Chapter 5

Ghislaine Destais, Julien Fouquau and Christophe Hurlin

Economic Development and Energy Intensity: a Panel Data Analysis

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1. Observing and understanding the relationship between economic development and energy intensity.

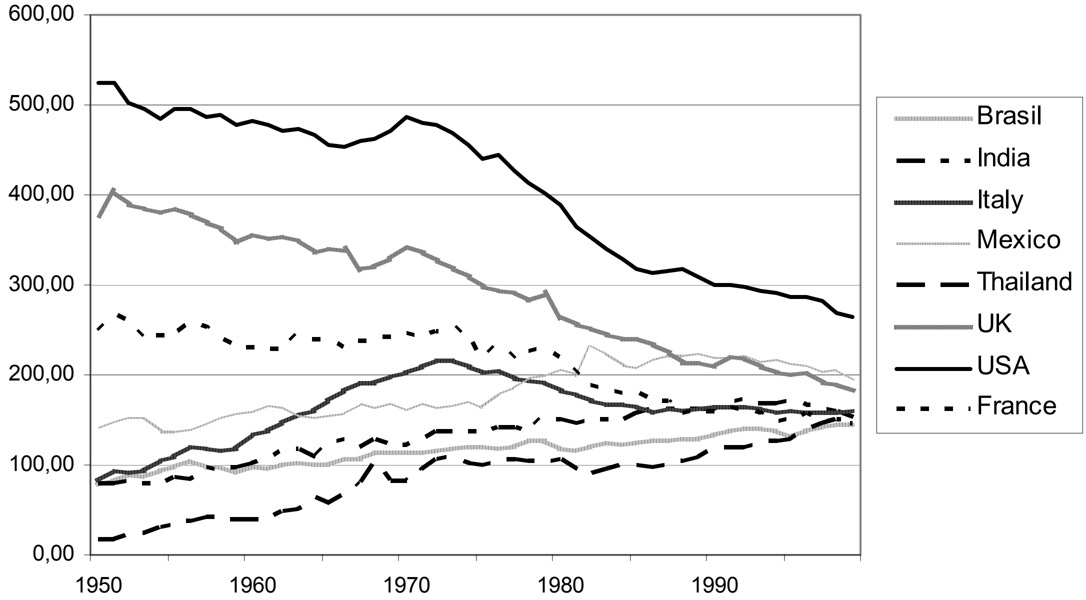
The energy-GDP ratio, or ratio of total national primary energy consumption to GDP, is a measure of the Energy Intensity of the economy (henceforward noted as EI). It represents the energy required to generate a unit of national output. Its evolution over time shows whether the economy becomes more or less energy intensive. Projections of national energy demand under different growth scenarios depend upon the explicit or implicit value of this ratio. It can also be used to define an objective of energy policy.

Another way of looking at the evolution of the energy-GDP ratio is to talk in terms of GDP-elasticity of energy consumption (noted e). A constant energy-GDP ratio means energy consumption grows at the same rhythm as economic activity, in other words that the value of the elasticity is equal to one. A decreasing ratio corresponds to elasticity lower than one. But, as noted by Ang (2006), '*Unlike the energy-GDP ratio, the elasticity is often unstable. When the annual growth rate of GDP is close to zero and that of energy consumption is not, the coefficient is either a large positive or negative number, which is of little practical value*'. In like manner, a constant decreasing rate of EI (2% for example, which is the French objective beyond 2015) leads to a value of e inversely proportional to the rate of economic growth. The elasticity is equal to 0.5 if the economy grows at 4%, 0 (stagnation of energy consumption) for a 2% GDP growth, -1 for 1% and is indeterminate in case of economic stagnation. Conversely, a constant elasticity leads to a linear relation between the evolution of EI and economic growth. There is then a double-log relation between EI and GDP allowing for various monotone functional forms according to the value of the income elasticity.

Figure 1

Commercial Energy Intensity in Selected Countries

(Kilo of Oil Equivalent per thousand 1990 Geary-Khamis $)



Since the middle of the 20th century, energy economists have been trying to evaluate and compare the energy intensity of various economies and to discover the trends in their evolution (see, for example, Putnam (1953), Clark (1960), Percebois (1979), Martin (1988), etc.). In general, these authors have shown that the energy intensity of a country first passes through a more or less strong and long growth phase, before reaching a turning point which is sometimes marked, sometimes in the form of a plateau, and then decreases (see Figure 1). This bell-shaped or Inverted-U curve that had also been observed by S. Kuznets (1955) for the relationship between income inequality and economic development, has been popularised during the nineties under the name of '*Kuznets curve*' by environment economists who found the same type of relation between environmental pollutants and economic activity (Müller-Fürstenberger & al. (2004)).

In addition, an apparent convergence phenomenon of the level of the EI is observed, the range passing from 1 to 15 at the beginning of the 20th century to 1 to 3.5 at the beginning of the 21st century. However, it should be noted, along with Toman and Jemelkova (2003), that '*advanced industrialized societies [still] use more energy per unit of economic output (and far more energy per capita) than poorer societies*'.

