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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.

Keywords: Energy Sector, Panel Unit Roots, Panel Cointegration, Vector Error Correction Models, Granger Causality
J.E.L. classification: C01, C32, C33; O13; Q43

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 Jenelkova (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. If energy supply is considered a homogenous input for the production function, this means that if policy constraints affect energy supply, economic development is harmed. 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 supporting the shift from lower-quality (typically less efficient and more polluting) to higher-quality energy services could provide impulse to economic growth rather than be detrimental

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to the development process.

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]:

$$EC_{tj} = f(Y_{tj}, p_{tj}, \tau(Y_{tj}, p_{tj})) \qquad [1]$$

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) which is expressed as a function of output level and energy prices. In this specification, public regulation in the energy sector is expressed in terms of energy prices and there is endogenous technical change given by (τ) as a function of the economy and prices.

The opposite relation is adapted from Lee and Chang (2008) and Stern (2000), as expressed in eq. [2]:

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

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*). 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 greatest part of energy prices.

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.

By observing energy trends in the past five decades, energy used per unit of economic output (energy intensity) seems to have steadily declined especially in advanced economies. The principal reason for this evidence is the shift in energy use from direct use of fossil fuels to the use of higher quality fuels (from coal to natural gas) or electricity (Stern and Cleveland, 2004).

If we consider highly industrialized countries, total energy use has increased, energy efficiency has improved and energy intensity - the energy necessary to produce output - 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 effected using new energy efficient technologies, the trade-off between energy and growth becomes less severe.

In order to obtain decoupled trends in the energy and economic sectors, an effort should be explicitly directed to possible win-win outcomes of energy (and environmental) regulation policies which are oriented towards technological innovation and productivity improvements.

There are also changes in energy intensity that are not directly related to changes in the relative energy price but mainly explained by structural change in the productive composition (Stern, 1999). 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. This results in an increase in demand for energy services and therefore energy. 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 a 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 and have observed 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 the four energy sectors (industry, service, residential and transport) is analysed using alternative estimation methods for each country. If declining energy intensity is seen to be a valid pattern 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. As in Judson *et al.* (1999) and Medlock and Soligo (2001), the results are mixed if different energy sectors are considered. While the industrial sector shows a flat or declining energy/GDP ratio after the first oil shock, transport and household energy consumption is still increasing for advanced economies.

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. Recent efforts to adopt time series analysis for panel datasets have allowed the linkage between economic growth and energy demand to be examined in greater detail but results are still conflicting and often too partial to allow consistent policy suggestions. Far from being exhaustive and conclusive, the purpose of this paper is to shed some light on the possibility of obtaining a better understanding of causal linkages between the economy and energy consumption by analysing the main end-use energy sectors in a panel context. Moreover, accurate econometric models based on panel data allow estimating empirically the elasticity parameters which are necessary to calibrate energy simulation models when they work on aggregated regional data, as the vats majority of existing energy models (Löschel, 2002).

The econometric strategy for analysis of this kind should account for a number of specific issues.

The first one is the non-stationarity of the time series and appropriate panel unit root tests must be performed. Secondly, if the time series are non-stationary, a panel cointegration approach is needed to see if a long-run equilibrium relationship exists between non-stationary variables. We must then consider that there is a high probability that the included variables are endogenous so that the models should consider the existence of Granger causality. In a non-stationary and cointegrated panel with endogenous variables, a properly designed econometric specification is a necessary requirement for providing correct and unbiased estimations.

This paper is different from previous contributions in several aspects. The sample adopted for the dataset is 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 energy sector 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) who examined the 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 relationships. 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, 2000; Asafu-Adjaye, 2000; Oh and Lee, 2004). Fourth-generation studies employ recently developed panel methods to test for unit roots, cointegration and Granger causality (Al-Iriani, 2006; Lee, 2007, 2008; Mahadevan and Asafu-Adaye, 2007).

Pooling increases the sample size considerably, allowing for higher degrees of freedom and more accurate and reliable statistical tests; it also reduces collinearity 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 (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, 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 result 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-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 that is to be estimated 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, 2005). 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 (2000). The basic autoregressive model can be expressed as follows:

$$y_{it} = \rho_i y_{it-1} + \delta_i X_{it} + \varepsilon_{it} \quad [3]$$

where i=1, 2, …, N represent countries observed over periods t=1, 2, …, 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 ρ_i <1, y_i is said to be weakly trend-stationary. On the other hand, if ρ_i =1, then y_i contains a unit root. LLC, BRT, and Hadri tests assume that the ε_{it} are IID (0, σ_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. Pesaran and Smith (1995) stressed the importance of parameter heterogeneity in dynamic panel data models and analysed the potentially severe biases that could arise from including it in an inappropriate manner.

