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The Drivers of Rising Global Energy Demand: New Evidence

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Abstract: This paper provides an exhaustive analysis of the key factors that led to rising global energy demand, based on an OECD sample and a non-OECD sample over the period of 1980-2009. In addition to income and price elasticities traditionally examined, this research takes into account the effects of structural change, demographic change, technological change and temperature change on energy demand. Using newly developed panel data techniques allowing for spatial error dependence and spatial lag dependence, this research finds evidence for the existence of spatial lag dependence, a positive but declining income elasticity, a negative price elasticity, and the significant effects of industry/service value added, urbanization and technical innovations on energy demand. This research has important implications for public policies to induce energy savings, develop service sector and promote energy-efficient technologies towards a sustainable future.

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Keywords: Energy Demand; Structural Change; Demographic Change; Technological Change; Cross Section Dependence.

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1 Introduction

In the past decades, rapid economic growth in the world economy, especially emerging economies, spurred energy consumption considerably, which has put unprecedented pressure on achieving energy-saving. This research aims to identify the key drivers of rising global energy demand in the past decades.

The increases of per capita income and changes of lifestyle have fuelled the consumption of cars, refrigerators and other heating and cooling, lighting appliances, and intensive uses of transportation services nationally and internationally in recent years, for which more energy is undoubtedly required. Businesses need more energy for their production and delivery in each country to meet growing demand for goods and services. Developed countries still need huge amounts of energy to maintain their existing lifestyle. Middle income countries rely on enormous amounts of affordable energy provision for their growing economies. The 2010 World Energy Outlook (IEA, 2010a) predicts that world primary energy demand will increase by 36% between 2008 and 2035, or 1.15% per year on average, and world demand for oil, often used to proxy the world demand for energy, will increase from 2000 million tons of oil equivalent (Mtoe) to 17000 Mtoe in 2035.

Substantial research has been undertaken to examine the relationships between energy demand and some key economic factors such as income level and energy price. However, scant attention has been paid to the roles of demographic change, structural change, technological change and temperature change on energy demand. Does urbanization exert a distinctive and empirically verifiable impact on energy consumption? How important is technological progress for the levels of energy consumption? How significant is temperature for the rising energy consumption? This research examines the effects on energy demand of energy price, income per capita as well as structural change, demographic change, technological change and temperature change, using annual data between 1980 and 2009 for an OECD sample of 24 countries and a non-OECD sample of 39 countries.

This research focuses on the Common Correlated Effect (CCE) approach due to Pesaran (2006), further developed by Kapetanios *et al.* (2011), Chudik *et al.* (2011) and Pesaran and Tosetti (2011). It extends the model to allow for spatial lag dependence, in additional to spatial error dependence. The CCE approach is to estimate the heterogeneous panels with a multifactor structure which assumes that the cross section error dependence can be caused by a finite number of unobserved common factors. For the OECD sample, this research provides evidence for the existence of spatial lag dependence, and a positive but declining income elasticity, and a negative price elasticity of energy demand. It also finds that more industry value added and urbanization raise energy demand, while the developments of service economies and technical innovations tend to reduce energy demand. For the non-OECD sample, this research finds no evidence for spatial lag dependence, while confirming a positive income elasticity and a negative impact of service value added on energy demand.

This research contributes to a better understanding of the dynamics and trends in energy markets. As economies continue to grow, energy needs will be increasing. This has raised a long-term concern over energy security by many governments in the world given the limited capacity of our ecosystem. The findings of this research have important implications for public policies in terms of inducing energy savings, encouraging expansion of the service sector and promoting energy-efficient technologies that enable a switch from fossil fuels to renewable energy sources towards a sustainable future.

The remainder of the paper proceeds in Section 2 to review the literature. Section 3 describes the sample and data. Section 4 outlines the methodology employed. Section 5 conducts cross section dependence testing, panel unit root testing, panel cointegration testing and estimation. Section 6 concludes.

2 Energy Demand Studies

The energy demand studies across countries have flourished recently. Mahadevan and Asafu-Adjaye (2007) study the inter-linkages between energy consumption, economic growth and energy prices for 20 net energy importers and exporters from 1971 to 2002 where the consumer price index of base year 2000 is used to proxy energy prices.[1] Costantini and Martini (2010) exam-

[1] A core consumer price index typically excludes food and energy prices, and therefore might fail to proxy energy prices.

ine the causality between energy consumption and economic growth for a large sample of developed and developing countries with four energy sectors. Two papers make use of similar approaches and reach similar conclusions; however, both of them do not allow for cross country correlation, which is especially relevant when energy exporters, importers or global economy are targeted. van Benthem and Romani (2009) examine the relationships between energy demand, economic growth and prices in 24 non-OECD countries for three sectors over the period 1978-2003. With linear and nonlinear income and price elasticities, van Benthem and Romani (2009) lead to similar results in terms of a positive income elasticity and a negative price elasticity. While van Benthem and Romani (2009) use fixed time effects to control for unobserved dynamic effects, it fails to control for the heterogeneous common effects and spatial correlation.

A number of specific country studies have also been conducted. Maddala *et al.* (1997) suggest a positive income elasticity and a negative price elasticity of residential demand of electricity and natural gas in the United States based on 49 states over 21 years using shrinkage estimators. Pesaran *et al.* (1998) study the long-run income and price elasticities of energy demand for 10 Asian developing economies over the period of 1974-1990 at aggregate, sectoral and industrial levels. In general, they find a positive elasticity with respect to per-capita GDP and a negative elasicity with respect to energy prices, with substantial heterogeneity across countries. By using unit root and cointegration tests and error correction model, Buranakunaporn and Oczkowski (2007) also find a positive income elasticity and a negative price elasticity of energy demand in Thailand.

The majority of existing energy demand research restrict their attention to income elasticity and price elasticity. However, numerous factors have been found important for the recent increases of energy use, including demographic changes, structural change, technological change and temperature change.

Historically, economic growth has been achieved with a large scale shift of labour force from primary agriculture to urban-based industries. Urban lifestyles and urban economic activities are expected to directly and indirectly exert an excessive pressure on the levels of resource consumption, especially energy usage. Significant movements of population from rural to urban areas necessitate the increased provision of public infrastructure including transportation systems, communication systems, energy systems, water supply and sanitation and drainage systems, resulting in greater energy use. Population growth is also related to energy use as population growth leads to the increases in demand for goods and services, residential and commercial housing, and transportation, which drive the rises of energy use.

Among others, Ngai and Pissarides (2007) show that structural change in terms of shifts in employment shares (or values added) in the economy, from agriculture to industry to services, has important implications for the growth rates of total factor productivity, which is closely related to energy use. Schäfer (2005) suggests, based on 11 world regions for the period of 1971-1998, that structural change in the economy causes similar structural change in final energy use, and for the higher-income regions most of the reduction in final energy intensity is firstly attributed to the industry sector and secondly the service sector. Hofman and Labar (2007) find that a sectoral shift towards industry in the majority of provinces in China leads to the recent rebound in energy intensity in its economy, which is partly offset by the intra-sectoral energy savings in industry and other sectors. Buranakunaporn and Oczkowski (2007) find a positive impact of changing industrial structure on Thailand energy demand.

Technological change has been a central issue in global energy-environment-economy modelling. There is overwhelming evidence that technological change is endogenous and induced by the needs and pressures, not an exogenous variable. Research and development expenditure, spillovers from research and development and technology learning have been the major approaches to model induced technological change. These approaches capture the process of new energy-saving technical advances and replacing the ineffcient technologies with energy-saving techniques. The induced technological change tends to reduce the costs of abatement and speed up abatement process (Wing, 2006). But technological innovation might lead to higher energy uses due to a "rebound effect".

The temperature effect on energy demand has received considerable attention. Peirson and Henley (1994) study the electricity demand in the UK and find that the relationship between electricity load and air temperature has an important dynamic component. Pardo *et al.* (2002) examine the relationship between electricity demand and weather in Spain and find weather to be significant and important in the model. Petrick *et al.* (2010) find that energy use goes down with rising temperature due to a reduction of energy demand for heating purposes, based on an unbalanced panel of 137 countries over three decades.

With new data and method, this research will be a comprehensive and renewed study of energy demand, aiming to provide new evidence and insights into this crucial issue.

3 The Data

This section describes the samples and data. This research focuses on two samples, one is the OECD sample of 24 countries and the other is the non-OECD sample of 39 countries. For both samples, we exclude countries with fewer than 25 annual observations of either energy price defined below, GDP per capita, value added, manufactured exports ratio or mean temperature over the period of 1980-2009.

