointegration with two tests performed on individual panel members and two tests applied to the panel as a whole (Persyn and Westerlund, 2008). Even in this case, the panel cointegration tests revealed the existence of a long-run cointegrating relationship between the economic and the energy dimensions in all the five specifications we adopted (general, and the four end-use sectors). The same applies for the cointegration analysis including energy prices, tested only on the OECD sample.[10]

[10] For the sake of simplicity, we have not reported the results for Persyn and Westerlund cointegration tests, but they are available upon request from the authors.

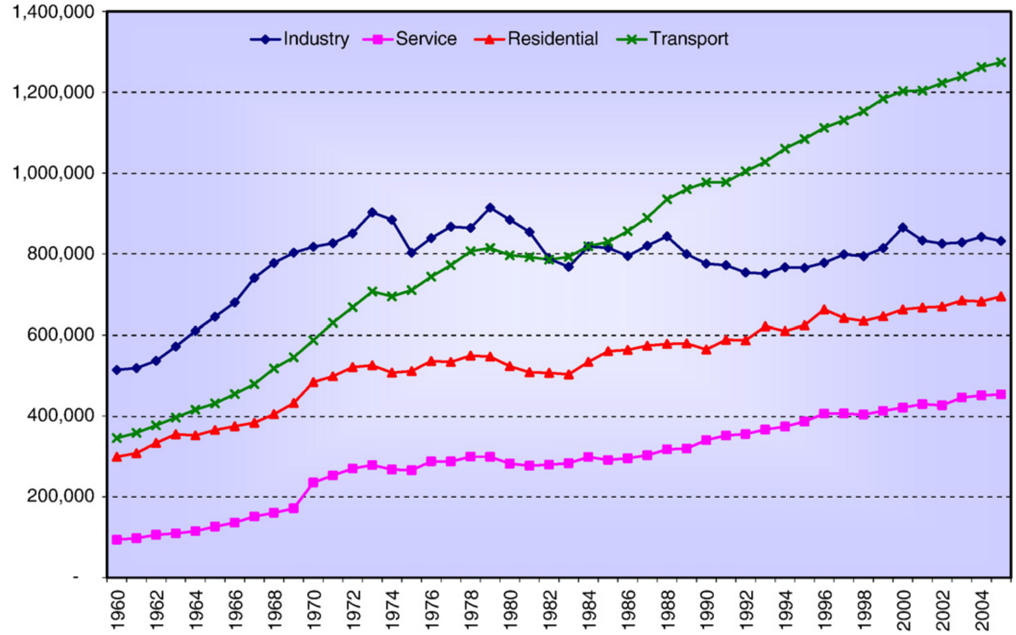

Fig. 1. Trends in energy consumption for OECD countries (ktoe).
Source: our processing of IEA data (2008).

4. Empirical results

Considering that we are working with a non-stationary and cointegrated panel dataset, the causality test must be performed using appropriate estimation instruments. We have chosen to adopt a Vector Error Correction Model (VECM) because it allows both the short-run and the long-run relationships to be considered whereas the VAR and ARDL models may only suggest a short-run relationship between variables, due to first differencing operators that remove the long-run information. Moreover, a VECM structure is suitable for modelling endogenous variables while considering a dynamic structure of the simultaneous equations system by using Generalized Methods of Moments estimator as suggested in Arellano and Bond (1991).

The long-run equilibrium relationship for a panel VECM (i.e., the ECT) is given by the residuals of an FMOLS estimation of separate equations, as many as the number of cointegrated variables. For bivariate models (without prices), we have therefore estimated Eq. (5) whereas for the multivariate models, we have estimated Eq. (6). The distinct residuals have been used as ECTs with one time lag in the correspondent equation of the VECM.

4.1. Results for the bivariate model

We have computed a bivariate VECM accounting for structural breaks with specific temporal dummy variables for each single country reflecting results from structural break tests. Including temporal dummy

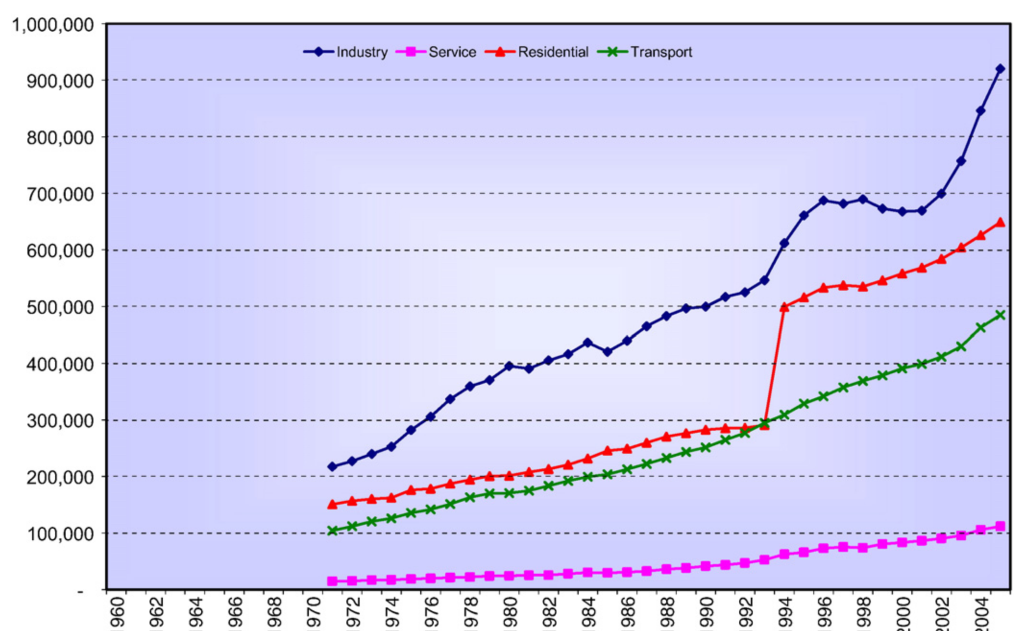

Fig. 2. Trends in energy consumption for non-OECD countries (ktoe).
Source: our processing of IEA data (2008).