Of the different panel unit root tests developed in the literature, LLC and IPS seem to be the most popular. Both of the tests are based on the ADF principle. However, LLC assumes homogeneity in the dynamics of the autoregressive coefficients for all panel members. In contrast, IPS allows for heterogeneity in these dynamics (namely, it allows for a heterogeneous coefficient of y_{it-1}); therefore, it is described as a heterogeneous panel unit root test. 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. Moreover, IPS proposes averaging the augmented Dickey-Fuller (ADF) tests, that is $\varepsilon_{it} = \sum_{j=1}^{p_i} \phi_{ij} \varepsilon_{it-j} + u_{it}$, allowing for different orders of serial correlation.

If this expression is transformed into the equation [3], the IPS test specifies a separate ADF regression for each cross-section as expressed in eq. [4]:

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

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^2_i. 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).

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. As a result, subsequent studies have modified the test so that it allows for one unknown breakpoint that can be determined endogenously from the data. The first test was proposed by Perron (1989) and it does not work in a panel context: it is able to capture a structural break that produces different consequences, namely a temporary or permanent change in level, a permanent change in the slope and a permanent change both in level and slope. The asymptotic critical values for t statistics are tabulated in Andrews and Zivot (1992). 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. The test of the null hypothesis of stationarity in a panel context could also follow Hadri (2000) who designed a test statistic that is the average of the univariate stationarity test in Kwiatkowski *et al*. (1992).

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 on single cross section units to investigate the existence of structural breaks. We have not performed panel unit root tests with structural breaks because we are aware that it is almost impossible to have homogeneous breaks in time series in a significantly heterogeneous panel like the one we have considered especially for variables such as income and energy consumption. We have therefore checked for non-stationarity in single time series with structural breaks, 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.

2.2 Panel cointegration

Earlier tests of cointegration include the simple two-step test by Engle and Granger (1987) or, alternatively, the Engle and Yoo (1987) three-step procedure; both methods cannot deal with situations where more than one cointegrating relationship is possible. Conversely, Johansen's Vector Auto Regression (VAR) test of integration (Johansen, 1988) uses a system approach to cointegration that allows determination of up to r linearly-independent cointegrating vectors ($r \leq g-1$, where g is the number of variables tested for cointegration). Johansen's procedure is useful when conducting individual cointegration tests but does not deal with cointegration test in panel settings since it threats the cointegrating vector as homogeneous across members.

Pedroni's cointegration tests (1999, 2000) allow for cross-sectional interdependence with different individual effects in the intercepts and slopes of the cointegrating equation. This technique significantly improves the conventional cointegration analysis applied on single country series: in fact, 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. For the first type, four tests are based on pooling the residuals of the regression along the within-dimension of the panel (panel tests); for the second type, three tests are based on pooling the residuals of the regression along the between-dimension of the panel (group tests)[1]. 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. The estimators used in the computation of the test statistics average the individually estimated coefficients for each member; each of the test statistics is able to accommodate individual specific short-run dynamics, individual specific fixed effects and deterministic trends (within-dimension) as well as individual specific slope coefficients (between-dimension).

Other residual-based panel cointegration tests include the contribution by Westerlund (2005) that is based on variance ratio statistics and does not require corrections for the residual serial correlations, Persyn and Westerlund (2008) that develops an error correction based cointegration test and Westerlund and Edgerton (2008) that takes into account the existence of structural breaks within the panel.[2]

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

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[1] The seven Pedroni tests are based on the estimated residuals from the following long-run model: $y_{it} = \alpha_{it} + \sum_{j=1}^{m} \beta_{ij} x_{ijt} + \varepsilon_{it}$ where $\varepsilon_{it} = \rho_i \varepsilon_{i(t-1)} + w_{it}$ are the estimated residuals from the panel regression. The null hypothesis tested is whether ρ_i is unity. The seven statistics are normally distributed. The statistics can be compared to appropriate critical values: if critical values are exceeded, then the null hypothesis of no cointegration is rejected, implying that a long-run relationship between the variables does exist; the relevant critical values can be found in Pedroni (1999). With a null of no cointegration, the panel cointegration test is essentially a test of unit roots in the estimated residuals of the panel: in the presence of a cointegrating relation, the residuals are expected to be stationary. These tests 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. However, according to Pedroni (2004), r and pp tests tend to under-reject the null in the case of small samples.

[2] 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 (2005).

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 and Pedroni's heterogeneous panel cointegration 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 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, 2005).

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:

$$Y_{i,t} = \alpha_i + \delta_i t + \beta_i EN_{i,t} + \varepsilon_{it} \qquad [5]$$

$$EN_{i,t} = \alpha_i + \delta_i t + \beta_i Y_{i,t} + \eta_{it}$$

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

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

An alternative approach for the calculation of the cointegrating relationship is the error correction-based pooled mean estimator (PMG) developed by Pesaran *et al.* (1999), represented by eq. [7]:

$$\Delta Y_{i,t} = \phi\left(Y_{i,t-1} + \gamma EN_{i,t}\right) + \sum_{j=1}^{p} \alpha_j^y \Delta Y_{i,t-j} + \sum_{s=0}^{q} \beta_j^y \Delta EN_{i,t-s} + \varepsilon_{i,t} \quad [7]$$

where ϕ is the error correction speed of adjustment parameter to be estimated, γ is a $(k\ x\ 1)$ vector of parameters, $\left(Y_{i,t-1} + \gamma EN_{i,t}\right)$ is the error correction term, α are p parameters to be estimated, β are q parameters to be estimated, p and q represent the number of lags for the economic variable and the energy variable respectively and ε_{it} is the error term. In addition to the traditional dynamic fixed effects models, PMG takes into account pooled mean group estimators, meaning that only the coefficient associated with the long-run relationship is homogeneous for all the cross section units (γ in eq. [7]) while allowing for maximum heterogeneity for the short-run dynamics (α_j^y and β_j^y coefficients $\forall j$). Nonetheless, the *ECT* obtained by the eq. [7] is quite different from an FMOLS estimation and does not seem appropriate for our purpose.[3]