The dependent variable is energy demand per capita, denoted by **ED**. The data for final consumption of total energy (in Mtoe) and population (in thousands) are taken from the Enerdata (2010). In this research we use the natural logarithm of final consumption of total energy per capita.

To measure income elasticity, GDP per capita in log and its squared term, denoted by **GDPPC** and **GDPPC**^{2}, are used. Data for real GDP per capita (constant prices: chain series) are taken from the Penn World Table 7.0 due to Heston *et al.* (2011). GDP per capita has been widely considered as the main driver of energy demand, and we expect to have a positive sign for **GDPPC**. The sign for **GDPPC**^{2} could be either negative or positive, with the former representing more energy intensity and the latter meaning less energy intensity of the economy.

To gauge price elasticity, this analysis makes use of two energy prices, denoted by **EPRICE**. For OECD sample, energy price, denoted by **EPRICE1**, uses the natural logarithm of real price index of total energy for industry and households, taken from the IEA (2011). For the non-OECD sample, energy price, denoted by **EPRICE2**, uses the natural logarithm of the derived consumer price index for energy, which is consumer price index (of the non-OECD countries) times the averaged ratios of consumer price index for energy to the consumer price index (of 24 OECD countries).[2] Data for consumer price index for energy (or "CPI energy") for OECD countries and consumer price index (CPI) for all countries are taken from the IEA (2011). The squared terms of the two energy prices are also used in the analysis, separately. Normally higher energy prices induce lower energy demand; therefore a negative sign is expected for either **EPRICE1** or **EPRICE2**.

To capture the effect of structural change, this research makes use of two variables, value added over GDP of industry, denoted by **INADD**, and value added over GDP of services, denoted by **SEADD**. Data for the value added of both industry and services are obtained from the World Bank (2011). Both **INADD** and **SEADD** are taken in log.

The demographic variable considered in this analysis is the urbanization rate in log, denoted by **URBAN**. Data for urbanization rate are from the World Bank (2011). As suggested by the literature, **URBAN** is among the key drivers of rising energy demand.

This analysis uses the natural logarithm of manufactured exports as the proxy for technological change, denoted by **MANU**. Data for manufactured exports (% of merchandise exports) are from the World Bank (2011). Energy-efficient technical innovations tend to introduce more energy-saving appliances to households and industries, reducing the amount of energy required. We expect to have a negative sign for **MANU**.[3]

[2] The ratios of consumer price index for energy (CPI energy) to consumer price index (CPI) for 24 OECD countries exhibit a certain pattern where the ratios are within the interval of (1, 1.5) for the periods of 1980-1985 and 2005-2009 and less than 1 for the period of 1986-2004. Due to the lack of energy price data for non-OECD countries, this analysis assumes that the non-OECD countries have CPI energy which, in relation to the CPI, follow the similar pattern of OECD countries. The means of the above ratios over time for 24 OECD countries have been calculated and used to multiply the CPI of 39 non-OECD countries, resulting in the CPI energy for those countries.

[3] The sign could actually be either negative or positive, due to a "rebound effect" in the sense that technical innovations that reduce energy demand could cause even more energy consumption.

This analysis studies the temperature effect using the natural logarithm of mean temperature, denoted by **TEMP**. The original temperature dataset is the CRUTEM3 global surface temperature dataset from the University of East Anglia's Climatic Research Unit (2010). It has temperature data (in degrees Celsius) at a monthly frequency at a 0.5 degree by 0.5 degree latitude/longitude grid spatial resolution, from 1900-2010. We use the CRUTEM3 dataset to calculate the average yearly temperature within each country.[4]

Missing values for **EPRICE2**, **INADD**, **SEADD**, **MANU** and **TEMP** have been both interpolated and extrapolated based on **GDPPC**.[5] Appendix Table 1 contains the description and sources of the variables and Appendix Table 2 has the list of countries in this analysis.

4 Methodology: Common Correlated Effect Approach

This section firstly outlines the methodologies developed by Pesaran (2006), Kapetanios *et al.* (2011), Chudik *et al.* (2011) and Pesaran and Tosetti (2011). It then introduces the extension to allow for spatial lag dependence, in additional to the spatial error dependence. The issue of spatial lag dependence due to the presence of social and spatial interactions is believed to be important for this context. One example is that the total energy imports of OECD countries increase from 1779 Mtoe in 1973 to 3195 Mtoe in 2008, while their total energy exports increase from 404 Mtoe in 1973 to 1430 Mtoe in 2008 (IEA, 2010b).

We assume that the long-run relationships between energy demand and energy price, income level, structural change, demographic change, technological change and temperature change can be written as a log-linear form with a multi-factor structure:[6]

[4] Russell Layberry and Mark Syddall have kindly helped get this work done.

[5] There are 4 missing data of **EPRICE2**, 39 missing data of **INADD**, 40 missing data of **SEADD**, 52 missing data of **MANU** and 7 missing data of **TEMP**, respectively.

[6] We also include the squared terms of **GDPPC** and **EPRICE** to allow for the non-monotonic relationships between energy demand, GDP per capita and energy prices.

$$
\begin{aligned}
\mathbf{ED}_{it} &= \alpha_i^{'}\mathbf{d}_t + \beta_{i1j}\mathbf{EPRICE}_{i,t-1} + \beta_{i2j}\mathbf{GDPPC}_{i,t-1} \\
&\quad +\beta_{i3j}\mathbf{INADD}_{i,t-1} + \beta_{i4j}\mathbf{SEADD}_{i,t-1} + \beta_{i5j}\mathbf{URBAN}_{i,t-1} + \\
&\quad \beta_{i7j}\mathbf{MANU}_{i,t-1} + \beta_{i8j}\mathbf{TEMP}_{it} + \gamma_i^{'}\mathbf{f}_t + \varrho_{it} \qquad (1) \\
i &= 1, 2, ..., T \text{ and } t = 1, 2, ..., N
\end{aligned}
$$

where α_i is a $l \times 1$ vector of factor loading and $\mathbf{d}_t$ is a $l \times 1$ vector of observed common effects including deterministic components (such as intercepts or seasonal dummies) and stochastic common effects (here l is the number of observed common effects). $\beta_{i1j} - \beta_{i8j}$ are coefficients to be estimated for variables explained in previous section. $\mathbf{f}_t$ is a $r \times 1$ vector of unobserved common shocks or common factors, which could be global or regional or could be technological, macroeconomic or environmental, and γ_i is $(r \times 1)$ vector of factor loading, such that $\gamma_i^{'}\mathbf{f}_t = \gamma_{i1}^{'}\mathbf{f}_{t1} + \gamma_{i2}^{'}\mathbf{f}_{t2} .... + \gamma_{ir}^{'}\mathbf{f}_{tr}$ (here r is the number of common factors). ϱ_{it} are the idiosyncratic errors.

For simplicity, let y_{it} denote the dependent variable, $\mathbf{ED}_{it}$, and x_{it} denote a $k \times 1$ ($k = 8$) vector of the independent variables, $x_{it} = (\mathbf{EPRICE}_{i,t-1}$, $\mathbf{GDPPC}_{i,t-1}$, $\mathbf{INADD}_{i,t-1}$, $\mathbf{SEADD}_{i,t-1}$, $\mathbf{URBAN}_{i,t-1}$, $\mathbf{MANU}_{i,t-1}$, $\mathbf{TEMP}_{it})^{'}$.[7] β_i is a vector of heterogeneous slope coefficients that reflect the existence and direction of any specific effects on energy demand, $\beta_i = (\beta_{i1j}, \beta_{i2j}, \beta_{i3j}, \beta_{i4j}, \beta_{i5j}, \beta_{i6j}, \beta_{i7j}, \beta_{i8j})^{'}$. Equation (1) can be simplified as:

$$
\mathbf{y}_{it} = \alpha_i^{'}\mathbf{d}_t + \beta_i^{'}\mathbf{x}_{it} + \gamma_i^{'}\mathbf{f}_t + \varrho_{it} \qquad (2)
$$

The above representations with a factor structure are believed to be very general. Since common factors are unobservable, standard regression methods are not applicable. Pesaran (2006) proposes a novel estimation approach, called Common Correlated Effect (CCE) approach, for one type of large heterogeneous panels, where the common factors, $\mathbf{f}_t$, are assumed to be weakly stationary.[8] Two types of CCE approaches are proposed, one

[7] The inclusion of the lagged values of these variables except for $\mathbf{TEMP}_{it}$ in the model is to avoid the potential endogeneity bias.