variables partially solves the absence of heterogeneous cointegration up to 1978. In order to correct for auto-correlated residuals (as stressed in Lee and Chang, 2008), we have used an instrumental variable estimator to deal with the correlations between the error terms and the lagged dependent variables. The number of lagged instruments included has been chosen by starting with $k=1$, and continuing until serial correlation is excluded and the instruments are over-identified. We have reached the optimal lagged instruments structure of $k=5$ by using the Portmanteau test for serial correlation of the residuals.[11] After establishing the number of lagged instruments, the *J*-stat Sargan tests for each model have rejected the null of over-identified instrumental variables validating a lag order of 5. The Jarque–Bera test for normal residuals was also performed in the final VECM specification for all the alternative models by using Cholesky orthogonalization criterion.

Having estimated the VECM for all the sectors and distinct sub-samples, we performed a simple Wald test with a *Chi-squared* statistic distribution on the significance of the coefficients, evaluating three different Granger causality relationships: a short-run causality, testing the significance of the coefficients related to the lagged economic and energy variables (H_0: $\delta_i=0$ and $\gamma_i=0$ for all i in Eq. (7)), a long-run causality related to the coefficient for the ECT term (H_0: $\beta_i=0$ for all i in Eq. (7)), and a strong causality to test whether the sources of causation are jointly significant (H_0: $\beta_i=\delta_i=0$, $\beta_i=\gamma_i=0$ for all i in Eq. (7)). The strong Granger causality test can be interpreted as a test of weak exogeneity (Engle et al., 1983) of the dependent variable (as suggested in Asafu-Adjaye, 2000) and only when both the *t* and Wald *Chi-sq* statistics in the VECM reveal the absence of causality nexus, this will imply that the dependent variable is weakly exogenous.

The results of the VECM with two simultaneous equations for the analysis of the causal relationships between energy consumption and economic growth are reported in Tables 2 and 3 for the three alternative country samples and for the whole economy and the four energy sectors separately. Table 2 reports results in terms of Wald test on the coefficients whereas in Table 3, the same results are summarized in a qualitative fashion with the explicit reference to the coefficient values only when they are statistically significant.

The parameters β_i represent the long-run speed of adjustment at which the values of Y_t and EN_t come back to long-run equilibrium levels, once they violate the equilibrium relationship. These parameters are of particular interest as they have important implications for the dynamics of the system. The negative sign of the estimated speed of adjustment coefficients are in accord with the convergence toward long-run equilibrium. The larger the value of β_i, the stronger is the response of the variable to the deviation from long-run equilibrium, if any. On the contrary, in the case of low coefficient values, any deviation from long-run equilibrium of the value of Y_t and EN_t requires a much longer time for the equilibrium to get restored. When the β_i is statistically significant in both the models, a change in one variable is expected to affect the other variable through a feedback system, implying a bi-directional causal relationship between income and energy consumption.

When the bivariate VECM model is performed on the whole economy, the three alternative samples present quite homogeneous results, with a bi-directional short-run causality and a unidirectional long-run relationship where the economic output is a driver for energy consumption and not *vice versa*, as addressed in Toman and Jemelkova (2003). From these first results one can argue that policies for promoting energy efficiency will negatively affect economic performance only in the short-run due to increasing production costs, but they will be neutral on the long-run economic growth path.

If we consider alternative VECMs specified for each single end-use sector, the picture changes dramatically and results strongly support our research hypothesis that specific sector models could provide contrasting results, reinforcing the requirement of *ad hoc* policy evaluations. For example, the industrial sector seems to be the most coherent when we compute causality tests on the different sub-samples but it is quite divergent from the results obtained for the whole economy. As we can see, short-run causality is unidirectional when energy consumption is caused by industrial production. This clearly indicates that energy demand is strongly dependent from the economic performance of the industrial sector, while energy policies for reducing energy consumption should not affect the economic performance.

When we look at long-run equilibrium, the two sub-samples present different results, putting evidence on the necessity to explore energy–economic growth relationships by adopting different models and country samples. The direction of the causal relationship remains stable for the non-OECD sample even in the long-run, meaning that energy consumption is strongly affected by the industrial sector demand. On the other hand, in the OECD sample, the long-run causality goes in the opposite direction and could be explained by the energy-saving measures adopted after the first oil crisis which mainly concerned the industrial sector. This specific result is in line with those studies addressing the role of energy services as a necessary input for the production function, and energy-saving and energy efficiency measures could be harmful for the economic development process (Stern and Cleveland, 2004). In this case, even if a bi-directional causality relationship is not found in the same temporal dimension, nonetheless some accuracy in modelling endogenous variables seems to be necessary in order to catch transitional effects in the dynamics of the industrial sectors (Lee and Chang, 2008).