The second step for building a Granger causality model with a dynamic error correction term based on Holtz-Eakin *et al.* (1988) 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. In a panel of N countries covering T years, the bivariate

[3] The FMOLS estimator is preferred to the DOLS because in the latter the co-variates are included in first differences and not in levels. Moreover, according to Pedroni (2001) and Breitung and Pesaran (2005), FMOLS and DOLS estimators possess 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 NO-OECD samples rely on 35 years. FMOLS is therefore a suitable estimator.

vector auto-regressions with fixed effects have the following form:

$$Y_{i,t} = \sum_{j=1}^{m} \alpha_j^y Y_{i,t-j} + \sum_{s=0}^{q} \beta_s^y EN_{i,t-s} + \eta_i^y + \phi_i^y + u_{i,t}$$

$$EN_{i,t} = \sum_{j=0}^{m} \alpha_j^e Y_{i,t-j} + \sum_{s=1}^{q} \beta_s^e EN_{i,t-s} + \eta_i^e + \phi_i^e + v_{i,t} \qquad [8]$$

where $Y_{i,t}$ and $EN_{i,t}$ are the two cointegrated variables for country i at time t; η_i and φ_i are individual fixed and time effects for the i-th panel member and $u_{i,t}$ and $v_{i,t}$ are the random disturbances whose distribution approximates normal.

The specifications of model [8] as a set of equations imply that the error terms are orthogonal to the fixed and time effects as well as the lag values of the endogenous variables. In the equations [8], 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. The resulting model is therefore as follows:

$$\Delta Y_{i,t} = \sum_{j=1}^{m} \alpha_j^y \Delta Y_{i,t-j} + \sum_{s=0}^{q} \beta_s^y \Delta EN_{i,t-s} + \Delta u_{i,t}$$

$$\Delta EN_{i,t} = \sum_{j=0}^{m} \alpha_j^e \Delta Y_{i,t-j} + \sum_{s=1}^{q} \beta_s^e \Delta EN_{i,t-s} + \Delta v_{i,t} \qquad [9]$$

However, differencing introduces a simultaneity problem because lagged endogenous variables on the right-hand side are correlated with the differenced error term. In addition, heteroschedasticity 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:

$$\Delta Y_{i,t} = \alpha_i^y + \beta_i^y ECT_{i,t-1}^y + \sum_{j=1}^{m} \delta_{i,j}^y \Delta Y_{i,t-j} + \sum_{s=1}^{q} \gamma_{i,s}^y \Delta EN_{i,t-s} + u_{i,t}$$

[10]

$$\Delta EN_{i,t} = \alpha_i^e + \beta_i^e ECT_{i,t-1}^e + \sum_{j=1}^{m} \delta_{i,j}^e \Delta Y_{i,t-j} + \sum_{s=1}^{q} \gamma_{i,s}^e \Delta EN_{i,t-s} + v_{i,t}$$

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 dependent variables in equations [10]. First, for weak Granger causality, we test H_0: $\delta_i^{y,e} = 0$ and $\gamma_i^{y,e} = 0$, $\forall i$ in equations [8].[4] 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 tolerate 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, univocal or bi-directional causality exists. Since all the variables are entered into the model in stationary form, a standard Wald F-test can be used to test the null hypothesis of no

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

causality (or weak exogeneity of the dependent variable).

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

$$\begin{aligned}
\Delta Y_{i,t} &= \alpha_i^y + \beta_i^y ECT_{i,t-1}^y + \sum_{j=1}^{m} \delta_{i,j}^y \Delta Y_{i,t-j} + \sum_{s=1}^{q} \gamma_{i,s}^y \Delta EN_{i,t-s} + \sum_{v=1}^{r} \lambda_{i,v}^y \Delta P_{i,t-v} + u_{i,t} \\
\Delta EN_{i,t} &= \alpha_i^e + \beta_i^e ECT_{i,t-1}^e + \sum_{j=1}^{m} \delta_{i,j}^e \Delta Y_{i,t-j} + \sum_{s=1}^{q} \gamma_{i,s}^e \Delta EN_{i,t-s} + \sum_{v=1}^{r} \lambda_{i,v}^e \Delta P_{i,t-v} + v_{i,t} \qquad [11] \\
\Delta P_{i,t} &= \alpha_i^p + \beta_i^p ECT_{i,t-1}^p + \sum_{j=1}^{m} \delta_{i,j}^p \Delta Y_{i,t-j} + \sum_{s=1}^{q} \gamma_{i,s}^p \Delta EN_{i,t-s} + \sum_{v=1}^{r} \lambda_{i,v}^p \Delta P_{i,t-v} + \eta_{i,t}
\end{aligned}$$

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-Lütkepohl (1996) and Toda-Yamamoto (1995) methods. Altinay and Karagol (2005), 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 and serial correlation and heteroschedastic standard errors to be corrected.