[8] More specifically, rather than estimating the unobserved common factors and factor loadings, Pesaran (2006) proposes to run the standard panel regressions where the observed

is the common correlated effect pooled ($CCEP$) estimator, a generalization of the within groups estimator that allows for the possibility of cross section correlation, and the other is the common correlated effects mean group ($CCEMG$) estimator, a generalization of the mean group estimator of Pesaran and Smith (1995) that is adapted for the possibility of cross section correlation.

The CCE procedure allows for unobserved common factors, $\mathbf{f}_t$, to be possibly correlated with exogenous regressors and idiosyncratic components, ϱ_{it}, to be independent across countries (although they can be serially correlated over time). The CCE estimators hold for any number of unobserved common factors as long as the number is fixed. They have been shown to be asymptotically unbiased and consistent as $N \to \infty$ and $T \to \infty$, and to have generally satisfactory finite sample properties.

Kapetanios *et al.* (2011) extend the work of Pesaran (2006) by considering the case where common factors, $\mathbf{f}_t$, are integrated of order 1, or $I(1)$. Kapetanios *et al.* (2011) suggest that the CCE estimator is robust to the integration properties of unobserved factors, which are often unknown, as long as the number of unobserved common factors is fixed when the sample size is increased. The CCE estimator has also been found robust to a wide range of data generation processes.

Chudik *et al.* (2011) extend the work of Pesaran (2006) to the case where there are infinite number of factors, a fixed number of strong factors assumed to be possibly correlated with the regressors and a large number of weak, semi-weak or semi-strong factors assumed to be uncorrelated with the regressors.[9] Chudik *et al.* (2011) show that the CCE estimator continues to be consistent and asymptotically normal under these types of infinite-factor error structures.

The assumption for the error terms considered by Pesaran (2006), Kapetanios *et al.* (2011) and Chudik *et al.* (2011) is that the idiosyncratic components, ϱ_{it}, are cross-sectionally uncorrelated although possibly serially cor-

regressors are augmented with the (weighted) cross section averages of the dependent variable and the individual specific regressors, which are used to approximate the linear combinations of the common factors.

[9] The common factor structure in Pesaran (2006) represents a strong factor structure.

related. Pesaran and Tosetti (2011) relax this assumption by assuming that the idiosyncratic error, ϱ_{it}, is a weakly dependent process with bounded row and column norms of its variance matrix, which includes spatial autoregressive or spatial moving average processes considered in the literature. Pesaran and Tosetti (2011) show that the CCE estimator is robust to the presence of various forms of error cross section dependence.[10]

According to Anselin *et al.* (2007), spatial dependence is a special case of cross-sectional dependence in the sense that spatial dependence is present when cross-sectional correlations follow a certain type of spatial ordering which characterises the neighbour relation, while spatial dependence is reduced to a simple cross-sectional dependence when information on the spatial ordering is lacking. There are two types of spatial dependence, spatial lag dependence pertaining to the spatial correlation in the dependent variable and spatial error dependence, which refers to the spatial correlation in the error terms. Accordingly, there are two classes of model specifications, spatial lag model and spatial error model. Anselin *et al.* (2007) suggest that a spatial lag model where a spatially lagged dependent variable is added is the formal specification for the equilibrium outcome of a spatial or social interaction process where "the value of the dependent variable for one agent is jointly determined with that of the neighbouring agents". The spatial error model is a special case of a non-spherical error covariance matrix, where the error term can be either expressed as some spatial error processes, a spatial autoregressive process or a spatial moving average process, or specified as a common factor structure (Anselin *et al.*, 2007)[11].

Essentially, Pesaran and Tosetti (2011) deal with the presence of spatial error dependence, in the sense of Anselin *et al.* (2007). However, the CCE procedure has not been extended to study the case of spatial lag dependence. This research extends the work of Pesaran (2006), Kapetanios *et al.* (2011),

[10] Kapoor *et al.* (2007) generalize the generalized moments estimators of Kelejian and Prucha(1999) to a panel data model with spatial autoregressive errors and define a feasible generalized least squares procedure for regression parameters. In contrast, Fingleton (2008) proposes a generalized method of moments estimator for a panel data model with spatial moving average errors.

[11] Andrews (2005) provides a general framework for the spatially correlated errors including factors, which may differ across the population units in a discrete or continuous fashion, and may be local or global in nature.

Chudik *et al.* (2011) and Pesaran and Tosetti (2011) by using the *CCE* procedure to estimate a panel data model to which the spatially lagged dependent variable is added.[12]

More specifically, this research considers the spatial lag model with a multi-factor structure in the error terms as follows,

$$\mathbf{y}_{it} = \alpha_i^{'}\mathbf{d}_t + \lambda_i \sum_{j=1}^{N} w_{ij}\mathbf{y}_{jt} + \beta_i^{'}\mathbf{x}_{it} + \gamma_i^{'}\mathbf{f}_t + \varrho_{it} \tag{3}$$

where w_{ij} is the element (i, j) of the spatial weighting matrix, W_N, λ_i is the spatial autoregressive coefficient. The cross section in each period $t = 1, 2, ..T$, is as follows,

$$\mathbf{y}_t = \alpha^{'}\mathbf{d}_t + \lambda W_N \mathbf{y}_t + \beta^{'}\mathbf{x}_t + \gamma^{'}\mathbf{f}_t + \boldsymbol{\varrho}_t \tag{4}$$

where $\mathbf{y}_t$ is a $N \times 1$ vector of cross-sectional observations of dependent variable for time period t, $\mathbf{x}_t$ is a $N \times k$ vector of cross-sectional observations of explanatory variables for time period t, $\boldsymbol{\varrho}_t$ is a $N \times 1$ vector of cross-sectional disturbances for time period t, α is a $l \times 1$ vector of cross-sectional factor loading, $\boldsymbol{\gamma}$ is a $r \times 1$ vector of cross-sectional factor loading, λ is the spatial autoregressive coefficient, and $\boldsymbol{\beta}$ is a $k \times 1$ vector of cross-sectional regression coefficients.

The idiosyncratic errors, $\boldsymbol{\varrho}_t$, are assumed to be distributed independently of $\mathbf{x}_t$ and $\mathbf{d}_t$ although cross-sectionally uncorrelated and serially correlated over time. The unobserved common factors, $\mathbf{f}_t$, stationary or nonstationary, are allowed to be possibly correlated with exogenous regressors, suggesting that

$$\mathbf{x}_t = \mathbf{A}^{'}\mathbf{d}_t + \boldsymbol{\Gamma}^{'}\mathbf{f}_t + \varepsilon_t \tag{5}$$

where $\mathbf{A}$ and $\boldsymbol{\Gamma}$ are $l \times k$ and $r \times k$ matrices of factor loadings with fixed and bounded components, respectively, ε_t are the individual specific components of $\mathbf{x}_t$ assumed to be distributed independently of common factors and follow general covariance stationary process.

[12] Fingleton (2008b) develops a generalized method of moments estimator for a spatial panel model with an endogenous spatial lag and spatial moving average errors.

Taking Equations (4) and (5) together, we have

$$\underset{(k+1)\times 1}{\mathbf{z}_t} = \begin{pmatrix} \mathbf{y}_t \\ \mathbf{x}_t \end{pmatrix} = \underset{(k+1)\times l}{\mathbf{B}'} \underset{l\times 1}{\mathbf{d}_t} + \underset{(k+1)\times r}{\mathbf{C}'} \underset{r\times 1}{\mathbf{f}_t} + \underset{(k+1)\times 1}{\epsilon_t} \tag{6}$$

where

$$\epsilon_t = \begin{pmatrix} \varrho_t + (I_N - \lambda W_N)^{-1}\beta' \boldsymbol{\varepsilon}_t \\ \boldsymbol{\varepsilon}_t \end{pmatrix} = \begin{pmatrix} 1 & (I_N - \lambda W_N)^{-1}\beta' \\ 0 & I_k \end{pmatrix} \begin{pmatrix} \varrho_t \\ \boldsymbol{\varepsilon}_t \end{pmatrix} \tag{7}$$

$$\mathbf{B} = \begin{pmatrix} \alpha(I_N - \lambda W_N)^{-1} & \mathbf{A} \end{pmatrix} \begin{pmatrix} 1 & 0 \\ \beta(I_N - \lambda W_N)^{-1} & I_k \end{pmatrix} \tag{8}$$

$$\mathbf{C} = \begin{pmatrix} \gamma(I_N - \lambda W_N)^{-1} & \mathbf{\Gamma} \end{pmatrix} \begin{pmatrix} 1 & 0 \\ \beta(I_N - \lambda W_N)^{-1} & I_k \end{pmatrix} \tag{9}$$

where I_N and I_k are an identity matrix of order N and k, respectively. The rank of $\mathbf{C}$ is subject to the rank of the matrix of the unobserved factor loadings $\begin{pmatrix} \gamma & \mathbf{\Gamma} \end{pmatrix}$.