The service and residential sectors apparently seem to have quite heterogeneous results both from the whole economic sector model and in the between group dimension. As we can see from Table 3, there is a bi-directional short-run causality in the service sector if we consider the full sample, no short-run causality in the OECD countries, and a unidirectional causality–going from value-added to energy consumption–in the non-OECD sample. On the contrary, the residential sector only shows a unidirectional short-run causality for the OECD sample, whereas for strong causality there exists a bi-directional nexus. In our opinion this divergence could be interpreted as a sign of model misspecification, in a sense that some additional information as specific energy policies in the form of incentives and energy taxes could help explaining such contrasting results, as we have proved in a multivariate context for OECD countries.

The transport sector shows more homogeneous results whether we compare it with the whole economic sector or in the between-dimension. In this case, it is interesting to note the large gap in the elasticity values for OECD and non-OECD (0.12 and 0.37, respectively). The higher value of non-OECD countries short-run elasticity could be explained by the increasing role of trade flows in GDP structure for emerging economies, such as Brazil, China and India, that belong to the non-OECD sample. Considering that the greatest part of GDP growth rate (the economic variable used for transport sector) for emerging economies is explained by trade flows, typically characterized by intensive energy consumption, a variation in GDP per capita in the non-OECD countries would imply a larger variation in energy consumption in the transport sector than in the OECD sample.

It is also interesting to note that when the causal relation from income to energy consumption is investigated (arrows pointing right, see note to Table 3), the values of short and long-run causality show substantial changes if alternative country samples are investigated. In the short-run causality, non-OECD sample reveals higher coefficients for all the five specifications in respect of OECD countries. This empirical

[11] The Portmanteau residual serial correlation LM test is specifically set for VAR models with a lagged dependent variable built on Box–Pierce/Ljung–Box *Q*-statistics. Under the null hypothesis of no serial correlation up to lag *h*, both statistics are approximately distributed as a χ^2 with degrees of freedom equal to $k^2(h-p)$ where *p* is the VAR lag order. We have computed both first and second-order serial correlation test and H_0 is accepted in both cases.

Table 2
Panel VECM causality test results for bivariate models.

Dependent variable	Full sample					OECD sample					Non-OECD SAMPLE				
	Short-run		Long-run	Strong causality		Short-run		Long-run	Strong causality		Short-run		Long-run	Strong causality	
Economy	ΔGDP	ΔENTOT	ECT	Joint (ECT and ΔENTOT)	Joint (ECT and ΔGDP)	ΔGDP	ΔENTOT	ECT	Joint (ECT and ΔENTOT)	Joint (ECT and ΔGDP)	ΔGDP	ΔENTOT	ECT	Joint (ECT and ΔENTOT)	Joint (ECT and ΔGDP)
ΔGDP	–	3.15*	1.75	4.00	–	–	5.39**	2.49	22.89***	–	–	3.72*	0.17	4.43	––
ΔENTOT	4.06**	–	9.67***	–	18.53***	3.27*	–	48.16***	–	62.31***	18.64***	–	4.10**	–	24.21***
Industry	ΔIND	ΔENIND	ECT	Joint (ECT and ΔENIND)	Joint (ECT and ΔIND)	ΔIND	ΔENIND	ECT	Joint (ECT and ΔENIND)	Joint (ECT and ΔIND)	ΔIND	ΔENIND	ECT	Joint (ECT and ΔENIND)	Joint (ECT and ΔIND)
ΔIND	–	2.34	1.54	6.81**	–	–	2.25	4.40**	11.52***	–	–	0.20	0.02	2.44	––
ΔENIND	25.14***	–	2.38	–	26.64***	4.30**	–	0.14	–	4.64*	18.35***	–	2.99*	–	20.44***
Services	ΔSER	ΔENSER	ECT	Joint (ECT and ΔENSER)	Joint (ECT and ΔSER)	ΔSER	ΔENSER	ECT	Joint (ECT and ΔENSER)	Joint (ECT and ΔSER)	ΔSER	ΔENSER	ECT	Joint (ECT and ΔENSER)	Joint (ECT and ΔSER)
ΔSER	–	2.82*	0.49	3.42	–	–	0.70	14.06***	15.77***	–	–	2.55	2.56	5.13*	––
ΔENSER	9.49***	–	20.71***	–	27.02***	0.39	–	41.75***	–	45.15***	8.24***	–	14.07***	–	18.95***
Residential	ΔHFCEXP	ΔENRES	ECT	Joint (ECT and ΔENRES)	Joint (ECT and ΔHFCEXP)	ΔHFCEXP	ΔENRES	ECT	Joint (ECT and ΔENRES)	Joint (ECT and ΔHFCEXP)	ΔHFCEXP	ΔENRES	ECT	Joint (ECT and ΔENRES)	Joint (ECT and ΔHFCEXP)
ΔHFCEXP	–	0.57	12.78***	7.13**	–	–	3.32*	2.73*	5.59*	–	–	0.01	2.93*	6.19**	––
ΔENRES	1.48	–	25.64***	–	26.82***	0.84	–	22.61***	–	23.05***	0.41	–	10.49***	–	10.54***
Transport	ΔGDP	ΔENTRA	ECT	Joint (ECT and ΔENTRA)	Joint (ECT and ΔGDP)	ΔGDP	ΔENTRA	ECT	Joint (ECT and ΔENTRA)	Joint (ECT and ΔGDP)	ΔGDP	ΔENTRA	ECT	Joint (ECT and ΔENTRA)	Joint (ECT and ΔGDP)
ΔGDP	–	4.61**	0.77	7.06**	–	–	23.33***	3.41*	47.56***	–	–	0.78	3.59*	5.44**	––
ΔENTRA	44.94***	–	5.57**	–	66.29***	2.85*	–	17.749***	–	26.65***	35.35***	–	1.29	–	42.35***