Although 'the interpretation of this ratio entails great care' (Ang (2006)), it is possible to identify at least three important explanations for these evolutions: the increase of energy efficiency, the different stages of economic development and inter-energy substitutions. Firstly, it has often been attributed to a more efficient way of producing and using energy, due partly to autonomous technical progress but mainly to increasing energy prices. Secondly, many authors state that the energy intensity of a country first rises along with the economic development process, in the industrialisation phase, and then declines in the post-industrialisation phase because of the increase of services and high technology industries, that is with the dematerialisation of the economy, despite the development of transportation. Quantification of these effects of structural changes on the evolution of energy intensity has been made by means of index decomposition analysis (see, for example, Sun (1998), Schäfer (2003)). Thirdly, primary energy consumption is an aggregated value of the various energy sources used in an economy, each having its own efficiency. Substitution among them and the development of new energy sources will then influence the EI ratio independently of the delivered service, the main phenomenon until now being the development of the use of electricity and gas.

Other authors also point out the disparities between countries (Ang (1987)). For example, the United States and Canada have greater energy intensities than the other industrialized countries for a number of reasons already presented by Darmstadter & al. (1977): the very low price of fuel, geographical characteristics which lead to greater transportation needs, large houses and a high level of consumption in the electrical sector. Martin (1988) mentions the persistent influence of the past, like the availability of natural resources in the United States in the 19^{th} century.

These observations illustrate, in an obvious manner, the problem of the homogeneity of the world-wide energy models. Is it possible to assume the existence of a model for the evolution of long-term energy intensities which would pertain to all parts of the world, perhaps even shifted in time or susceptible of being slowed down or accelerated? How can one take account of the individual specificities of the various countries of the world in the construction of a model for world-wide energy demand? These are some of the many questions which can only be approached using a cross-section or panel model. That is why, in this chapter, we begin by presenting a review of the various technical approaches used in cross-section or panel models to illustrate the question of homogeneity / heterogeneity of the energy models. Then, we will propose an original panel model with a threshold and a smooth transition which makes it possible, in a global model, to test for and take account of any possible heterogeneity in the income elasticity of the energy demand.

2. Panel data analysis

Let us now consider a cross-section model of the relationship between income and energy demand. Like Zilberfarb & Adams (1981) or Shrestha (2000), let us consider a double-log specification of the energy demand equation. Defining c_i as the logarithm of the consumption of primary energy *per capita* of the i^{th} country of a sample of N countries for the year studied, and y_i the logarithm of the corresponding *per capita* GDP, this approach leads to an estimation using the following model:

$$c_i = \alpha + \beta\, y_i + \varepsilon_i \qquad i = 1,..,N \tag{5.1}$$

where α and β are constants for one or several years and ε_i is *i.i.d.*$\left(0, \sigma_\varepsilon^2\right)$. In this simple model, the constant long-term elasticity is common for all the countries and is given by $e_i = \beta,\ \forall i$. The corresponding energy intensity is equal to:

$$\mathrm{EI_i} = \gamma * \mathrm{Y_i}^{(\beta-1)} \tag{5.2}$$

where Y is the level of GDP and γ is a constant. With 1989 data for 41 countries of various levels of development, Shrestha found an income elasticity of 1.6 for commercial energy consumption and 1.4 for both commercial and traditional energy.

A general drawback of the cross-section approach is that, as noted by Medlock and Soligo (2001), '*it suffers from implicitly assuming that the same regularities apply to all nations*'. There are two ways to deal partially with this problem: the introduction of dummy variables and the pooling of countries by classes. Zilberfarb & Adams (1981) introduced dummy variables representing, among other things, the differences between countries at various levels of development, but they couldn't discover any 'development effect' in a data set of 47 developing countries in 1970-74-76. They found that the elasticity was '*in the neighbourhood of 1.35*'.

Furthermore the log-log structural relationship has the great disadvantage of being intrinsically unable to reproduce the empirical evidence of the Inverted-U curve, which implies that the relationship between energy intensity and income is non-monotonic and, therefore, that income elasticity of energy demand may depend on income level. One way to deal with the problem is to use a quadratic logarithmic specification as Ang (1987) does and to consider the cross-section model:

$$c_i = \alpha + \beta\, y_i + \lambda\, y_i^2 + \varepsilon_i \qquad i = 1,..,N \qquad [5.3]$$

where β is expected to be greater than 1 and λ negative. This quadratic form function can be viewed as an approximation to a more complex function and constitutes an alternative solution to non-parametric approaches (Judson, Schmalensee, Stocker, 1999). It leads to an elasticity equal to $e_i = \beta + 2\lambda\, y_i$. In this case, then, energy intensity might depend on the level of economic development. Its maximum occurs when $e = 1$, that is when $\bar{y} = (1-\beta)/2\lambda$. Ang conclude, with 1975 data for 100 countries, pooled into four levels of *per capita* GDP, that '*commercial energy elasticities are consistently higher for developing than for developed countries*'; for industrial countries, the best fit is to a double-log relation, yielding 1.73 for the value of the elasticity.

However, in these approaches, the temporal dimension is not explicitly dealt with, although Brookes (1973) had previously shown, with the use of year by year estimations of a log-log relationship for 22 countries from 1950 to 1965, that the elasticity would decrease over time. The development of *panel data econometrics* makes it possible to take into account the two-fold dimension, individual and temporal, of the related data. As stated by Hsiao (2003), panel data sets possess several major advantages over conventional cross-sectional or time-series data sets. Obviously, the fact of using data observed for *N* entities (countries, regions, cities, firms etc.) over *T* periods gives the researcher a large number of observations, increasing the number of degrees of freedom and reducing the co-linearity among explanatory variables. Besides, it is well known that panel data models are better able to deal, in a more natural way, with the effects of missing or unobserved variables.