Pesaran (2006) suggests to use the cross section weighted averages of $\mathbf{y}_t$ and $\mathbf{x}_t$ as proxies for the unobserved common factors. Below is the simple cross section averages of Equation (6),

$$\bar{\mathbf{z}}_t = \bar{\mathbf{B}}' \mathbf{d}_t + \bar{\mathbf{C}}' \mathbf{f}_t + \bar{\boldsymbol{\epsilon}}_t \tag{10}$$

where

$$\bar{\mathbf{z}}_t = \frac{1}{N}\sum_{i=1}^{N} \mathbf{z}_{it}; \bar{\mathbf{B}} = \frac{1}{N}\sum_{i=1}^{N} B_i;\ \bar{\mathbf{C}} = \frac{1}{N}\sum_{i=1}^{N} C_i; \bar{\boldsymbol{\epsilon}}_t = \frac{1}{N}\sum_{i=1}^{N} \epsilon_{it} \tag{11}$$

The unobserved common factors can be expressed as follows when the Rank($\bar{\mathbf{C}}$)=$r \leq k+1$,

$$\mathbf{f}_t = (\bar{\mathbf{C}}\bar{\mathbf{C}}')^{-1}\bar{\mathbf{C}}(\bar{\mathbf{z}}_t - \bar{\mathbf{B}}' \mathbf{d}_t - \bar{\boldsymbol{\epsilon}}_t) \tag{12}$$

When $N \to \infty$, $\bar{\boldsymbol{\epsilon}}_t \to 0$ and $\bar{C} \xrightarrow{p} C$, and the following condition holds,

$$\mathbf{f}_t - (CC)^{-1}C(\bar{\mathbf{z}}_t - \bar{\mathbf{B}}' \mathbf{d}_t - \bar{\boldsymbol{\epsilon}}_t) \to 0 \tag{13}$$

This suggests that the finding of Pesaran (2006) by using cross section weighted averages to proxy common factors continues to hold. Therefore, when N is sufficiently large, $(\mathbf{d}_t', \bar{\mathbf{z}}_t')'$ are valid proxies for $\mathbf{f}_t$.

Following Pesaran (2006), the CCE mean group estimator (CCEMG), $\hat{b}_i$, of β_i, is a simple average of the individual CCE estimator[13],

$$\hat{b}_{CCEMG} = N^{-1}\sum_{i=1}^{N}[(\mathbf{X}_i'\bar{\mathbf{M}}\mathbf{X}_i)^{-1}\mathbf{X}_i'\bar{\mathbf{M}}\mathbf{Y}_i] \tag{14}$$

where $\mathbf{X}_i = (\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{x}_{i3}, ..., \mathbf{x}_{iT})'$, $\mathbf{Y}_i = (\mathbf{y}_{i1}, \mathbf{y}_{i2}, \mathbf{y}_{i3}, ..., \mathbf{y}_{iT})'$, $\bar{\mathbf{M}} = \mathbf{I}_T - \bar{\mathbf{H}}(\bar{\mathbf{H}}'\bar{\mathbf{H}})^{-1}\bar{\mathbf{H}}'$ with $\bar{\mathbf{H}} = (\tau_T, \bar{\mathbf{Z}})$, where τ_T is a $T \times 1$ vector of ones and $\bar{\mathbf{Z}}$ is a $T \times (k+1)$ matrix of observations $\mathbf{z}_t$.

The CCE pooled estimator (CCEP) is given as follows[14]

$$\hat{b}_{CCEP} = \left(\sum_{i=1}^{N}\mathbf{X}_i'\bar{\mathbf{M}}\mathbf{X}_i\right)^{-1}\sum_{i=1}^{N}\mathbf{X}_i'\bar{\mathbf{M}}\mathbf{Y}_i \tag{15}$$

5 Econometric Evidence

5.1 Cross Section Dependence Test

This research carries out a cross section dependence (CD) test due to Pesaran (2004), which is to test for the general unspecified error cross section dependence and does not require the specification of a spatial weighting matrix. The CD test statistic can be applied to a large number of dynamic heterogeneous panel data models with short T and large N, either stationary or nonstationary, with or without structural breaks. The CD test statistic is the average of pairwise correlations of the OLS residuals of the individual specific regressions,

[13]The $CCEMG$ approach uses OLS to estimate an auxiliary regression for each country in which the time dummies and the (weighted) cross sectional averages of the dependent variable and the individual specific regressors are added.

[14]The $CCEP$ estimator is the within groups estimator with time dummies and the (weighted) cross sectional averages, the interactions between some dummy variables and means of the dependent variable and individual specific regressors, included in the model.

$$\widehat{\varrho}_{ij} = \mathbf{y}_{it} - \alpha_i^{'}\mathbf{d}_t - \widehat{\beta}_i^{'}\mathbf{x}_{it} \tag{16}$$

The CD test statistic can be caluated as

$$CD = \sqrt{\frac{2T}{n(n-1)}}\left(\sum_{i=2}^{n-1}\sum_{j=i+1}^{n}\widehat{\rho}_{ij}\right) \tag{17}$$

where

$$\widehat{\rho}_{ij} = \sum_{t-1}^{T}\frac{\widehat{\varrho}_{it}\widehat{\varrho}_{jt}}{(\widehat{\varrho}_i^{'}\widehat{\varrho}_i)^{1/2}(\widehat{\varrho}_j^{'}\widehat{\varrho}_j)^{1/2}} \tag{18}$$

where $\widehat{\varrho}_i$ and $\widehat{\varrho}_j$ are the $T \times 1$ residual vectors for each cross-sectional unit. As $N \rightarrow \infty$, the CD test statistic is asymptotically distributed as standard normal.

Insert Table 1 here

Table 1 reports the CD test statistics for the OECD and non-OECD samples over the periods 1980-1989, 1990-1999 and 2000-2009. The CD test statistics are based on the OLS residuals from the AR(2) regressions in total energy consumption with a constant and linear trend. The hypothesis that total energy demand is cross sectionally independent is clearly rejected for three periods in two samples, highlighting the importance of taking into account the cross section dependence in this context.

5.2 Panel Unit Root Test

Over recent decades a number of panel unit root testing procedures have been proposed in the literature. Given the presence of cross section dependence, this research applies the panel unit root test proposed by Pesaran (2007), the $CIPS$ test. Pesaran (2007) considers a heterogeneous and linear panel data model whose level equation and first-differenced equation are as follows,

$$\mathbf{y}_{it} = (\mathbf{1}-\theta_i)\boldsymbol{\mu}_i + \theta_i\mathbf{y}_{i,t-1} + \gamma_i^{'}\mathbf{f}_t + \varrho_{it} \tag{19}$$

$$\Delta\mathbf{y}_{it} = (\mathbf{1}-\theta_i)\boldsymbol{\mu}_i + (\theta_i - 1)\mathbf{y}_{i,t-1} + \gamma_i^{'}\mathbf{f}_t + \varrho_{it} \tag{20}$$

Following the CCE approach, Pesaran (2007) suggests to augment Equation (20) with cross-sectional averages of lagged levels and first differences, leading to the following Cross-sectionally Augmented Dickey-Fuller ($CADF$) equation,

$$\Delta \mathbf{y}_{it} = (\mathbf{1}-\theta_i)\boldsymbol{\mu}_i + (\theta_i - 1)\mathbf{y}_{i,t-1} + c_i\bar{y}_{t-1} + d_i\Delta\bar{y}_t + \varepsilon_{it} \tag{21}$$

The $CIPS$ test statistic can be obtained as

$$CIPS = N^{-1}\sum_{t-1}^{N}\widetilde{t}_i \tag{22}$$

where $\widetilde{t}_i$ is the OLS $t-$ratio of $(\theta_i - 1)$ in the above $CADF$ equation (21).