The heteroskedasticity of the error terms is corrected by using White robust standard errors both in periods (White period system robust covariances) and in cross sections (coefficient covariance method: White cross section system robust). The method for iteration control for GLS and GMM weighting specifications is to iterate weights and coefficients sequentially to convergence. To correct for possible autocorrelation we use the Newey–West estimator of the weighting matrix in the GMM criterion.

*Significant at 10% level. **Significant at 5% level. ***Significant at 1% level.

Table 3
Causality directions in four end-use energy sectors in bivariate models.

Sectors	Samples	No. obs.	Energy variable	Economic variable	Short-run causality			Long-run causality			Strong causality
					γ_i^y		δ_i^e	β_i^y		β_i^e	
Economy	Full	2226	ΔENTOT	ΔGDP	(0.06)	↔	(0.13)		→	(−0.10)	→
	OECD	979	ΔENTOT	ΔGDP	(0.06)	↔	(0.12)		→	(−0.26)	↔
	Non-OECD	1247	ΔENTOT	ΔGDP	(0.05)	↔	(0.17)		→	(−0.04)	→
Industry	Full	1807	ΔENIND	ΔIND		→	(0.21)		–		↔
	OECD	713	ΔENIND	ΔIND		→	(0.10)	(−0.06)	←		↔
	Non-OECD	1094	ΔENIND	ΔIND		→	(0.20)		→	(−0.07)	→
Services	Full	1713	ΔENSER	ΔSERV	(0.01)	↔	(0.24)		→	(−0.20)	→
	OECD	713	ΔENSER	ΔSERV		–		(−0.43)	↔	(−0.25)	↔
	Non-OECD	1000	ΔENSER	ΔSERV		→	(0.24)		→	(−0.21)	↔
Transport	Full	2198	ΔENTRA	ΔGDP	(0.03)	↔	(0.36)		→	(−0.07)	↔
	OECD	979	ΔENTRA	ΔGDP	(0.11)	↔	(0.12)	(−0.06)	↔	(−0.18)	↔
	Non-OECD	2438	ΔENTRA	ΔGDP		→	(0.37)	(−0.03)	←		↔
Residential	FULL	1898	ΔENRES	ΔHFCEX		–			→	(−0.23)	↔
	OECD	949	ΔENRES	ΔHFCEX	(0.12)	←			→	(−0.14)	↔
	Non-OECD	949	ΔENRES	ΔHFCEX		–	(−0.05)		↔	(−0.36)	↔

Note: The causality directions must be read looking at energy and economic variables and related arrows. Arrows pointing right stand for causality going from the economic variable to the energy variable, while arrows pointing left mean that the causality direction goes from the energy dimension to the economic variable. Arrows double pointing stand for a mutual causal relationship. The coefficients relative to Eq. (7) are reported in parenthesis only when they are statistically significant.

evidence is a sign of structural divergences between developed and developing countries that hardly affect the speed of reaction of the energy demand due to modification in the economic system. According to the standard economic convergence theory (Barro and Sala-i-Martin, 1995), developed countries have lower economic growth rates than developing countries on average and, at the same time, they are characterized by higher technical progress, or in other words, they have more energy-efficient equipment. Higher energy prices together with stringent energy-saving regulations have forced manufacturing firms in OECD countries to make considerable efforts in technical innovation oriented toward a significant reduction in energy intensity, and this is explained by lower elasticities for the short-run causal relationship between economic and energy consumption variables.

4.2. Results for the multivariate model

To the best of our knowledge, the only paper that estimates energy demand functions in a panel cointegrated context using a multivariate model (including energy prices) is Al-Rabbaie and Hunt (2006), where a unique energy demand function is estimated by using FMOLS without investigating the existence of mutual causality relationships and without specifying alternative functions for different energy sectors. As suggested in Guttormsen (2004), a multivariate framework is particularly appropriate in the empirical examination of the association between energy and income where multiple indirect effects could be transmission channels for short and long-run changes. As clearly explained in Ghali and El-Sakka (2004), the effects related to omitted variables could lead to misleading conclusions in terms of optimal energy policy.

In our study, five distinct specifications are provided and each energy sector is modelled by using appropriate energy price variables.

Results for a multivariate VECM specification as Eq. (8) for Granger causality in a dynamic cointegrated panel are reported in Table 4 with all the Wald tests and the values of coefficients when the *Chi-squared* test rejects the null hypothesis of a redundant variable. It is worth noticing that results change substantially when energy prices are included, especially in the short-run causality nexus.