Two ways of using panel models can be found in the energy literature: the first is based on micro-panels (with a short time dimension and a very large number of entities) and is usually devoted to the study of the behaviour of energy producers or consumers (firms, households) (see for example Li, Maddala, Trost (1996), Baltagi & Griffin (1997) and Garcia-Cerrutti (2000)). The second category, less developed, corresponds to macro-panels (with similar time and individual dimensions) which are devoted to global energy consumption. In this latter case, the panel models are generally estimated only on post-war data in order to allow using balanced samples with the same time dimension for all the countries.

If it is assumed that all the parameters of the quadratic demand function are identical for all the countries of the panel; the specification is the same as [5.2] with the introduction of time in the variables

$$c_{it} = \alpha + \beta y_{it} + \lambda y_{it}^2 + \varepsilon_{it} \qquad i = 1,..,N \;\; t = 1,..,T \tag{5.4}$$

where ε_{it} is $i.i.d.\left(0, \sigma_\varepsilon^2\right)$. As for the cross-section model, it is considered to be totally *homogeneous*; non-heterogeneity is considered in the energy demand model. It implies that, for a given level of *per capita* GDP, the average level of energy consumption *per capita* $E(c_{it})$, and that the energy-GDP ratio is the same for all the countries of the sample. If the panel includes Canada and Mexico, this assumption may be doubtful. It is, therefore, generally admitted that it is necessary to introduce a minimum of heterogeneity into the model in order to take account of the specificities of the various countries of the sample.

The simplest method for introducing parameter *heterogeneity* consists of assuming that the constants of the model [5.3] vary from country to country. This is precisely the specification of the well known *individual or fixed effect model (FEM)*:

$$c_{it} = \alpha_i + \beta y_{it} + \lambda y_{it}^2 + \varepsilon_{it} \tag{5.5}$$

The *individual effects* α_i (or individual constants) allow capturing all the time-less (or structural) dimensions of the energy demand model. More precisely, they capture the influence of all the unobserved time-less variables (climate, industrial organisation, etc.) that affect the level of the energy demand. These individual effects can be fixed or random. When individual effects are assumed to be fixed, the simple OLS estimator is the BLUE (Best Linear Unbiased Estimator) and is commonly called a *Within* estimator. When individual effects are specified as random variables, they are assumed to be *i.i.d.* and independently distributed over the explanatory variable, the level of *per capita* GDP. In this case, the BLUE is a GLS estimator (see Hsiao (2003) for more details). The choice between these two specifications depends on the assumption of independence between α_i and y_{it}, and may be determined by a standard Hausman (1978) test.

However this model only allows heterogeneity of the average level of *per capita* energy consumption; in other words it only affects the Y-axis intercepts of the Inverted-U curve. National intensities are displayed along homothetic parabolas; the gap between the national curves is determined by the level of individual effects α_i. In addition, the turning point of the quadratic function is identical for all the countries of the sample, since it depends only on β and λ. This model has been used in particular by Medlock & Soligo (2001) for a sectoral panel of 28 countries (1978-95). In this study, they provide various specification tests, including homogeneity tests. They show, for instance, that the industrial sectors are substantially more heterogeneous than the other sectors. This problem of heterogeneity / homogeneity is particularly important as shown by H. Vollebergh & al. (2005) who found that the Inverted-U curve of CO_2 emissions is very sensitive to the degree of heterogeneity assumed in the specifications and in the estimation techniques. These authors suggest leaving enough heterogeneity in order to avoid abusive correlations from estimations of reduced forms on panel data. Ignoring such parameter heterogeneity could lead to inconsistent or meaningless estimates of interesting parameters.

From an elasticity point of view, the slope parameters β and λ that determine the income elasticity (equal to $\beta + 2\lambda\, y_{it}$) are assumed to be cross-section homogeneous. Consequently, in this model, at a particular date, if the income elasticity for Canada is different from the income elasticity for Mexico, it is only due to the difference in their *per capita* GDP, that is the difference in y_{it}. Since, the parameters that determine income elasticities are assumed homogenous, when Mexico will have achieved the same *per capita* GDP as Canada, their income elasticities will be identical. This assumption may or may not be valid; that is not the question. The question is: does an econometrician have the right to impose *ex-ante* such an assumption?

An alternative consists of using a *heterogeneous panel model*. In such a model, the slope parameters of the energy demand model are assumed to be cross-sectionally heterogeneous:

$$c_{it} = \alpha_i + \beta_i\, y_{it} + \lambda_i\, y_{it}^2 + \varepsilon_{it} \qquad [5.6]$$

where α_i denotes an individual effect (fixed or random) and ε_{it} is *i.i.d.*$\left(0, \sigma_\varepsilon^2\right)$. Many approaches can be used to estimate a heterogeneous panel model. The simplest consists of assuming that these *slope parameters* are *randomly distributed*. These models are generally called Random Coefficient Models (RCM). The most popular is the simple Swamy model (1970) in which we assume that the parameters β_i and λ_i are randomly distributed according to distributions with homogenous means and homogenous variances (see Hsiao & Pesaran 2004 for a survey on RCM models). The aim is then to estimate the mean and the variance (more precisely the variance-covariance matrix) of the distribution of the parameters of the model. Galli (1998) tried this approach on Asian emerging countries from 1973 to 1990 but she couldn't obtain any significant income coefficient and went back to the FEM.