Insert Table 2 here

Table 2 contrasts the panel unit root test statistics for OECD sample and non-OECD sample. We allow for an intercept and a linear trend in the data. For OECD sample, apart from $\mathbf{EPRICE1}_{it}$ and $\mathbf{TEMP}_{it}$ for which the null hypothesis of a unit root is clearly rejected, the null can not be rejected for other variables, which seems independent of the choice of augmentation order of the underlying CADF regressions. For non-OECD sample, the null can not be rejected for variables other than $\mathbf{INADD}_{it}$, $\mathbf{SEADD}_{it}$ and $\mathbf{TEMP}_{it}$. After taking first differences for those variables, the null of unit roots is rejected at the 1% significance level, especially for the augmentation order of one. For the whole sample of 63 countries, panel unit root test statistics suggest that $\mathbf{INADD}_{it}$, $\mathbf{SEADD}_{it}$, $\mathbf{MANU}_{it}$, and $\mathbf{TEMP}_{it}$ are stationary.[15] This analysis therefore treats those variables as I(0) while $\mathbf{ED}_{it}$, $\mathbf{GDPPC}_{it}$, $\mathbf{EPRICE1}_{it}$ and $\mathbf{EPRICE2}_{it}$ as I(1) variables.

5.3 Panel Cointegration Tests

This research then makes use of the panel cointegration tests developed by Westerlund (2007) and Persyn and Westerlund (2008), which test for the absence of cointegration by determining whether error correction exists for individuals or for the panel as a whole. Westerlund (2007) considers the

[15] Results are available from the author upon request.

following error correction model, where all variables in levels are assumed to be I(1),

$$\Delta \mathbf{y}_{it} = \alpha_i^{'}\mathbf{d}_t + \theta_i \mathbf{y}_{i,t-1} + \lambda_i^{'}\mathbf{x}_{i,t-1} + \sum_{j=1}^{p_i} \theta_{ij}\mathbf{y}_{i,t-j} + \sum_{j=0}^{p_i} \gamma_{ij}\mathbf{x}_{i,t-j} + \varepsilon_{it} \quad (23)$$

where θ_i is the error-correction parameter measuring the speed of adjustment towards the long run equilibrium. If $-2 < \theta_i < 0$, Equation (23) can be seen as an error-correction model, implying that $\mathbf{y}_{i,t-1}$ and $\mathbf{x}_{i,t-1}$ are cointegrated. Westerlund (2007) proposes two group mean statistics and two panel mean statistics to test the null hypothesis of no cointegration between $\mathbf{y}_{i,t-1}$ and $\mathbf{x}_{i,t-1}$, based on least squares estimates of θ_i in Equation (23) and its t-ratio.

Two group mean statistics are as follows

$$G_\tau = N^{-1} \sum_{t-1}^{N} \frac{\hat{\theta}_i}{SE(\hat{\theta}_i)} \quad (24)$$

$$G_\alpha = N^{-1} \sum_{t-1}^{N} \frac{T\hat{\theta}_i}{\hat{\theta}_i(1)} \quad (25)$$

where $SE(\hat{\theta}_i)$ is the conventional standard error of $\hat{\theta}_i$ and $\hat{\theta}_i(1) = 1 - \sum_{j-1}^{p_i} \hat{\theta}_{ij}$.

The two panel mean statistics are as follows

$$P_\tau = \frac{\hat{\theta}}{SE(\hat{\theta})} \quad (26)$$

$$P_\alpha = T\hat{\theta} \quad (27)$$

where $SE(\hat{\theta})$ is the conventional standard error of $\hat{\theta}$, which is defined in Westerlund (2007).

In comparison to the existing residual-based panel cointegration tests, the panel cointegration test of Westerlund (2007) allows for the differences between the long-run cointegrating vector and short-run adjustment process and heterogeneous specifications of both the long- and short-run parts of the error correction model. To allow for cross section dependence, Westerlund (2007) simulates the finite sample distribution of each test statistic through bootstrapping.

Insert Table 3 here

Table 3 presents the panel cointegration test results for both OECD sample and non-OECD sample of $\mathbf{ED}_{it}$, $\mathbf{GDPPC}_{it}$ and $\mathbf{EPRICE}_{it}$. We use three different kernel windows with a constant, one lag and one lead in the error correction test regression. For the OECD sample, the evidence of robust p-values suggests that we can reject the null of no cointegration using any statistics, which is robust to the kernel windows chosen. For the non-OECD sample, the results of both p-values and robust p-values are not satisfactory. However, both p-values and robust p-values indicate that we can reject the null of no cointegration reasonably using P_τ statistic for any of the three kernel windows. According to the simulation results of Westerlund (2007) which show that P_τ is quite robust to cross section correlations, we move on taking these three variables as cointegrated in the non-OECD sample as well.

5.4 Panel Error Correction Estimation

Given the presence of cointegration between energy demand and its key drivers, we now proceed to estimate the corresponding error correction model to Equation (3), which governs the co-movements of the series of energy demand and its potential drivers over time as follows

$$\begin{aligned}\Delta \mathbf{y}_{it} &= \boldsymbol{\alpha}_i^{'}\mathbf{d}_t + \lambda_i \sum_{j=1}^{N} w_{ij}\mathbf{y}_{jt} + \theta_i(\mathbf{y}_{i,t-1} - \beta_i^{'}\mathbf{x}_{i,t-1}) + \\ &\quad \delta_{1i}^{'} \triangle \mathbf{y}_{i,t-1} + \delta_{2i}^{'} \triangle \mathbf{x}_{i,t-1} + \gamma_i^{'}\Delta\mathbf{f}_t + \varepsilon_{it} \qquad (28)\end{aligned}$$

where parameter θ_i measures the speed of adjustment of energy demand to a shock, namely the speed at which the system returns to its equilibrium after a sudden shock hits one of the model variables.

This analysis compares three different estimation approaches with different assumptions. We firstly apply the within groups (WG) approach to

Equation (28), which ignores the existence of spatial lag dependence captured by spatially lagged dependent variable and spatial error dependence captured by common factors.

Second, we employ the CCEP approach to estimate the parameters of Equation (28) without the spatially lagged dependent variable, which allows for spatial error dependence due to Pesaran (2006) and Pesaran and Tosetti (2011). The associated cross section weighted averages of $\bar{\mathbf{y}}_{i,t-1}$, $\bar{\mathbf{x}}_{i,t-1}$, $\Delta\bar{\mathbf{y}}_{i,t-1}$and $\Delta\bar{\mathbf{x}}_{i,t-1}$ are added to the regressions.[16]

Finally, we calculate the parameters using CCEP approach for the Equation (28), to control for both spatial lag dependence and spatial error dependence.[17] As usual, the cross section weighted averages of $\bar{\mathbf{y}}_{i,t-1}$, $\bar{\mathbf{x}}_{i,t-1}$, $\Delta\bar{\mathbf{y}}_{i,t-1}$and $\Delta\bar{\mathbf{x}}_{i,t-1}$are added to the models. For convenience, we call it "Spatial CCEP".

For each model above, in the first instance the long-run income and price elasticities of energy demand are examined, controlling for $\mathbf{INADD}_{i,t-1}$, $\mathbf{SEADD}_{i,t-1}$, $\mathbf{URBAN}_{i,t-1}$, $\mathbf{MANU}_{i,t-1}$ and $\mathbf{TEMP}_{it}$. The squared terms of variables $\mathbf{GDPPC}_{it}$ and $\mathbf{EPRICE}_{it}$ are then added to the model to investigate whether the relationships between energy demand, GDP per capita and energy prices follow a non-linear pattern. A positive (or negative) coefficient of $\mathbf{GDPPC}^2_{it}$ indicates that income elasticity increases (or decreases) with the level of income, and any extra unit of GDP per capita produced requires more (or less) energy input and is therefore more (or less) energy intensive. A negative (or positive) coefficient of $\mathbf{EPRICE}^2_{it}$ means more (or less) responsiveness of the economies to further rises in energy price.

The controlled variables are included to examine the robustness of the findings and whether they are the drivers of rising energy demand in the past decades, together with income and energy prices.

[16]The shares of GDP per capita have been used as the weights to compute the cross section weighted averages.

[17]The inverse-distance spatial weighting matrix is used in this analysis which gives the inverse of the distance between two sample points. The spatial weighting matrix is row-standardized of one. The information on latitude and longitude of each country used to calculate the distance is taken from the Central Intelligence Agency (CIA) World Factbook.

Insert Table 4 here

Table 4 examines what the key drivers of increasing energy demand are for 24 OECD countries over 1980-2009. The coefficients of spatial lag dependence, λ_i, are positively significant at 1% level, highlighting the spatial lag dependence being an important phenomenon to be taken into account in this context. The coefficients corresponding to the speeds of adjustment of six models in Table 4 (as well as Table 5) are significantly negative and quite small, suggesting a rapid short-run adjustment process towards the long-run equilibrium per capita energy use, as price and/or income changes.