In the industry sector, causality relationships still remain valid in all three specifications (short, long and strong) with only one significant direction, related to the impact of increasing industrial production on energy consumption. At a first sight this could be interpreted as a neutrality condition of energy policies, that is public action oriented towards energy-saving will not harm economic growth. By using a multivariate framework it is easier to understand this result, because we can model directly energy policies by including energy prices. As we have already mentioned, in OECD countries a large portion of energy prices is related to energy taxes, so that energy policies (in the form of taxes) will increase production costs harming industrial output growth path. Even though the negative elasticity −0.03 is a bit lower than other estimations (see Al-Rabbaie and Hunt, 2006), it is interesting to note that there is only an indirect effect on the economic variable related to energy prices and there is no direct effect on the energy demand. This is explained partially by the fact that energy demand is mainly driven by industrial output whereas energy prices slightly affect the choice of firms in terms of energy consumption. This result has an important policy implication: when considering public actions oriented towards energy-saving by market price intervention, they have no effect on energy demand whereas they could constitute harmful policies for the industrial sector.

This result offers some advice on the effectiveness of bivariate causality models in evaluating the harmfulness of energy-saving policies. In this case, we have obtained contrasting results, thus meaning that the energy–economy binomial should be carefully investigated with appropriate models.

The results for the service sector are also interesting, if we consider the negative impact of increasing value-added on energy prices. Considering that we have adopted energy price for industry, we can consider the fact that an output increase in the service sector represents a typical substitution condition in energy consumption, and as development theory tells us, when the structural composition changes, even the energy mix is likely to be severely affected. The indirect negative effect on energy price means that when service sector is growing more rapidly than industry, the structural energy consumption downward trend could be offset by the reduction in industry energy prices. This phenomenon can be directly linked to the rebound effect as emphasized in Binswanger (2001) and more recently in Barker et al. (2007) and Turner (2009), where a low but statistically significant rebound effect has been found for all economic sectors.

The results for the transport sector remain stable with the multivariate model with mutual causal relationships between almost all the pairs of variables. In our opinion, this is a clear signal of omitted variables in the setting of an energy demand function: if the model considers the role of international transactions, both in terms of people and goods as well as the availability of infrastructures, we believe that the picture will change substantially, obtaining more appropriate information on the

Table 4
Panel VECM Granger causality test results for OECD sample with energy prices.

Causality relationship	Short-run causality		Long-run causality		Strong causality
	$\gamma_i^{y,p}$; $\delta_i^{e,p}$; $\lambda_i^{y,e}$	Wald Chi-sq	$\beta_i^{y,e,p}$ECT coefficient	Wald Chi-sq	Joint Wald Chi-sq
Economy					
ΔGDP → ΔENTOT	(0.43)	18.61***	(−0.25)	25.72***	45.39***
ΔENPR → ΔENTOT	(−0.14)	42.04***			25.25***
ΔENTOT → ΔGDP	(0.13)	6.31***	(−0.18)	1.51	6.74***
ΔENPR → ΔGDP	(−0.04)	5.88**			6.42**
ΔGDP → ΔENPR		0.35	(−0.04)	14.86***	14.86***
ΔENTOT → ΔENPR		1.43			15.47***
Industry					
ΔIND → ΔENIND	(0.12)	6.15**		0.18	6.17**
ΔINDPR → ΔENIND		0.37			0.55
ΔENIND → ΔIND		0.21	(−0.20)	3.23*	9.61***
ΔINDPR → ΔIND	(−0.03)	3.28*			4.77*
ΔIND → ΔINDPR		0.41	(−0.19)	15.98***	16.06***
ΔENIND → ΔINDPR		2.19			18.07 ***
Services					
ΔSER → ΔENSER	(0.42)	4.81**	(−0.20)	44.56***	47.61***
ΔINDPR → ΔENSER		0.55			47.42***
ΔENSER → ΔSER		0.16		0.51	1.43
ΔINDPR → ΔSER		0.37			1.72
ΔSER → ΔINDPR	(−0.55)	7.96***	(−0.07)	4.46**	4.75*
ΔENSER → ΔINDPR		0.01			4.47*
Transport					
ΔGDP → ΔENTRA	(0.19)	4.15**	(−0.19)	18.76***	23.46***
ΔGASPR → ΔENTRA	(−0.09)	24.14***			40.96***
ΔENTRA → ΔGDP	(0.91)	5.34**	(−0.16)	6.15**	11.83***
ΔGASPR → ΔGDP	(−0.13)	8.72***			10.13***
ΔGDP → ΔGASPR		0.89	(−0.30)	36.73***	36.95***
ΔENTRA → ΔGASPR	(0.52)	20.99***			38.17***
Residential					
ΔHFCEX → ΔENRES	(0.44)	19.46***	(−0.08)	45.04***	45.05***
ΔRESPR → ΔENRES		0.24			46.37***
ΔENRES → ΔHFCEX		0.28	(−0.25)	11.98***	12.19***
ΔRESPR → ΔHFCEX	(−0.03)	3.21**			19.07***
ΔHFCEX → ΔRESPR		1.31	(−0.07)	4.76**	6.34**
ΔENRES → ΔRESPR		2.14			6.68**

The heteroskedasticity of the error terms is corrected by using White robust standard errors both in periods (White period system robust covariances) and in cross-sections (coefficient covariance method: White cross-section system robust). The method for iteration control for GLS and GMM weighting specifications is to iterate weights and coefficients sequentially to convergence. To correct for possible autocorrelation we use the Newey–West estimator of the weighting matrix in the GMM criterion.
*Significant at 10% level. **Significant at 5% level. ***Significant at 1% level.
The coefficients relative to Eq. (8) are reported in parenthesis only when they are statistically significant.

real drivers of energy consumption and, consequently, a more accurate evaluation of the impact of energy and innovation policies.