This kind of approach is statistically very attractive, but it has some drawbacks. The simple assumption that an economic variable is generated by a parametric probability distribution function that is identical for all individuals at all times may not be a realistic one. Moreover it does not offer an economic interpretation of the heterogeneity of the slope parameters (and, therefore, of the income elasticities). It does not allow identifying a set of explanatory variables q_{it} that explain why income elasticities may be not equal for the same levels of GDP. Given these various observations, we now propose another original solution to specify the heterogeneity of the energy demand models in a panel sample, based on threshold panel specifications.

3. Threshold panel specifications

One way to circumvent the previously mentioned issues is to introduce threshold effects in a linear panel model. In fact, the idea that income elasticity of energy demand depends on income level, clearly corresponds to the definition of a threshold regression model: '*threshold regression models specify that individual observations can be divided into classes based on the value of an observed variable*', (Hansen (1999), page 346). In this context, a natural solution consists of using a potentially linear relationship between energy demand and income that depends on the income level. In a simple Panel Threshold Regression (PTR) model (Hansen (1999)), the idea is very simple: at each date in the threshold model the countries are divided into a small number of classes with the same elasticity according to an observable variable, called the threshold variable. This threshold variable can, for example, correspond to *per capita* GDP. In a PTR, the transition mechanism between extreme regimes is very simple; at each date, if the threshold variable observed for a given country is smaller than a given value, called the threshold parameter, the income-demand relationship is defined by a particular model (or regime) which is different from the model used if the threshold variable is larger than the threshold parameter. The advantage of this model is that even if the extreme regime models are linear (and not quadratic as in the literature), the income elasticity depends on the level of the threshold variable. For example, let us consider a PTR model with two extreme regimes:

$$c_{it} = \alpha_i + \beta_0 y_{it} + \beta_1 y_{it} \, g(q_{it}, c) + \varepsilon_{it} \qquad [5.7]$$

The variable q_{it} denotes a threshold variable, c is a threshold parameter and the transition function $g(q_{it}; \partial)$ corresponds to the indicator function:

$$g(q_{it}, c) = \begin{cases} 1 & if \;\; q_{it} > c \\ 0 & otherwise \end{cases} \qquad [5.8]$$

In this two extreme regimes model, the income elasticity is equal to β_0 if the threshold variable (the income, for example) is smaller than δ and is equal to $\beta_0 + \beta_1$ if the threshold variable is larger than δ. Consequently, we have exactly the same situation as in the quadratic model; the income elasticity depends on the income level (or on other economic variables). The main difference is that we specify a functional form of this dependency in a threshold model. However, in a PTR model, the transition mechanism between the regimes is too simple to show interesting non-linear effects of the income level on the income elasticity. As is often shown in the threshold model literature, the solution is to use a model with a smooth transition function. This kind of model has been recently extended to panel data with the Panel Smooth Threshold Regression (PSTR) model proposed by Gonzalez, Teräsvirta & Van Dijk (2004).

Let us consider the simplest case with two extreme regimes and a single transition function. The corresponding PSTR energy demand model is defined as:

$$c_{it} = \alpha_i + \beta_0 \, y_{it} + \beta_1 y_{it} \; g(q_{it};\gamma,c) + \varepsilon_{it} \qquad [5.9]$$

In this case, the transition function $g(q_{it};\gamma,c)$ is a continuous and bounded function of the threshold variable q_{it}. Gonzalez, Teräsvirta & Van Dijk (2004), following the work of Granger & Teräsvirta (1993) for the time series STAR models, consider the following transition function:

$$g(q_{it};\gamma,c) = \left[1 + \exp\left(-\gamma \prod_{z=1}^{m} (q_{it} - c_z)\right)\right]^{-1}, \quad \gamma > 0, \;\; c_1 \le \ldots \le c_m \qquad [5.10]$$

The vector $c = (c_1,..,c_m)'$ denotes an m-dimensional vector of location parameters and the parameter γ determines the slope of the transition function.

In our context, the PSTR energy demand model has three main advantages. The first is that it allows the parameters (and consequently the income elasticity) to vary between countries (heterogeneity issue) but also with time (stability issue). It provides a parametric approach to the cross-country heterogeneity and the time instability of the slope coefficients of the energy demand model. It allows the parameters to change smoothly as a function of the threshold variable q_{it}. More precisely, the income elasticity is defined by the weighted average of the parameters β_0 and β_1. For example, if the threshold variable q_{it} is different from the income level, the income elasticity for the i^{th} country at time t is defined by:

$$e_{it} = \frac{\partial c_{it}}{\partial y_{it}} = \beta_0 + \beta_1 \, g(q_{it};\gamma,c) \qquad [5.11]$$