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, 2005, 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 NO-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 NO-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 construct combines several sources. For the energy sectors, we have collected data from the IEA publications on OECD and NO-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 as 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).

<<< INSERT HERE TABLE 1 >>>

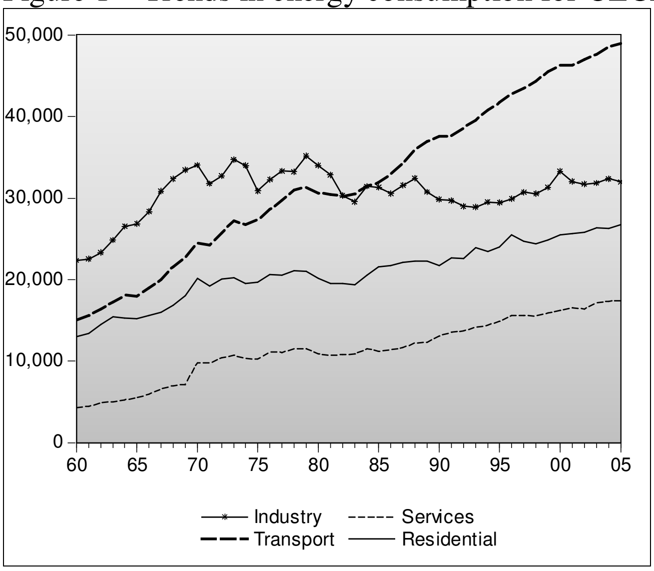
Data for energy prices are provided by IEA statistics on energy prices and taxes (quarterly) for OECD countries only for the time period 1978-2005. We have collected data for the whole energy sector and the four specific end-use sectors we have included in our analysis. We have considered four different 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.

We are aware that we could specify energy sectors with prices even for NO-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.

For bivariate models, data availability allows considering the period 1970-2005 for the full sample and the NO-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.

Figures 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 an incisive 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 NO-OECD economies, the 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.

Figure 1 – Trends in energy consumption for OECD countries (ktoe)

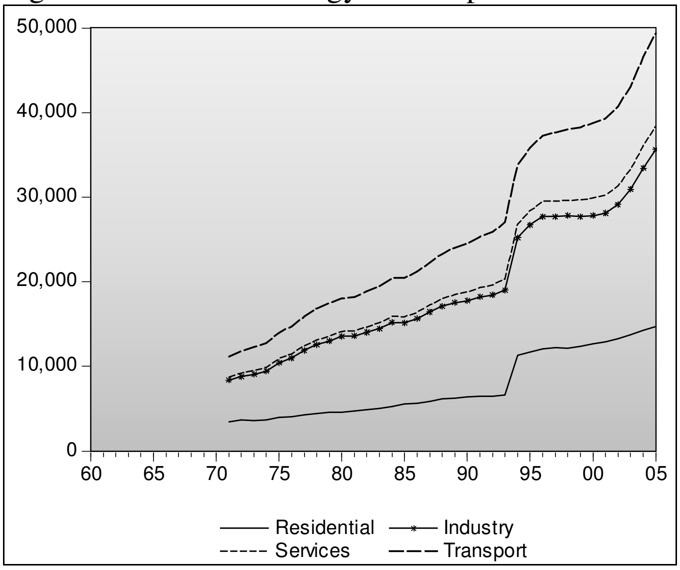


Source: our processing of IEA data (2008)

The energy trend for all the sectors in NO-OECD countries is hardly 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. We have considered this shock in the energy variables by modelling a country-specific time dummy for that period.

Figure 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 the potential divergent effects of different policy settings.

Figure 2 – Trends in energy consumption for NO-OECD countries (ktoe)



Source: our processing of IEA data (2008)

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.*, 2002), BRT (Breitung, 2000) and LLC (Levin *et al.*, 2003). Tests have been computed under two different specifications, represented by the inclusion of individual effects or individual effects and trends as reported in Table 2.

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 that we have examined, the full sample, the OECD and the NO-OECD sample.

<<< INSERT HERE TABLE 2 >>>

Energy prices are also I(1) - specified as total energy price, energy price for industry, energy price for households and gasoline price - because the series became stationary after first differencing (Table 3).

<<< INSERT HERE TABLE 3 >>>

For a robustness check of the stationarity results, we performed two alternative unit root tests - the Zivot-Andrews test (Andrews and Zivot, 1992) that allows for a single structural break and the CLEM test (Clemente *et al*., 1998) that allows for two structural breaks - on the single time series to check for the existence of one or multiple structural breaks as suggested in Lee and Chang (2007), and the series still remain non-stationary and integrated of order one I(1) for the vast majority of the cross section units.