Looking at the results for the residential sector, in the multivariate model the direction of causality goes from household final consumption expenditures to final energy consumption, showing how the expenditure level plays a key role in determining household energy demand. This could imply the exclusion of regressivity associated to energy policies when it is measured on total expenditure (as a proxy of income) since the estimated coefficients show how a proportional relationship exists between energy demand and households' total expenditure. A very low causality nexus also exists between energy price and household final consumption expenditures, suggesting that energy policies that modify energy prices–such as energy taxes–are likely to weakly affect household final consumption expenditures. The results for the long-run and strong causality confirm the existence of mutual causal relationships between the variables examined, as seen in the previous specification; also in this case, including omitted variables, such as demographic characteristics or habits, would probably help a clearer pattern to emerge.

As a final conclusion, our results suggest that in our non-stationary cointegrated panel dataset, energy consumption, income and price are all endogenous, and therefore single equation estimations of one or the other separately could be misleading. In this case endogeneity of energy prices could be explained by considering the fact that energy taxes (as a large portion of energy prices in OECD countries) are the expression of energy policies devoted to a reduction in energy demand. Security of energy supply and escaping from carbon lock-in are policy goals typical of a highly industrialized country, where willingness to pay for energy security and environmental protection are higher due to higher income per capita level (Popp, 2002; Unruh, 2000, 2002).

5. Conclusions

This paper provides new empirical insights into the analysis of the causal relationship between energy consumption and economic growth when considering a large sample of developed and developing countries and a sectoral specification. Standard results for non-stationarity and panel cointegration analysis have been found for both economic and energy variables in the period 1960–2005, both for the whole sample and for the two sub-samples considered here. The presence of non-stationary and cointegrated time series in a panel context makes more complex econometric estimates necessary using recent models such as the FMOLS developed by Pedroni (2000). The possible existence of mutual causal relationships between economic and energy variables must be considered in a Granger causality framework by using a Vector Error Correction Model that includes the long-run cointegrating relationship obtained by the FMOLS. The empirical analysis carried out on the full sample and on separate sub-samples, on the whole economy and at disaggregated level has shown a number of interesting results. These implications should be considered when such models are used to calculate income elasticity or when assisting policy makers in energy policy design.

Differences in the causality direction have been detected in sub-samples of countries, particularly in the specific sector analysis. In the industrial sector, there is a converging trend in the short-run but the causality directions diverge when a strong causality hypothesis is tested separately for the two sub-samples.

For the transport sector, all three kinds of causality show contrasting results for OECD and non-OECD countries revealing that the application of similar energy policies in structurally divergent countries could bring to contrasting effects. On the contrary, when considering the residential sector, it is clear that there are no univocal causality relationships in both developed and developing countries, meaning that policy evaluations and model settings should be performed with caution accounting for endogeneity and mutual causality.

These results cast some doubt on the capacity of bivariate models to shape causal relationships in the energy–economy binomial especially when different sectors are investigated. While Zachariadis (2007) has shown that there are divergent results when using alternative estimators or datasets for single countries, we have shown that the same scepticism on bivariate models applies even in a panel context. Working with specific sectors allows the existence of divergent trends to be considered even in a quite homogeneous country sample such as the OECD one. A strong policy advice should come from these first results, when the international community try to involve developing countries in virtuous energy-saving actions, without an explicit effort in shaping policy design appropriately for underdeveloped countries. Looking at the industry and transport sectors, it is worth noting that the causality direction changes when different time horizons are accounted for. In the short-run, it is the economic growth process that determines the energy consumption trend so that it is mainly driven by production demand, and policies oriented towards promoting energy-saving do not seem to affect economic development negatively. On the contrary, long-run causality is bi-directional, showing that changes in energy consumption could influence economic performance and vice versa.

When energy prices are included, the picture becomes much clearer, thus stimulating further research in multivariate sectoral energy models. Far from being conclusive, this study allows us to open new research directions in the assessment of public policies and technological innovation in the energy sector. Future research should consider the capital/labour ratio, the role of energy prices and taxes and energy regulation on the economic system more appropriately by adopting an induced technical change framework and focusing on a homogeneous country sample such as OECD or the European Union. Further applications of this empirical framework could be the estimation of short and long-run elasticities of energy services related to more disaggregated sectors, in order to calibrate the matrix used by energy models thus producing scenarios on the basis of relationships estimated from observed behaviours.

Acknowledgement

The authors gratefully acknowledge the support provided by the research network ENEA-INEA-UNIROMA TRE on “Integrating bottom-up and top-down energy models: the case of GTAP-E and Markal-Italy” of which this work is a part. The paper is the first step in a regional assessment of end-use energy sectors elasticities necessary to calibrate both GTAP-E and Markal. We are also indebted to Caterina Conigliani and Antonio Musolesi for their helpful suggestions, and to Luca Moroni for his research assistance. The usual disclaimers apply.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.eneco.2009.09.013.