When a linear specification for both $\mathbf{GDPPC}_{it}$ and $\mathbf{EPRICE}_{it}$ is used, WG, CCEP and Spatial CCEP estimates suggest a positive income elasticity of $(0.3, 0.4)$ and a negative price elasticity of $(-0.2, -0.3)$ for energy demand, which are consistent with the literature. Once a non-linear specification for both $\mathbf{GDPPC}_{it}$ and $\mathbf{EPRICE}_{it}$ is used, WG, CCEP and Spatial CCEP estimates suggest a declining income elasticity of energy demand for further output increases. This finding indicates that less energy intensive sectors have been developing relatively rapidly in OECD countries in the past decades, or the energy intensive sectors have been outweighed by the less energy intensive sectors, such as service sectors. The WG estimate finds more responsiveness of energy demand to price increases; however, both the CCEP and Spatial CCEP estimates find no evidence for such a price effect on energy demand as prices increase. Allowing for spatial lag dependence and/or spatial error dependence, this analysis finds that the consumers in OECD countries are less sensitive to energy price changes, which is likely to be associated with their higher disposable income.

The CCEP and Spatial CCEP estimates suggest no evidence for the effect on energy demand of $\mathbf{GDPPC}_{it}$ and $\mathbf{EPRICE}_{it}$ as well as their squared terms. Industry value added, $\mathbf{INADD}_{i,t-1}$, and urbanization, $\mathbf{URBAN}_{i,t-1}$, have been found contributing to energy demand increases, not least due to the rising energy demand from industrial sectors and urban areas for infrastructures, heating and cooling, etc. The CCEP and Spatial CCEP estimates, when using a non-linear specification for both $\mathbf{GDPPC}_{it}$ and $\mathbf{EPRICE}_{it}$, suggest that service value added, $\mathbf{SEADD}_{i,t-1}$, is conducive to lower energy intensity, which supports the above observation regarding a declining income elasticity of energy demand for further output increases. The economic structural changes from industrialized economies to service economies lead to energy savings. Manufactured exports, $\mathbf{MANU}_{i,t-1}$, a proxy used to measure the extent of technological progress in a country, has been found playing a positive role in reducing energy demand. In additional to economic structural change to service economies, making technological progress or breakthroughs towards energy efficiency improvements is another way to approach the low carbon society. Both WG and CCEP estimates show that temperature, $\mathbf{TEMP}_{it}$, is negatively associated with energy demand. This is probably because the increase of energy demand for cooling in the summer is less than the reduction of energy required for heating in the winter due to global warming. This observation might be true because most of OECD countries have relatively higher latitudes, in comparison to many African countries and Asian countries. When spatial lag dependence is allowed, Spatial CCEP estimates suggest no evidence for a significant effect of temperature on energy demand.

In sum, this research provides evidence for the existence of spatial lag dependence. It finds a positive but declining income elasticity and a negative price elasticity of energy demand. Energy demand is boosted by an increase of industry value added and urbanization, while being reduced by the developments of service economies and technologies.

Insert Table 5 here

Table 5 examines the key drivers of increasing energy demand for 39 non-OECD countries over 1980-2009. The coefficients of spatial lag dependence, λ_i, are not significant, which is likely due to the fact that the sample countries are situated widely across regions. We naturally restrict our attention to the CCEP estimates.

For the linear specification for both $\mathbf{GDPPC}_{it}$ and $\mathbf{EPRICE}_{it}$, both WG and CCEP estimates suggest a positive and sizeable income elasticity of energy demand. A positive but negligible price elasticity of energy demand is also observed, which is unusual. Once a non-linear specification for both $\mathbf{GDPPC}_{it}$ and $\mathbf{EPRICE}_{it}$ is used, both WG and CCEP estimates suggest no evidence for income elasticity of energy demand when additional output is produced. The CCEP estimates find no evidence for a significant price effect on energy demand as prices increase. However, both WG and CCEP estimates provide strong evidence for a short-run negative and rising price elasticity for any further price rises. This evidence implies that in the short-run the consumers in non-OECD countries are very responsive to energy price increases, not necessarily in the long-run, because their energy expenditure accounts for a large share of their limited disposable income. For controlled variables, the WG and CCEP estimates in general confirm the findings of Table 4 regarding a negative impact of service value added on energy demand. No evidence has been found for $\mathbf{INADD}_{i,t-1}$, $\mathbf{URBAN}_{i,t-1}$, $\mathbf{MANU}_{i,t-1}$ and $\mathbf{TEMP}_{it}$.

As mentioned in Section 3, due to the lack of data for aggregate energy price index for both industry and households, this analysis uses the derived consumer price index for energy, which is for the energy consumers only. The use of derived consumer price index for energy might not be sufficient to pick up the effect of price changes on energy demand, with negative impacts on the results of other variables. An effort has been made to see the differences of using the consumer price index for energy, taken from the IEA (2011), for OECD sample. The results can be found in Appendix Table 3. Among others, CCEP and Spatial CCEP estimates reveal, for the linear specification of $\mathbf{GDPPC}_{it}$ and $\mathbf{EPRICE}_{it}$, a significantly larger income elasticity and an insignificantly smaller price elasticity of energy demand. Therefore, Table 5 might overestimate the income elasticity while producing a smaller price elasticity (with a wrong sign) for non-OECD countries; nevertheless it gives us some sense of the impacts of income and energy price on energy demand for those countries. Further research is needed to develop energy price index for non-OECD countries to enable meaningful energy demand studies for those countries, some of them have increasingly become large energy consumers in recent years.

6 Conclusion

This paper investigates the relationships between aggregate energy demand and its potential factors, using a panel data set with 63 countries including 24 OECD countries and 39 non-OECD countries over 1980-2009.

Cross section dependence tests have been conducted for two samples over three periods, separately. The results clearly suggest cross section dependence to exist. The results from panel unit root analysis and panel cointegration analysis allowing for cross section dependence for two samples separately indicate the presence of non-stationary and cointegrated time series in two panels. This research firstly applies the CCE approach due to Pesaran (2006) to estimate the energy demand equation for two sample, respectively. It further adds the spatially lagged dependent variable to the model and estimates it using CCE approach to allow for spatial lag dependence, in addition to spatial error dependence. For the OECD sample, this research provides evidence for the existence of spatial lag dependence, and a positive but declining income elasticity and a negative price elasticity of energy demand. It also finds that more industry value added and urbanization are both followed by rising energy demand, while the development of service economies and technical innovations tends to reduce energy demand. For the non-OECD sample, this research finds no evidence for spatial lag dependence, while confirming a positive income elasticity and a negative impact of value-added produced by service sector on energy demand.

This analysis has assessed the role of economic output, energy policy (price, taxes, cap, etc.), structural change and technical innovations in the process of rising global energy demand in recent decades. It has produced significant insights for the sound development of energy sector towards a sustainable future. Stabilization of green-house gas concentrations requires considerable reductions in fossil energy use. Energy regulation or policies via energy price or a carbon tax can induce substantially lower energy uses, provide incentives for innovations in efficient and clean energy technologies and scale up the deployment of clean energy technologies. However, pricing policy alone is not enough; technology policies are also important. Energy efficiency and renewable energy are the two largest low-cost sources of potential emission reductions and energy demand reductions. Renewable energy can also help diversify energy supplies, reduce reliance on limited energy sources and reduce exposure to fuel price shocks. Public policies are also needed to increase the value-added produced by the service sector and direct urbanization towards building low-carbon cities with climate-smart urban designs, energy efficient buildings and lighting, green transportation and vehicles.

Energy policy has to balance four competing objectives: sustaining economic growth, increasing energy access, enhancing energy security and improving the environment (World Bank, 2010). Economic development and environmental protection can be achieved by sufficient developments of the clean energy technology portfolio, which require energy regulations, financial mechanisms, institutional reforms, capacity building and consumer awareness.

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Table 1. Cross Section Dependence of Energy Demand (ED)

Samples	CD Statistics		
	1980-1989	1990-1999	2000-2009
OECD Sample	3.131***	18.682***	11.134***
Non-OECD Sample	1.761*	2.116**	2.144**

Note: This table reports the Cross Section Dependence (CD) test statistics due to Pesaran (2004). The test statistics for the null of cross section independence are calculated for two samples based on the OLS residuals from the AR(2) regressions in total energy demand with an intercept and a linear trend. See Appendix Table 2 for the list of countries.