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 heterogeneous panel statistics (1999) 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 Table 4, 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 NO-OECD sample, and the transport sector for OECD countries.

<<< INSERT HERE TABLE 4 >>>

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 allowed, 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 (Table 5).

<<< INSERT HERE TABLE 5 >>>

The existence of structural breaks may significantly affect the panel cointegration results. We have not applied the test developed by Westerlund and Edgerton (2008) on cointegration for dependent panels with structural breaks but we have 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.[5]

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.

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

[5] 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.

identified. We have reached the optimal lagged instruments structure of $k = 5$ by using the Portmanteau test for serial correlation of the residuals.[6] 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.[7]

Having estimated the VECM for all the sectors and distinct sub-samples, we performed a simple Wald *F*-test 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. [10]), a long-run causality related to the coefficient for the ECT term (H_0: $\beta_i = 0$ for all i in eq. [10]), 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. [10]). 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 *F*-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 6 and 7 for the three alternative country samples and for the whole economy and the four energy sectors separately. Table 6 reports results in terms of Wald *F*-test on the coefficients whereas in Table 7, the same results are summarized in a qualitative fashion with the explicit reference to the short and long-run elasticities when the coefficients are statistically significant.

<<< INSERT HERE TABLE 6 >>>

<<< INSERT HERE TABLE 7 >>>

When the bivariate VECM model is performed on the whole economy, the three alternative samples present quite homogeneous results, with a bidirectional 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 Jenelkova (2003).

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[6] 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 $k^2(h\text{-}p)$ where p is the VAR lag order. We have computed both first and second-order serial correlation test and in both cases, H_0 is accepted.

[7] The Jarque-Bera statistic has a distribution with two degrees of freedom under the null hypothesis of normally distributed errors. All results have been omitted from tables for the sake of simplicity, and they are available from the authors upon request.

The parameters β_i represent the speed of adjustment coefficients which measure the speed at which the values of Y_t and EN_t come back to long-run equilibrium levels, once they violate the long-run 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 previous period's 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 we consider alternative VECMs specified for each single end-use sector, the picture changes dramatically and results seem to support our research hypothesis that specific sector models could provide contrasting results. 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 in the short-run causality for the whole economy; as we can see, short-run causality is unidirectional when energy consumption is caused by industrial production. It is interesting to see that the direction of the causal relationship remains stable for the NO-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 bidirectional 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 7, there is a bidirectional 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 NO-OECD sample. On the contrary, the residential sector only shows a unidirectional short-run causality for the OECD sample whereas for both long-run and strong causality, there is a bi-directional nexus.

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 NO-OECD. This could be explained by the increasing role of trade flows in GDP structure for emerging countries such as Brazil, China and India that belong to the NO-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 7), the values of short and long-run elasticities show substantial changes if alternative country samples are investigated. In the short-run causality, NO-OECD sample reveals higher elasticities for all the five specifications for OECD countries. This empirical evidence is a sign of structural divergences between developed and developing countries that hardly affects the speed of reaction of the energy demand due to modification in the economic system. According to a 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.

<<< INSERT HERE TABLE 8 >>>

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. [11] for Granger causality in a dynamic cointegrated panel are reported in Table 8 with all the Wald *F*-stat and the values of elasticities when *F*-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) while a second causality linkage should be added, related to the negative impact of raising energy prices for the economic performance of the industrial sector. The negative elasticity -0.03 is a bit lower than other estimations (see Al-Rabbaie and Hunt, 2006) but 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 do not 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, the effect on energy demand is neutral whereas they could constitute harmful policies for the industrial sector. It is also possible to partially estimate an indirect effect on energy consumption if we consider that increasing energy prices produce a reduction in the industrial output and, consequently, a decrease in energy consumption.

We would like to stress this result in order to offer some advice on the effectiveness of bivariate causality models in the formulation of policy conclusions on 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.

Results for the service sector are 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 are growing more rapidly than industry, the energy consumption tend to downward with a relative reduction in industry energy prices. This impact can be directly linked to the rebound effect as in Binswanger (2001).

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, we believe that the picture will change substantially, obtaining more appropriate information on the 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 energy policies' regressivity when it is measured on total expenditure (as proxy of income) since energy demand grows with household total expenditure. A very low causality 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: in this case too, there is likely to be a problem of omitted variables.

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.

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 sector 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 which 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 there is strong causality for the two sub-samples.

For the transport sector, all three kinds of causality show divergent results for OECD and NO-

OECD countries revealing that the application of similar energy policies in divergent countries could have contrasting results. 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. 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 energy consumption 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 the opposite, showing that reductions in energy consumption could reduce economic performance by increasing production costs.

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 these 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.