References

Akara, A., Long, T., 1980. On the relationship between energy and GNP: a re-examination. Journal of Energy Development 5, 326–331.
Al-Iriani, M.A., 2006. Energy–GDP relationship revisited: an example from GCC countries using panel causality. Energy Policy 34, 3342–3350.
Al-Rabbaie, A., Hunt, L.C., 2006. OECD Energy Demand: Modelling Underlying Energy Demand Trends using the Structural Time Series Model. SEEDS Surrey Energy Economics Discussion Paper Series, N. 114.
Altinay, G., Karagol, E., 2004. Structural break, unit root, and the causality between energy consumption and GDP in Turkey. Energy Economics 26, 985–994.
Arellano, M., Bond, S.R., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58, 277–297.
Asafu-Adjaye, J., 2000. The relationship between energy consumption, energy prices and economic growth: time series evidence from Asian developing countries. Energy Economics 22, 615–625.
Barker, T., Ekins, P., Roxon, T., 2007. The macro-economic rebound effect and the UK economy. Energy Policy 35, 4935–4946.
Barro, R.J., Sala-i-Martin, X., 1995. Economic Growth. McGraw-Hill, New York.
Bentzen, J., 2004. Estimating the rebound effect in US manufacturing energy consumption. Energy Economics 26, 123–134.
Binswanger, M., 2001. Technological progress and sustainable development: what about the rebound effect? Ecological Economics 36, 119–132.
Breitung, J., 2000. The local power of some unit root tests for panel data. Advances in Econometrics 15, 161–177.
Breitung, J, Pesaran, MH, 2008. Unit roots and cointegration in panels. In: Matyas, L, Sevestre, P (Eds.), The Econometrics of Panel Data: Fundamentals and Recent Developments in Theory and Practice. Kluwer Academic Publishers, pp. 279–322.
Brookes, L., 1990. The greenhouse effect: the fallacies in the energy efficiency solution. Energy Policy 18, 199–201.
Carrion-i-Silvestre, J.L., Barrio-Castro, T.D., Lopez-Bazo, E., 2005. Breaking the panels: an application to GDP per capita. Econometrics Journal 8, 159–175.
Chen, P., Lee, C.C., 2007. Is energy consumption per capita broken stationary? New evidence from regional-based panels. Energy Policy 35, 3526–3540.
Cheng, S.B., Lai, W.T., 1997. An investigation of co-integration and causality between energy consumption and economic activity in Taiwan, Province of China. Energy Economics 19, 435–444.
Choi, I., 2001. Unit root tests for panel data. Journal of International Money and Finance 20, 249–272.
Dickey, D.A., Fuller, W.A., 1979. Distribution of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association 74, 417–431.
Dolado, J., Lütkepohl, H., 1996. Making Wald tests work for cointegrated VAR systems. Econometric Reviews 15, 369–386.
Engle, R.F., Granger, C.W.J., 1987. Cointegration and error-correction: representation, estimation and testing. Econometrica 55, 251–276.
Engle, R.F., Hendry, D.F., Richard, J.F., 1983. Exogeneity. Econometrica 51, 277–304.
Ghali, K.H., El-Sakka, M.I., 2004. Energy use and output growth in Canada: a multivariate cointegration analysis. Energy Economics 26, 225–238.
Granger, C.W.J., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37, 424–438.
Granger, C.W.J., 1981. Some properties of time series data and their use in econometric model specification. Journal of Econometrics 16, 121–130.
Granger, C.W.J., 1988. Causality, cointegration and control. Journal of Economic Dynamics and Control 12, 551–559.
Guttormsen, A.G., 2004. Causality between Energy Consumption and Economic Growth, Discussion Paper 24. Department of Economics and Resource Management Agricultural University of Norway, Norway.
Hadri, K., 2000a. Testing for stationarity in heterogeneous panel application. Econometric Journal 3, 148–161.
Hadri, K., 2000b. Testing for stationarity in heterogeneous panel application. Econometric Journal 3, 148–161.
Holtz-Eakin, D., Newey, W., Rosen, H., 1998. Estimating vector autoregressions with panel data. Econometrica 56, 1371–1395.
Im, K.S., Persaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. Journal of Econometrics 115, 53–74.
Im, K.S., Lee, J., Tieslau, M., 2005. Panel LM unit-root tests with level shifts. Oxford Bulletin of Economics and Statistics 67, 393–419.
Johansen, S., 1988. Statistical analysis of cointegration vectors. Journal of Economics Dynamic and Control 12, 231–254.
Johansen, S., 1991. Estimation and hypothesis-testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica 59, 1551–1580.
Khazzoom, D.J., 1980. Economic implications of mandated efficiency standards for household appliances. Energy Journal 1, 21–39.
Kraft, J., Kraft, A., 1978. On the relationship between energy and GNP. Journal of Energy and Development 3, 401–403.
Kwiatkowski, D., Phillips, P.C.B., Schmidt, P.J., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root? Journal of Econometrics 54, 159–178.
Lee, C.C., 2005. Energy consumption and GDP in developing countries: a cointegrated panel analysis. Energy Economics 27, 415–427.
Lee, C.C., 2006. The causality relationship between energy consumption and GDP in G-11 countries revisited. Energy Policy 34, 1086–1093.
Lee, C.C., Chang, C.P., 2007. Energy consumption and GDP revisited: a panel analysis of developed and developing countries. Energy Economics 29, 1206–1223.
Lee, C.C., Chang, C.P., 2008. Energy consumption and economic growth in Asian economies: a more comprehensive analysis using panel data. Resource and Energy Economics 30, 50–65.
Levin, A., Lin, C.F., Chu, C., 2002. Unit root tests in panel data: asymptotic and finite-sample properties. Journal of Econometrics 108, 1–24.
Lovins, A., 1988. Energy Savings Resulting from the Adoption of More Efficient Appliances: Another View. The Energy Journal 9 (2), 155–162.
Maddala, G.S., Wu, S., 1999. A comparative study of unit root tests with panel data and a new simple test. Oxford Bulletin of Economics and Statistics 631–652 Special Issue.
Mahadevan, R., Asafu-Adjaye, J., 2007. Energy consumption, economic growth and prices: a reassessment using panel VECM for developed and developing countries. Energy Policy 35, 2481–2490.
Masih, A.M.M., Masih, R., 1996. Energy consumption, real income and temporal causality: results from a multi-country study based on cointegration and error-correction modelling techniques. Energy Economics 18, 165–183.
Medlock, K.B., Soligo, R., 2001. Economic Development and End-Use Energy Demand. The Energy Journal 22 (2), 77–105.
Mehrara, M., 2007. Energy consumption and economic growth: the case of oil exporting countries. Energy Policy 35, 2939–2945.
Nachane, D.M., Nadkarni, R.M., Karnik, A.V., 1988. Co-integration and causality testing of the energy–GDP relationship: a cross-country study. Applied Economics 20, 1511–1531.
Newell, RG, Jaffe, AB, Stavins, RN, 1999. The induced innovation hypothesis and energy-saving technological change. The Quarterly Journal of Economics 114, 941–975.
Oh, W, Lee, K, 2004. Energy consumption and economic growth in Korea: testing the causality relation. Journal of Policy Modeling 26, 973–981.
Pedroni, P., 1999. Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bulletin of Economic and Statistics 61, 653–678.
Pedroni, P., 2000. Fully modified OLS for the heterogeneous cointegrated panels. Advances in Econometrics 15, 93–130.
Pedroni, P., 2001. Purchasing power parity tests in cointegrated panels. Review of Economics and Statistics 83, 727–731.
Perron, P., 1989. The great crash, the oil price shock and the unit root hypothesis. Econometrica 57, 1361–1401.
Persyn, D., Westerlund, J., 2008. Error correction based cointegration tests for panel data. Stata Journal 8 (2), 232–241.
Pesaran, M.H., Shin, Y., Smith, R.P., 1999. Pooled mean group estimation of dynamic heterogeneous panels. Journal of the American Statistical Association 94, 621–624.
Popp, D., 2002. Induced innovation and energy prices. American Economic Review 92, 160–180.
Rapach, D.E., Wohar, M.E., 2004. Testing the monetary model of exchange rate determination: a closer look at panels. Journal of International Money and Finance 23, 867–895.