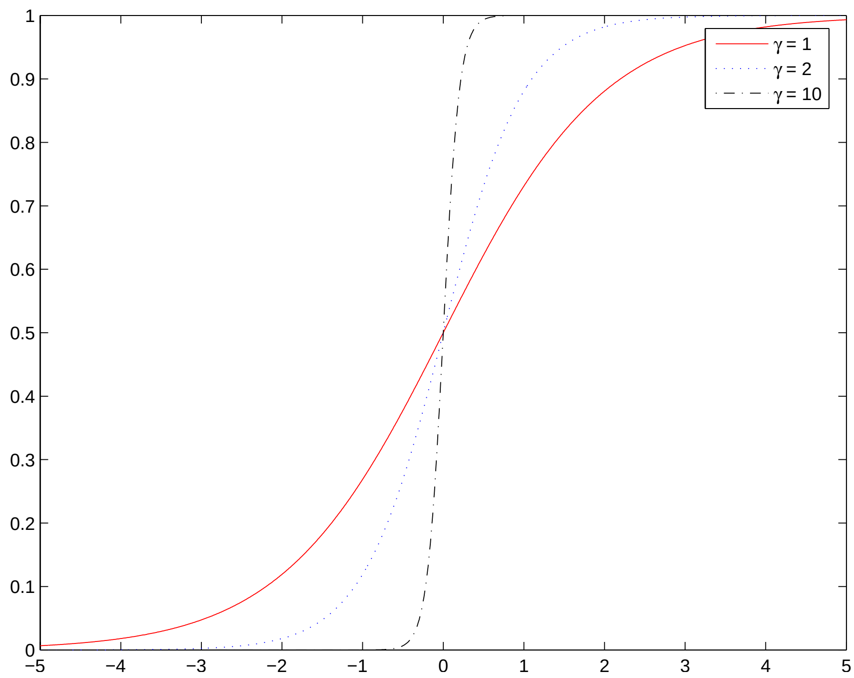
with, as defined by the transition function, $\beta_0 \le e_{it} \le \beta_0 + \beta_1$ if $\beta_1 > 0$ or $\beta_0 + \beta_1 \le e_{it} \le \beta_0$ if $\beta_1 < 0$.

The second advantage of the PSTR energy demand model is that the value of the income elasticity, for a given country, at a given date, can be different from the estimated parameters for the extreme regimes, that is parameters β_0 and β_1. As illustrated by the equation [5.11], these parameters do not directly correspond to income elasticity. The parameter β_0 corresponds to the income elasticity only if the transition function $g(q_{it};\gamma,c)$ tends to 0. For example, if the threshold variable corresponds to the *per capita* GDP, the parameter β_0 denotes the income elasticity only when the *per capita* income (in logarithms) tends to 0. The sum of the parameters β_0 and β_1 corresponds to the income elasticity only if the transition function $g(q_{it};\gamma,c)$ tends to 1. Between these two extremes, the income elasticity e_{it} is defined as a weighted average of the parameters β_0 and β_1. Therefore, it is important to note that it is often difficult to directly interpret the values of these parameters (as in a probit or logit model). It is generally preferable to interpret (*i*) as the sign of these parameters which indicates an increase or a decrease of the income elasticity with the value of the threshold variable and (*ii*) the time varying and individual elasticity given by the equation [5.11].

Finally, this model can be analyzed as a generalization of the Panel Threshold Regression (PTR) model proposed by Hansen (1999) and the panel linear model with individual effects. Figure 2 shows the transition function for various values of the parameter γ in the case where $m = 1$. It can be seen that when the parameter γ tends to infinity, the transition function $g(q_{it};\gamma,c)$ tends to the indicator function [5.8]. Thus, when $m = 1$ and γ tends to infinity the PSTR model gives the PTR model. When $m > 1$ and γ tends to infinity, the number of identical regimes remains two, but the function switches between zero and one at c_1, c_2, etc... When γ tends to zero the transition function $g(q_{it};\gamma,c)$ is constant and the model is the standard linear model with individual effects (the so-called '*within*' model), that is with constant and homogenous elasticities. The income elasticity is then simply defined by $e_{it} = \beta_0$, $\forall i = 1,..,N$ and $\forall t = 1,..,T$.

Figure 2

Transition Function with m=1 and c=0. Analysis of Sensitivity to the Slope Parameter



This PSTR model can be generalized to $r+1$ extreme regimes as follows:

$$c_{it} = \alpha_i + \beta_0\, y_{it} + \sum_{j=1}^{r} \beta_j y_{it}\ g_j\left(q_{it};\gamma_j,c_j\right) + \varepsilon_{it} \qquad [5.12]$$

where the r transition functions $g_j\left(q_{it};\gamma_j,c_j\right)$ depend on the slope parameters γ_j and on m location parameters c_j. In this generalization, if the threshold variable q_{it} is different from y_{it}, the income elasticity for the i^{th} country at time t is defined by the weighted average of the $r+1$ parameters β_j associated to the $r+1$ extreme regimes:

$$e_{it} = \frac{\partial c_{it}}{\partial y_{it}} = \beta_0 + \sum_{j=1}^{r} \beta_j\ g_j\left(q_{it};\gamma_j,c_j\right) \qquad [5.13]$$

The expression of the elasticity is slightly different if the threshold variable q_{it} is a function of income. For example, if we assume that the threshold variable corresponds to the income level, that is if $q_{it} = y_{it}$, the expression of the income elasticity is then defined as:

$$e_{it} = \frac{\partial c_{it}}{\partial y_{it}} = \beta_0 + \sum_{j=1}^{r} \beta_j \, g_j\left(y_{it};\gamma_j,c_j\right) + \sum_{j=1}^{r} \beta_j \, y_{it} \, \frac{\partial g_j\left(y_{it};\gamma_j,c_j\right)}{\partial y_{it}} \qquad [5.14]$$

Such an expression authorizes a variety of configurations for the relationships between income and energy demand (or energy intensity) as will be discussed in the next section.