Table 2. Panel Unit Root Test Statistics

Samples	Variables	Level				1st Difference			
		CADF(1)	CADF(2)	CADF(3)	CADF(4)	CADF(1)	CADF(2)	CADF(3)	CADF(4)
OECD Sample	ED_{it}	-2.273	-2.377	-2.292	-1.548	-3.647 ***	-3.086 ***	-3.430 ***	-2.683 **
	$GDPPC_{it}$	-1.624	-1.276	-1.147	-1.359	-3.538 ***	-2.397	-2.192	-1.877
	$EPRICE1_{it}$	-2.565 *	-2.319	-2.214	-2.160				
	$INADD_{it}$	-1.846	-1.460	-1.411	-1.455	-3.405 ***	-2.519	-2.121	-1.852
	$SEADD_{it}$	-2.354	-1.992	-1.925	-1.764	-3.572 ***	-2.572 *	-2.132	-1.895
	$URBAN_{it}$	-2.018	-2.071	-2.262	-2.501	-2.245	-2.259	-2.295	-3.556 ***
	$MANU_{it}$	-2.454	-2.232	-2.213	-2.047	-3.857 ***	-2.690 **	-2.476	-2.356
	$TEMP_{it}$	-3.603 ***	-2.989 ***	-2.297	-2.382				
Non-OECD Sample	ED_{it}	-2.472	-2.346	-2.284	-2.061	-3.737 ***	-2.928 ***	-2.720 ***	-2.464
	$GDPPC_{it}$	-2.266	-2.170	-1.898	-1.599	-3.548 ***	-2.904 ***	-2.783 ***	-2.291
	$EPRICE2_{it}$	-2.073	-1.883	-1.814	-1.074	-3.243 ***	-2.885 ***	-2.550 *	-1.567
	$INADD_{it}$	-2.574 **	-2.225	-2.225	-2.166				
	$SEADD_{it}$	-2.649 **	-2.400	-2.329	-2.068				
	$URBAN_{it}$	-0.797	-0.690	-0.674	-0.922	-1.635	-1.528	-1.274	-1.876
	$MANU_{it}$	-2.424	-2.068	-1.805	-1.985	-4.174 ***	-3.033 ***	-2.246	-2.179
	$TEMP_{it}$	-3.056 ***	-2.458	-2.325	-2.200				

Note: This table reports the Pesaran's CIPS (2007) statistics, which are the cross-sectional averages of Cross-sectionally Augmented Dickey-Fuller [CADF(p)] test statistics based on the AR(p) specifications in the level and first difference of the variables with an intercept and a linear trend. The relevant 10%, 5% and 1% crticital values for the CIPS statistics are -2.580 -2.660 and -2.810.
*,**,*** significant at 10%, 5%, 1%, respectively.

Table 3. Panel Cointegration Test Statistics

Samples	Kernel Window	Test	Value	P-value	Robust P-value
OECD Sample	**1**	Gt	-2.845	0.000	0.000
		Ga	-9.481	0.390	0.007
		Pt	-12.699	0.000	0.000
		Pa	-7.895	0.038	0.010
	2	Gt	-2.845	0.000	0.000
		Ga	-9.085	0.513	0.007
		Pt	-12.373	0.000	0.000
		Pa	-7.497	0.076	0.007
	3	Gt	-2.845	0.000	0.000
		Ga	-8.802	0.599	0.020
		Pt	-12.085	0.000	0.000
		Pa	-7.178	0.125	0.043
Non-OECD Sample	**1**	Gt	-2.091	0.351	0.063
		Ga	-6.403	0.997	0.367
		Pt	-12.170	0.077	0.187
		Pa	-4.794	0.884	0.393
	2	Gt	-2.091	0.351	0.097
		Ga	-5.950	0.999	0.603
		Pt	-12.025	0.099	0.143
		Pa	-4.396	0.950	0.530
	3	Gt	-2.091	0.351	0.100
		Ga	-5.684	1.000	0.653
		Pt	-11.851	0.132	0.120
		Pa	-4.176	0.970	0.567

Note: This table reports the panel cointegration test statistics due to Westerlund (2007). The test statistics for the null of no cointegration are calculated based on the error correction test regression with a constant, one lag and one lead. The p-values are for a one-sided test based on the normal distribution. The robust p-values are for a one-sided test based on the bootstrapped distribution with 300 bootstrap replications.

Table 4 . The Drivers of Rising Energy Demand in OECD Countries

Dependent Variable	WG		CCEP		Spatial CCEP	
λ_i					0.552***	0.544***
					[0.177]	[0.171]
Speed of adjustment						
α_i	-0.118***	-0.166***	-0.123***	-0.154***	-0.120***	-0.151***
	[0.016]	[0.024]	[0.019]	[0.025]	[0.020]	[0.025]
Long-run coefficients						
$GDPPC_{i,t-1}$	0.289	6.251***	0.367**	6.209***	0.375**	6.256***
	[0.237]	[1.632]	[0.184]	[1.349]	[0.190]	[1.397]
$(GDPPC_{i,t-1})^2$		-0.305***		-0.299***		-0.301***
		[0.080]		[0.066]		[0.068]
$EPRICE1_{i,t-1}$	-0.498***	3.432***	-0.234**	0.387	-0.249***	0.463
	[0.090]	[1.166]	[0.093]	[1.008]	[0.095]	[1.017]
$(EPRICE1_{i,t-1})^2$		-0.423***		-0.063		-0.073
		[0.130]		[0.112]		[0.113]
Short-run coefficients						
$\Delta GDPPC_{i,t-1}$	0.206**	-3.931***	0.129	-1.747	0.115	-1.680
	[0.099]	[1.139]	[0.098]	[1.414]	[0.094]	[1.452]
$(\Delta GDPPC_{i,t-1})^2$		0.211***		0.095		0.091
		[0.058]		[0.072]		[0.074]
$\Delta EPRICE1_{i,t-1}$	-0.036	0.571**	0.018	0.294	0.017	0.285
	[0.023]	[0.264]	[0.023]	[0.241]	[0.023]	[0.236]
$(\Delta EPRICE1_{i,t-1})^2$		-0.070**		-0.034		-0.032
		[0.031]		[0.030]		[0.030]
$INADD_{i,t-1}$	0.057**	0.008	0.048*	0.013	0.046*	0.012
	[0.022]	[0.025]	[0.025]	[0.024]	[0.025]	[0.024]
$SEADD_{i,t-1}$	0.046*	-0.051	0.013	-0.057**	0.015	-0.054**
	[0.028]	[0.033]	[0.024]	[0.024]	[0.024]	[0.024]
$URBAN_{i,t-1}$	0.103	0.041	0.106**	0.047	0.110**	0.052
	[0.063]	[0.055]	[0.050]	[0.044]	[0.051]	[0.046]
$MANU_{i,t-1}$	0.005	-0.004	-0.004	-0.012**	-0.003	-0.010*
	[0.008]	[0.006]	[0.008]	[0.005]	[0.008]	[0.006]
$TEMP_{it}$	-0.098	-0.097*	-0.094*	-0.093*	-0.081	-0.081
	[0.060]	[0.058]	[0.056]	[0.055]	[0.051]	[0.050]
Trend	-0.000	0.001**	0.000	-0.005	0.000	-0.010
	[0.001]	[0.000]	[0.007]	[0.018]	[0.006]	[0.018]
Observations	672	672	672	672	672	672
Number of Countries	24	24	24	24	24	24

Note: 24 OECD countries, 1980-2009. This table presents the within group estimates (WG), CCEP estimates due to Pesaran (2006) and Spatial CCEP estimates allowing for spatial lag dependence. See text for the definitions of variables. Standard errors are reported in the brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5. The Drivers of Rising Energy Demand in Non-OECD Countries