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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$ per ton of oil equivalent)	International Energy Agency (IEA), Energy Prices and Taxes
$INDPR_{it}$	Total Industry Price (constant 2000 US$ per ton of oil equivalent)	
$RESPR_{it}$	Total Household Price (constant 2000 US$ per ton of oil equivalent)	
$GASPRS_{it}$	Total Gasoline Price (constant 2000 US$ per 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)	

Table 2 – Panel unit root tests for energy and economic variables (1960-2005/1970-2005)

Variable	Panel Specifica-tions	Unit root tests	FULL SAMPLE Levels	FULL SAMPLE First differences	OECD Levels	OECD First differences	NO-OECD Levels	NO-OECD First differences
GDP	Individual effects	LLC	5.63	-13.08***	2.24	-17.98***	9.16	-21.73***
		IPS	11.13	-14.94***	9.05	-18.52***	8.16	-24.47***
	Individual effects and trends	LLC	8.21	-21.69***	0.35	-17.84***	4.32	-24.55***
		BRT	9.18	-1.06	-1.11	-14.85***	5.33	-16.67***
		IPS	8.42	-19.08***	0.25	-17.05***	3.99	-24.38***
IND	Individual effects	LLC	7.19	-17.04***	2.63	-18.14***	8.28	-24.53***
		IPS	7.12	-17.21***	1.76	-18.84***	7.17	-25.68***
	Individual effects and trends	LLC	6.71	-18.53***	-0.57	-15.78***	3.93	-23.46***
		BRT	8.93	-9.27***	-0.08	-12.85***	5.43	-14.82***
		IPS	6.64	-17.26***	-0.93	-16.63***	4.03	-23.66***
SER	Individual effects	LLC	6.83	-12.60***	4.27	-8.24***	14.23	-14.83***
		IPS	13.91	-13.59***	12.06	-9.38***	10.08	-15.63***
	Individual effects and trends	LLC	4.27	-12.53***	1.12	-7.26***	-0.64	-15.37***
		BRT	10.11	-6.84***	4.39	-5.39***	9.07	-9.85***
		IPS	6.31	-11.19***	-0.66	-7.78***	0.85	-15.93***
HFCEX	Individual effects	LLC	5.71	-9.51***	0.21	-6.25***	2.34	-14.82***
		IPS	8.69	-6.35***	-0.28	-7.03***	8.51	-8.41***
	Individual effects and trends	LLC	4.89	-9.18***	-0.25	-7.48***	0.67	-14.59***
		BRT	4.27	-8.83***	2.01	-7.68***	8.19	-15.29***
		IPS	9.51	-11.05***	8.17	-9.15***	6.57	-16.57***
ENTOT	Individual effects	LLC	0.01	-24.31***	-1.93**	-14.10***	2.07	-19.59***
		IPS	2.81	-14.33***	2.04	-12.09***	1.94	-9.18***
	Individual effects and trends	LLC	3.05	-20.04***	0.81	-13.05***	3.21	-15.25***
		BRT	-3.05***	-26.84***	1.67	-16.70***	2.43	-20.76***
		IPS	2.43	-24.33***	0.39	-16.95***	4.74	-17.70***
ENIND	Individual effects	LLC	-0.79	-27.12***	-1.75**	-17.94***	1.13	-21.09***
		IPS	1.76	-24.21***	-0.51	-14.14***	2.59	-19.66***
	Individual effects and trends	LLC	-1.80*	-29.71***	-1.95**	-18.05***	-0.45	-23.80***
		BRT	0.98	-16.57***	0.81	-8.49***	0.58	-15.08***
		IPS	0.93	-25.99***	0.18	-13.34***	1.03	-22.52***
ENSER	Individual effects	LLC	7.76	-22.68***	6.26	-14.96***	4.95	-16.81***
		IPS	9.78	-19.59***	6.11	-12.79***	7.64	-14.88***
	Individual effects and trends	LLC	1.91	-23.94***	0.71	-16.14***	2.29	-17.50***
		BRT	5.13	-5.59***	4.19	-1.97***	3.06	-6.66***
		IPS	2.86	-18.77***	0.87	-12.97***	2.91	-13.84***
ENTRA	Individual effects	LLC	0.32	-14.68***	4.34	-6.26***	2.27	-13.87***
		IPS	5.61	-14.62***	3.42	-7.71***	4.21	-12.51***
	Individual effects and trends	LLC	3.84	-15.70***	3.56	-8.14***	1.99	-13.69***
		BRT	4.62	-6.94***	3.17	-3.51***	3.39	-6.23***
		IPS	3.81	-13.71***	3.51	-7.46***	2.11	-11.55***
ENRES	Individual effects	LLC	-0.94	-27.45***	11.8	-21.33***	-0.58	-18.01***
		IPS	2.35	-23.80***	2.18	-18.54***	3.71	-15.81***
	Individual effects and trends	LLC	0.59	-24.93***	41.8	-19.04***	1.88	-16.59***
		BRT	0.21	-15.07***	1.05	-11.19***	0.06	-10.56***
		IPS	-0.07	-20.75***	1.36	-16.35***	1.74	-13.66***

Selection of lags based on Modified Akaike Information Criterion; Newey-West bandwidth selection using Bartlett kernel; Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality; H_0: Unit root (assumes individual unit root process).
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Table 3 – Panel unit root tests for energy prices (OECD sample, 1978-2005)