4. Estimation and Specification Tests

The estimation of the parameters of the PSTR model consists of eliminating the individual effects α_i by removing individual-specific means and then by applying non-linear least squares to the transformed model (see Gonzalez, Teräsvirta & Dijk (2004) or Colletaz & Hurlin (2006) for more details). Gonzalez, Teräsvirta & Van Dijk propose a testing procedure of order (*i*) to test the linearity against the PSTR model and (*ii*) to determine the number, *r*, of transition functions, that is the number of extreme regimes which is equal to $r+1$. Lets us consider an energy demand model with only one location parameter ($m=1$) and assume that the threshold variable q_{it} is known. Testing the linearity in a PSTR model (equation [5.5]) can be done by testing $H_0 : \gamma = 0$ or $H_0 : \beta_0 = \beta_1$. But in both cases, the test will be non-standard since, under H_0 the PSTR model contains unidentified nuisance parameters. A solution consists of replacing the transition function $g_j\left(q_{it};\gamma_j,c_j\right)$ by its first-order Taylor expansion around $\gamma = 0$ and by testing an equivalent hypothesis in an auxiliary regression:

$$c_{it} = \alpha_i + \beta_0 \, y_{it} + \theta_1 \, y_{it} \, q_{it} + \theta_2 \, y_{it} \, q_{it}^2 + \ldots + \theta_m \, y_{it} \, q_{it}^m + \varepsilon_{it} \qquad [5.15]$$

In this first-order Taylor expansion, the parameters θ_i are proportional to the slope parameter γ. Thus, testing the linearity against the PSTR model simply consists of testing $H_0 : \theta_1 = .. = \theta_m = 0$ in this linear panel model. If we denote SSR_0 the panel sum of squared residuals under H_0 (linear panel model with individual effects) and SSR_1 the panel sum of squared residuals under H_1 (PSTR model with two regimes), the corresponding F-statistic is then defined by:

$$LM_F = \left[\left(SSR_0 - SSR_1\right)/ m\right] / \left[SSR_0 / \left(TN - N - m\right)\right] \quad [5.16]$$

Under the null hypothesis, the F-statistic has an approximate *F(m,TN-N-m)* distribution. The logic is similar when testing the number of transition functions in the model or, equivalently, the number of extreme regimes. The idea is as follows: we use a sequential approach by testing the null hypothesis of no remaining non-linearity in the transition function. For instance, let us assume that we have rejected the linearity hypothesis. The issue is then to test whether there is one transition function ($H_0 : r = 1$) or whether there are at least two transition functions ($H_0 : r = 2$). Let us assume that the model with $r = 2$ is defined as:

$$c_{it} = \alpha_i + \beta_0\, y_{it} + \beta_1 y_{it}\;\, g_1\left(q_{it};\gamma_1,c_1\right) + \beta_2 y_{it}\;\, g_2\left(q_{it};\gamma_2,c_2\right) + \varepsilon_{it} \quad [5.17]$$

The logic of the test consists of replacing the second transition function by its first-order Taylor expansion around $\gamma_2 = 0$ and then testing linear constraints on the parameters. If we use the first-order Taylor approximation of $g_2\left(q_{it};\gamma_2,c_2\right)$, the model becomes:

$$c_{it} = \alpha_i + \beta_0\, y_{it} + \beta_1\, y_{it}\;\, g_1\left(q_{it};\gamma_1,c_1\right) + \theta_1\, y_{it}\, q_{it} + ... + \theta_m\, y_{it}\, q_{it}^m + \varepsilon_{it} \quad [5.18]$$

and the test of no remaining non-linearity is simply defined by $H_0 : \theta_1 = .. = \theta_m = 0$. Let us define SSR_0 as the panel sum of squared residuals under H_0, that is in a PSTR model with one transition function. Let us define SSR_1 as the sum of squared residuals of the transformed model (equation [5.18]). As in the previous cases, the F-statistic LM_F can be computed according to the same definitions by adjusting the number of degrees of freedom. The testing procedure is then the following. Given a PSTR model with $r = r^*$, we will test the null $H_0 : r = r^*$ against $H_1 : r = r^* + 1$. If H_0 is not rejected, the procedure ends. Otherwise, the null hypothesis $H_0 : r = r^* + 1$ is tested against $H_1 : r = r^* + 2$. The testing procedure continues until the first acceptance of H_0. Given the sequential aspect of this testing procedure, at each step of the procedure the significance level must be reduced by a factor $\rho = 0.5$ in order to avoid excessively large models (Gonzalez, Teräsvirta & Van Dijk (2004)).

5. Data and Results

In this study, we consider a panel of 44 countries over the period 1950-99. The energy data base that we have used was worked out in Grenoble by Jean-Marie Martin-Amouroux and is presently managed by the enterprise Enerdata. It evaluates world-wide primary energy consumption over the long run (nearly 200 years) on a geographic basis by distinguishing between 'commercial' consumption (including coal, petroleum products, gas and electricity) measured by country and 'biomass', evaluated at the level of world regions. Two special characteristics of these data should be mentioned. First of all, data available over a long period allow only an indirect evaluation of consumption starting from national production, increased by imports, decreased by exports and stored quantities and corrected by variations in stocks. Secondly, total consumption is the sum of consumption by source aggregated on the basis of its net calorific value and expressed in tonnes of oil equivalent by adopting the convention that 1 toe = 42 GJ. For primary electricity (of nuclear, hydraulic, geothermic, wind or solar origin), the consumption equivalence (1kWh = 860 kcal) is retained, except for the nuclear case where 2600 kcal is used to take account of the efficiency of transformation of heat into electricity in these stations.

Population and GDP data have been gathered from the last publication of A.Maddison in OECD (2003). For international comparisons, the GDPs must be expressed in the same units. It is well known that the best converters are the purchasing power parities (ppp) which aim at neutralizing the effect of broad disparities of prices among countries, and R. Shrestha (2000) shows that choosing a wrong unit of measure of GDP (market exchange rates for example) may lead to misleading results in this area. The converters used by A.Maddison are the Geary-Khamis 1990$ ppp which allow multilateral comparisons by taking into account the ppp of currencies, and international average prices of commodities, and by weighting each country by its GDP.