Saikkonen, P., 1991. Asymptotic efficient estimation of cointegration regressions. Econometric Theory 7, 1–21.
Sims, C.A., 1972. Money, income, and causality. American Economic Review 62, 540–552.
Stern, D.I., 2000a. A multivariate cointegration analysis of the role of energy in the U.S. macroeconomy. Energy Economics 22, 267–283.
Stern, D.I., 2000b. A multivariate cointegration analysis of the role of energy in the US macroeconomy. Energy Economics 22, 267–283.
Stern DI, Cleveland CJ. Energy and Economic Growth. Rensselaer Polytechnic Institute 2004, Rensselaer Working Papers in Economics No. 0410,
Toda, H.Y., Yamamoto, T., 1995. Statistical inference in vector autoregressions with possibly integrated processes. Journal of Econometrics 66, 225–250.
Toman, M., Jemelkova, B., 2003. Energy and Economic Development: An Assessment of the State of Knowledge. Resources for the Future Discussion Paper No. 03–13, April 2003, Washington DC, USA.
Turner, K., 2009. Negative rebound and disinvestment effects in response to an improvement in energy efficiency in the UK economy. Energy Economics 31, 648–666.
Unruh, G.C., 2000. Understanding carbon lock-in. Energy Policy 28, 817–830.
Unruh, G.C., 2002. Escaping carbon lock-in. Energy Policy 30, 317–325.
Westerlund J. New Simple Tests for Panel Cointegration, Lund University 2005, Department of Economics Working Papers N. 8.
Westerlund, J., Edgerton, D.L., 2008. A simple test for cointegration in dependent panels with structural breaks. Oxford Bulletin of Economics and Statistics 70, 665–704.
Wolde-Rufael, Y., 2006. Electricity consumption and economic growth: a time series experience for 17 African countries. Energy Policy 34, 1106–1114.
Yu, E.S.H., Choi, J.Y., 1985. The causal relationship between energy and GNP: an international comparison. Journal of Energy and Development 10, 249–272.
Yu, E.S.H., Wang, B.K., 1984. The relationship between energy and GNP: further results. Energy Economics 6, 186–190.
Zachariadis, T, 2007. Exploring the relationship between energy use and economic growth with bivariate models: new evidence from G-7 countries. Energy Economics 29, 1233–1253.
Zivot, E., Andrews, D., 1992. Further evidence on the Great Crash, the oil price shock, and the unit root hypothesis. Journal of Business and Economic Statistics 10, 251–270.