Variable	Test	Individual effects		Individual effects and trends	
		Levels	First differences	Levels	First differences
ENEPR	LLC	21.01	-2.75***	2.77	-12.19***
	IPS	3.49	-8.97***	-0.2	-13.91***
	BRT			-1.82**	-3.27***
INDPR	LLC	0.08	-8.10***	4.67	-17.20***
	IPS	0.79	-7.02***	6.02	-15.32***
	BRT			3.13	-10.73***
RESPR	LLC	10.11	-8.34***	2.11	-14.71***
	IPS	1.24	-10.39***	1.28	-14.88***
	BRT			0.02	-7.08***
GASPR	LLC	-0.79	-8.84***	3.89	-14.10***
	IPS	-0.98	-8.24***	2.56	-11.58***
	BRT			0.18	-6.35***

Selection of lags based on Modified Akaike Information Criterion; Newey-West bandwidth selection using Bartlett kernel; Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality; Null: Unit root (assumes individual unit root process).
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Table 4 – Heterogeneous Panel Cointegration tests for bivariate models (1978-2005)

SECTOR	FULL SAMPLE	OECD	NO-OECD
ECONOMY	*Series: ENTOT GDP*		
Panel v-Statistic	4.53***	8.33***	1.64*
Panel rho-Statistic	0.1	-1.90*	-2.80***
Panel PP-Statistic	-1.04	-2.76***	-5.43***
Panel ADF-Statistic	6.29	-0.03	-5.22***
Group rho-Statistic	1.63	-0.5	3.03
Group PP-Statistic	-2.10**	-3.65***	-2.09***
Group ADF-Statistic	7.09***	-0.55	3.17
INDUSTRY	*Series: ENIND IND*		
Panel v-Statistic	4.75***	2.20**	5.88***
Panel rho-Statistic	5.43	2.93	-0.95
Panel PP-Statistic	-6.93***	-3.04***	-5.46***
Panel ADF-Statistic	-3.69***	-3.45***	-6.19***
Group rho-Statistic	8.67	4.04	4.34
Group PP-Statistic	-6.98***	-4.82***	-3.99***
Group ADF-Statistic	-1.2	-0.46	-2.30**
SERVICES	*Series: ENSER SER*		
Panel v-Statistic	2.82***	2.02**	3.17***
Panel rho-Statistic	5.13	0.33	5.58
Panel PP-Statistic	-2.43**	-2.84***	-5.48***
Panel ADF-Statistic	-2.84***	-2.95***	-5.34***
Group rho-Statistic	7.89	4.04	7.64
Group PP-Statistic	-2.595**	-2.21**	-3.47***
Group ADF-Statistic	-1.93	-1.65	-1.66***
RESIDENTIAL	*Series: ENRES HFCEX*		
Panel v-Statistic	1.89*	4.48***	1.77*
Panel rho-Statistic	9.6	-1.11	4.47
Panel PP-Statistic	-4.09***	-4.82***	-2.04**
Panel ADF-Statistic	-4.09***	-4.74***	-1.97*
Group rho-Statistic	11.45	-0.02	6.72
Group PP-Statistic	-5.29***	-6.08***	-1.83*
Group ADF-Statistic	-3.52***	-5.78***	9.02
TRANSPORT	*Series: ENTRA GDP*		
Panel v-Statistic	3.90***	2.31**	2.82***
Panel rho-Statistic	-3.02***	-1.25	-3.56***
Panel PP-Statistic	-4.30***	-2.21**	-4.18***
Panel ADF-Statistic	-3.36***	-1.67**	-3.22***
Group rho-Statistic	3.34	1.52	2.3
Group PP-Statistic	-1.80*	-2.45*	-1.97**
Group ADF-Statistic	1.46	1.49	-1.73**

Heterogeneity assumptions: no intercept and no deterministic trend
Lag selection: based on Modified Akaike Information Criterion
Newey-West bandwidth selection with Bartlett kernel
Alternative hypothesis: common AR coefs. (within-dimension):
Panel v-Statistic
Panel rho-Statistic
Panel PP-Statistic
Panel ADF-Statistic
Alternative hypothesis: individual AR coefs. (between-dimension) the others test statistics
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Table 5 - Heterogeneous Panel Cointegration tests for multivariate models (OECD, 1978-2005)