As suggested by Hansen (1999), we consider a balanced panel since it is not known if the results of estimation and testing procedures presented below extend to unbalanced panels. This constraint led us to limit our study to the post 1950 data which detail the ‘commercial consumption’ of 44 countries. They have been set up using United Nations data, after some boundary changes and modifications of the equivalence coefficients to take into account the different qualities of fuels used over time and in various countries.

In our threshold specification, we consider two potential threshold variables. In the first model (called Model A), we assume that the transition mechanism in the energy demand equation is determined by the income level, *i.e.* $q_{it} = y_{it}$. This specification corresponds to the standard idea that income elasticity of energy demand depends on income level. We also consider a second specification (called model B) in which the transition mechanism is based on the income growth rate, $q_{it} = y_{it} - y_{i,t-1}$. This model may be more suitable when the *per capita* GDP is not stationary.

Table 1

LM_f Tests for Remaining Nonlinearity

Model	Model A			Model B		
Threshold Variable		y_{it}			Δy_{it}	
Number of Location Parameters	m = 1	m = 2	m = 3	m = 1	m = 2	m = 3
$H_0 : r = 0$ vs $H_1 : r = 1$	551.5	291.8	206.6	1.66	9.19	6.17
	(0.00)	(0.00)	(0.00)	(0.20)	(0.00)	(0.00)
$H_0 : r = 1$ vs $H_1 : r = 2$	2.36	0.001	8.65	__	0.96	3.54
	(0.12)	(0.99)	(0.00)		(0.38)	(0.01)
$H_0 : r = 2$ vs $H_1 : r = 3$	__	__	13.2	_	__	0.12
			(0.00)			(0.94)
$H_0 : r = 3$ vs $H_1 : r = 4$	__	__	2.10	__	__	__
			(0.10)			
$H_0 : r = 4$ vs $H_1 : r > 4$	__	__	__	__	__	__

Notes: For each model, the testing procedure works as follows. First, test a linear model (r= 0) against a model with one threshold (r = 1). If the null hypothesis is rejected, test the single threshold model against a double threshold model (r = 2). The procedure is continued until the hypothesis of no additional threshold is not rejected. The LM_F statistic has an asymptotic F [m , TN - N - (r+1) m] distribution under H_0 where m is the number of location parameters. The corresponding p-values are in parentheses.

The first step consists of testing the log-linear specification of energy demand against a specification with threshold effects. The results of these linearity tests and specification tests of no remaining non-linearity are reported on Table 1. For each definition of the threshold variable q_{it} (models A or B) we consider three specifications with one, two or three location parameters. For each specification, we compute the LM_F statistics for the linearity tests ($H_0 : r = 0$ versus $H_1 : r = 1$) and for the tests of no remaining non-linearity ($H_0 : r = a$ versus $H_1 : r = a + 1$). The values of the statistics are reported until the first acceptance of H_0.

The linearity tests clearly lead to the rejection of the null hypothesis of linearity of the relationships between income and energy demand. The only exception is found in model B with $m = 1$. Whatever the choice made for the threshold variable, the number of location parameters, the LM_F statistics lead to strongly reject the null $H_0 : r = 0$. For the energy demand model A, the lowest value of the LM_F statistic is obtained with two location parameters, but even in this case the value of the test statistic is largely below the critical value at standard levels. This first result confirms the non-linearity of the energy demand, but more originally shows the presence of strong threshold effects determined either by income level or income growth rate. Given the values of the LM_F statistics, we can see that the threshold effects are stronger when income level is used to characterize the transition mechanism between demand regimes.

The specification tests of no remaining non-linearity (see Table 1) lead to identify an optimal number of transition functions (or extreme regimes) in all cases. The optimal number of transition functions is always inferior to the maximum number of transition functions authorized in the algorithm. In other words, in a PSTR model, a small number of extreme regimes is sufficient to capture the non-linearity of the energy demand, or equivalently the cross-country heterogeneity and the time variability of the income elasticity. Recall that a smooth transition model, even with two extreme regimes ($r = 1$), can be viewed as a model with an infinite number of intermediate regimes. The income elasticities are defined at each date point and for each country as weighted averages of the values obtained in the two extreme regimes. The weights depend on the value of the transition function. So, even if $r = 1$, this model allows a '*continuum*' of elasticities (or regimes), with each one associated with a different value of the transition function *g*(.) between 0 and 1. Thus, the choice of *r* is just a question of specification of the model.

Table 2

Determination of the Number of Location Parameters

Model	Model A			Model B		
Number of Location Parameters	m = 1	m = 2	m = 3	m = 1	m = 2	m = 3
Optimal Number of Thresholds	1	1	3	0	1	2
Residual Sum of Squares	108.9	109	98	149	137.5	137.5
AIC Criterion	-2.979	-2.977	-3.067	-2.667	-2.744	-2.736
Schwarz Criterion	-2.968	-2.964	-3.025	-2.664	-2.731	-2.707

Notes: For each model, the optimal number of location parameters can be determined as follows. For each value of m, the corresponding optimal number of thresholds, denoted r*(m), is determined according to a sequential procedure based on the LM_F statistics of the hypothesis of non-remaining non-linearity. Thus, for each couple (m,r*), the value RSS of the model is reported. The total number of parameters is (r*+1) +r* (m+1)**.**