Dependent Variable	WG		CCEP		Spatial CCEP	
λ_i					-0.214	-0.215
					[0.155]	[0.157]
Speed of adjustment						
α_i	-0.143***	-0.154***	-0.153***	-0.165***	-0.154***	-0.165***
	[0.031]	[0.035]	[0.032]	[0.036]	[0.032]	[0.036]
Long-run coefficients						
$GDPPC_{i,t-1}$	0.775***	-0.269	0.837***	-0.509	0.837***	-0.530
	[0.094]	[0.768]	[0.093]	[0.816]	[0.094]	[0.831]
$(GDPPC_{i,t-1})^2$		0.057		0.075		0.076
		[0.045]		[0.048]		[0.049]
$EPRICE\ 2_{i,t-1}$	0.012*	-0.024	0.010*	-0.019	0.011*	-0.016
	[0.007]	[0.018]	[0.006]	[0.016]	[0.005]	[0.016]
$(EPRICE\ 2_{i,t-1})^2$		-0.002**		-0.001		-0.001
		[0.001]		[0.001]		[0.001]
Short-run coefficients						
$\Delta GDPPC_{i,t-1}$	-0.024	0.337	-0.044	0.429	-0.050	0.460
	[0.065]	[0.365]	[0.060]	[0.371]	[0.063]	[0.378]
$(\Delta GDPPC_{i,t-1})^2$		-0.021		-0.027		-0.030
		[0.024]		[0.024]		[0.025]
$\Delta EPRICE\ 2_{i,t-1}$	-0.011***	-0.013**	-0.010***	-0.010*	-0.011***	-0.010*
	[0.004]	[0.006]	[0.003]	[0.005]	[0.003]	[0.005]
$(\Delta EPRICE\ 2_{i,t-1})^2$		0.001***		0.001**		0.001**
		[0.000]		[0.001]		[0.001]
$INADD_{i,t-1}$	0.007	0.014	0.015	0.025	0.016	0.026
	[0.026]	[0.033]	[0.025]	[0.033]	[0.025]	[0.034]
$SEADD_{i,t-1}$	-0.103***	-0.099***	-0.103***	-0.095**	-0.102***	-0.094**
	[0.034]	[0.038]	[0.039]	[0.042]	[0.039]	[0.042]
$URBAN_{i,t-1}$	-0.008	-0.003	-0.006	-0.003	-0.007	-0.004
	[0.035]	[0.032]	[0.038]	[0.033]	[0.038]	[0.033]
$MANU_{i,t-1}$	0.002	0.003	-0.001	-0.001	-0.001	-0.001
	[0.006]	[0.006]	[0.005]	[0.005]	[0.005]	[0.005]
$TEMP_{it}$	-0.080	-0.077	-0.070	-0.066	-0.074	-0.069
	[0.052]	[0.053]	[0.047]	[0.048]	[0.047]	[0.048]
Trend	0.001	0.001	0.000	-0.001	-0.001	-0.002
	[0.001]	[0.001]	[0.021]	[0.023]	[0.020]	[0.022]
Observations	1092	1092	1092	1092	1092	1092
Number of Countries	39	39	39	39	39	39

Note: 39 non-OECD countries, 1980-2009. See Table 4 for further notes.

Appendix Table 1. The Variables

Variable	Description	Source
ED	Natural logarithm of final consumption of total energy per capita.	Calculated based on data from Enerdata (2010)
EPRICE1	Natural logarithm of real price index of total energy for industry and households.	Calculated based on data from IEA database (2011)
EPRICE2	Natural logarithm of consumer price index for energy (CPI Energy).	Calculated based on data from IEA database (2011)
GDPPC	Natural logarithm of real GDP per capita (constant prices: chain series).	Calculated based on data from Penn World Table 7.0 (2011)
INADD	Natural logarithm of value added over GDP of industry (% GDP)	Calculated based on data from World Development Indicators (WDI) (2011)
SEADD	Natural logarithm of value added over GDP of services (% GDP)	Calculated based on data from WDI (2011)
URBAN	Natural logarithm of urban population (% of total).	Calculated based on data from WDI (2011)
MANU	Natural logarithm of manufactures exports (% of merchandise exports).	Calculated based on data from WDI (2011)
TEMP	Natural logarithm of the mean temperature.	Calculated based on CRUTEM3 globle surface temperature dataset from the University of East Anglia's Climatic Research Unit (2010)

Appendix Table 2: The List of Countries in the Full Sample

Code	Country Name	Code	Country Name
ARG	Argentina	ITA*	Italy
AUS*	Australia	JOR	Jordan
AUT*	Austria	JPN*	Japan
BEL*	Belgium	KEN	Kenya
BLZ	Belize	KOR*	Korea, Rep. (South)
BOL	Bolivia	LCA	St. Lucia
BRA	Brazil	LKA	Sri Lanka
BRB	Barbados	MAR	Morocco
CAN*	Canada	MDG	Madagascar
COL	Colombia	MEX*	Mexico
CRI	Costa Rica	MLT	Malta
CYP	Cyprus	MWI	Malawi
DEU*	Germany	MYS	Malaysia
DMA	Dominica	NLD*	Netherlands
DNK*	Denmark	NOR*	Norway
DZA	Algeria	NZL*	New Zealand
EGY	Egypt, Arab Rep.	PAK	Pakistan
ESP*	Spain	PHL	Philippines
FIN*	Finland	PRT*	Portugal
FJI	Fiji	PRY	Paraguay
FRA*	France	SGP	Singapore
GBR*	United Kingdom	SWE*	Sweden
GRC*	Greece	SYC	Seychelles
GRD	Grenada	SYR	Syrian Arab Republic
GTM	Guatemala	THA	Thailand
HKG	Hong Kong, China	TTO	Trinidad and Tobago
HND	Honduras	TUN	Tunisia
HUN*	Hungary	TUR*	Turkey
IDN	Indonesia	URY	Uruguay
IND	India	USA*	United States
IRL*	Ireland	VEN	Venezuela, RB
ISL	Iceland		

Note: This table lists the country codes and names for 63 countries in the whole sample. Countrie codes with * are the members of the OECD sample.

Appendix Table 3: The Drivers of Rising Energy Demand in OECD Countries (Using CPI Energy)

Dependent Variable	WG		CCEP		Spatial CCEP	
λ_i					0.564***	0.550***
					[0.170]	[0.166]
Speed of adjustment						
α_i	-0.088***	-0.122***	-0.115***	-0.144***	-0.112***	-0.140***
	[0.017]	[0.026]	[0.019]	[0.023]	[0.020]	[0.024]
Long-run coefficients						
$GDPPC_{i,t-1}$	0.106	6.126***	0.446***	6.009***	0.444***	6.135***
	[0.262]	[2.148]	[0.164]	[1.516]	[0.166]	[1.479]
$(GDPPC_{i,t-1})^2$		-0.312***		-0.291***		-0.298***
		[0.109]		[0.078]		[0.075]
$EPRICE1_{i,t-1}$	-0.074**	-0.040	-0.008	-0.029	-0.012	-0.033*
	[0.037]	[0.025]	[0.017]	[0.019]	[0.017]	[0.018]
$(EPRICE1_{i,t-1})^2$		-0.007*		0.009***		0.009***
		[0.004]		[0.002]		[0.002]
Short-run coefficients						
$\Delta GDPPC_{i,t-1}$	0.196*	-4.774***	0.079	-2.207	0.065	-2.157
	[0.105]	[1.549]	[0.115]	[1.710]	[0.113]	[1.763]
$(\Delta GDPPC_{i,t-1})^2$		0.254***		0.118		0.115
		[0.079]		[0.086]		[0.089]
$\Delta EPRICE1_{i,t-1}$	-0.056**	-0.060**	-0.037**	-0.020	-0.039**	-0.021
	[0.028]	[0.027]	[0.017]	[0.013]	[0.016]	[0.013]
$(\Delta EPRICE1_{i,t-1})^2$		-0.004		0.001		0.001
		[0.004]		[0.003]		[0.003]
$INADD_{i,t-1}$	0.049**	0.021	0.030	0.001	0.029	0.000
	[0.022]	[0.025]	[0.024]	[0.025]	[0.025]	[0.025]
$SEADD_{i,t-1}$	0.044*	0.001	-0.012	-0.091***	-0.009	-0.087***
	[0.026]	[0.031]	[0.022]	[0.030]	[0.021]	[0.028]
$URBAN_{i,t-1}$	0.134*	0.074	0.084	0.086*	0.093	0.094**
	[0.080]	[0.057]	[0.058]	[0.045]	[0.059]	[0.046]
$MANU_{i,t-1}$	0.018**	0.010	-0.009	-0.012	-0.007	-0.009
	[0.007]	[0.007]	[0.010]	[0.009]	[0.011]	[0.009]
$TEMP_{it}$	-0.098*	-0.096**	-0.101*	-0.103*	-0.089*	-0.091*
	[0.053]	[0.049]	[0.059]	[0.057]	[0.053]	[0.052]
Trend	0.000	0.001	0.000	-0.007	0.001	-0.009
	[0.001]	[0.001]	[0.008]	[0.023]	[0.007]	[0.022]
Observations	672	672	672	672	672	672
Number of Countries	24	24	24	24	24	24

Note: 24 OECD countries, 1980-2009. CPI Energy taken from IEA database (2011) is used as energy price. See Table 4 for more notes.