SECTOR			
ECONOMY	*Series: ENTOT GDP ENPR*		
Panel v-Statistic	3.12***	Group rho-Statistic	-1.22
Panel rho-Statistic	-1.99**	Group PP-Statistic	-5.57***
Panel PP-Statistic	-4.35***	Group ADF-Statistic	-4.75***
Panel ADF-Statistic	-3.24***		
INDUSTRY	*Series: ENIND IND INDPR*		
Panel v-Statistic	3.56***	Group rho-Statistic	6.5
Panel rho-Statistic	4.74	Group PP-Statistic	-2.23**
Panel PP-Statistic	-2.21**	Group ADF-Statistic	-2.01**
Panel ADF-Statistic	-3.21***		
SERVICES	*Series: ENSER SER INDPR*		
Panel v-Statistic	1.76**	Group rho-Statistic	6.79
Panel rho-Statistic	5	Group PP-Statistic	-8.95***
Panel PP-Statistic	-3.10***	Group ADF-Statistic	-4.43***
Panel ADF-Statistic	-2.90***		
RESIDENTIAL	*Series: ENRES HFCEX RESPR*		
Panel v-Statistic	3.16***	Group rho-Statistic	4.45
Panel rho-Statistic	-2.68**	Group PP-Statistic	-8.77***
Panel PP-Statistic	-4.84***	Group ADF-Statistic	-5.17***
Panel ADF-Statistic	-5.41***		
TRANSPORT	*Series: ENTRA GDP GASPR*		
Panel v-Statistic	2.73***	Group rho-Statistic	5.21
Panel rho-Statistic	2.38	Group PP-Statistic	-1.84*
Panel PP-Statistic	-2.42**	Group ADF-Statistic	0.5
Panel ADF-Statistic	-2.09**		

Heterogeneity assumptions: no intercept and no deterministic trend
Lag selection: based on Modified Akaike Information Criterion
Newey-West bandwidth selection with Bartlett kernel
Alternative hypothesis: common AR coefs. (within-dimension):
Panel v-Statistic
Panel rho-Statistic
Panel PP-Statistic
Panel ADF-Statistic
Alternative hypothesis: individual AR coefs. (between-dimension) the others test statistics
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Table 6 – Panel VECM causality test results for bivariate models

Dependent variable	FULL SAMPLE					OECD SAMPLE					NO-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 (ECTand ΔENTOT)	Joint (ECT and ΔGDP)	ΔGDP	ΔENTOT	ECT	Joint (ECTand ΔENTOT)	Joint (ECT and ΔGDP)	ΔGDP	ΔENTOT	ECT	Joint (ECTand 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 heteroschedasticity 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 7 – Causality directions in four end-use energy sectors in bivariate models

SECTORS	SAMPLES	N° obs.	Economic variable	Energy variable	Short-run causality	Long-run causality	Strong causality
Economy	FULL	2226	Δgdp	Δentot	(0.06) ↔ (0.13)	→ (-0.10)	→
	OECD	979	Δgdp	Δentot	(0.06) ↔ (0.12)	→ (-0.26)	↔
	NO-OECD	1247	Δgdp	Δentot	(0.05) ↔ (0.17)	→ (-0.04)	→
Industry	FULL	1807	Δind	Δenind	→ (0.21)	—	↔
	OECD	713	Δind	Δenind	→ (0.10)	(-0.06) ←	↔
	NO-OECD	1094	Δind	Δenind	→ (0.20)	→ (-0.07)	→
Services	FULL	1713	Δserv	Δenser	(0.01) ↔ (0.24)	→ (-0.20)	→
	OECD	713	Δserv	Δenser	—	(-0.43) ↔ (-0.25)	↔
	NO-OECD	1000	Δserv	Δenser	→ (0.24)	→ (-0.21)	↔
Transport	FULL	2198	Δgdp	Δentra	(0.03) ↔ (0.36)	→ (-0.07)	↔
	OECD	979	Δgdp	Δentra	(0.11) ↔ (0.12)	(-0.06) ↔ (-0.18)	↔
	NO-OECD	2438	Δgdp	Δentra	→ (0.37)	(-0.03) ←	↔
Residential	FULL	1898	Δhfcex	Δenres	—	→ (-0.23)	↔
	OECD	949	Δhfcex	Δenres	(0.12) ←	→ (-0.14)	↔
	NO-OECD	949	Δhfcex	Δenres	—	(-0.05) ↔ (-0.36)	↔

Table 8 – Panel VECM Ganger causality test results for OECD sample with energy prices

	Short-run causality		Long-run causality		Strong causality
Causality relationship	VECM elasticity	Wald F-stat	VECM elasticity	Wald F-stat	Joint Wald F-stat
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 heteroschedasticity 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.

Appendix

Table A1 – List of countries included in the panel dataset

OECD		NO-OECD	
Australia	Turkey	Algeria	Kenya
Austria	United Kingdom	Argentina	Malaysia
Belgium	United States	Bolivia	Morocco
Canada		Brazil	Nepal
Denmark		Cameroon	Nigeria
Finland		Chile	Pakistan
France		China	Paraguay
Germany		Colombia	Peru
Greece		Congo, Dem. Rep.	Philippines
Hungary		Costa Rica	Romania
Iceland		Cote d'Ivoire	Saudi Arabia
Ireland		Ecuador	Senegal
Italy		Egypt	Singapore
Japan		Gabon	South Africa
Korea, Rep.		Ghana	Sri Lanka
Mexico		Guatemala	Sudan
Netherlands		Honduras	Syrian Arab Rep.
New Zealand		India	Thailand
Norway		Indonesia	Tunisia
Portugal		Iran	Uruguay
Spain		Israel	Venezuela
Sweden		Jamaica	Zimbabwe
Switzerland		Jordan	