Finally, in the PSTR model, it is necessary to choose the number of location parameters used in the transition functions, that is the value of *m*. The choice of *m* is not very important as long as we determine the corresponding number of transition functions, denoted $r(m)$, which assures that there is no remaining non-linearity in the model. The model is so flexible that different models with different couples m, $r(m)$ give the same quantitative, as well as qualitative, results when we estimate the individual elasticities. In Table 2, for each assumed value of *m* we report the corresponding optimal number of transition functions deduced from the LM_F tests of remaining non-linearity. We estimate the PSTR models for each potential specification m, $r(m)$, and report the number of parameters and the residual sum of squares. We suggest here the use of two standard information criteria (the Akaike and the Schwarz criteria) in order to choose a benchmark specification for each specification of the demand function. Consequently, we consider the specification with $m = 1$ and $r = 1$ as optimal for the model A ($q_{it} = y_{it}$) and the specification with $m = 2$ and $r = 1$ for the model B ($q_{it} = \Delta y_{it}$).

Table 3 contains the parameter estimates of the final PSTR models. Recall that the estimated parameters β_j cannot be directly interpreted as elasticities. As in logit or probit models, the value of the estimated parameters is not directly interpretable, but their signs can be interpreted. For instance, let us consider the model A with one transition function. A negative (or positive) parameter β_1 only signifies that when the threshold variable (income level) increases, the income elasticity decreases (or increases). This observation can be generalized in a model with more than one transition function ($r > 1$) even if things are slightly more complicated. In a model with two transition functions, if the parameter β_1 is positive and the parameter β_2 is negative, this implies that an increase of the threshold variable has two opposite effects on the income elasticity. The results of these two opposite effects will depend on the value of the (*i*) slope parameters γ_j and (*ii*) the location parameters c_j. No general result can be deduced here.

Table 3

Parameter Estimates for the Final PSTR Models

Specification Threshold Variable (m , r*)	Model A (1,1)	Model B (2,1)
Income Parameter β_0	1.569	1.1115
	(0.03)	(0.02)
Income Parameter β_1	-0.800	0.1314
	(0.04)	(0.02)
Location Parameters c_j		
First Transition Function	3.055	[0.0154 0.0154]
Second Transition Function	-	-
Slope Parameters $\square_0$	1.296	494.2

Notes: Model A corresponds to the threshold variable y_{it} and Model B to the threshold variable Δy_{it}. The standard errors in parentheses are corrected for heteroskedasticity. For each model and each value of m the number of transition functions r is determined by a sequential testing procedure (see Table 1). For the j^{th} transition function, with j=1,..r, the m estimated location parameters c_j and the corresponding estimated slope parameter g_j are reported.

We can observe that the estimated transition function in model A is not sharp. Recall that when the slope parameter tends to infinity, the transition function tends to an indicator function as in the threshold model without smooth transition. We can see in Table 4 that the estimated slope parameter for the transition function in the model A is equal to 1.2963. Consequently, this transition function is quite different from an indicator function. This point is particularly important, since it implies that the non-linearity of the energy demand cannot be reduced to a limited number of regimes with different income elasticities. Indeed, it is important to recall that, as opposed to a PTR model, a PSTR model with a smooth transition function can be interpreted as a model which allows a '*continuum*' of regimes. This '*continuum*' of regimes is clearly required when measuring the threshold effects of the energy demand (as assumed in the non-parametric approaches used, for instance, by Judson, Schmalensee, Stocker (1999)). This result also points out the fact that the solution which consists of grouping countries in a panel and estimating a relationship between income and energy demand, or energy intensity, may be unsatisfactory (even if the specification used is quadratic). It is well known that this approach neglects the heterogeneity of the relationships between the countries.

6. Individual Income Elasticities

In panel data models, published results usually refer solely to general values of the parameters whereas detailed results by country remain unpublished. Given the parameter estimates of our energy demand models, it is interesting and possible to compute, for each country of the sample and for each date, the time varying income elasticity, denoted e_{it}, *i=1,..,N* and *t=1,..,T* (see equation [5.15]). The averages of these individual smoothed income elasticities, as well as their variances, are reported in Table 4 for the 44 countries of the sample. These averages and standard deviations correspond to:

$$\bar{e}_i = \frac{1}{T}\sum_{t=1}^{T} e_{it} \qquad s_{e,i} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(e_{it} - \bar{e}_i\right)^2} \qquad \forall i = 1,...N \qquad [5.19]$$

In the case of model A (see Table 3 and equation [5.15]), we have:

$$e_{it} = \frac{\partial c_{it}}{\partial y_{it}} = 1.569 - \frac{0.800}{\left[1+\exp\left(-1.296\left(y_{it} - 3.055\right)\right)\right]} - 0.800\, y_{it}\, \frac{1.296 \times \exp\left[-1.296\left(y_{it} - 3.055\right)\right]}{\left[1+\exp\left(-1.296\left(y_{it} - 3.055\right)\right)\right]^2} \qquad [5.20]$$

It is interesting to compare these elasticities to the estimated elasticities obtained in panel data models with quadratic specifications (Galli (1998)). For this comparison, we also report in Table 4 the average and the standard deviation of the elasticities based on a fixed effect model with a quadratic specification of the energy demand as proposed by Galli (1998). Recall that in an FEM specification of a quadratic demand model (equation [5.5]), the elasticity is country and year specific, and is equal to $e_{it}^{q} = \beta + 2\lambda\, y_{it}$. For each country, the corresponding average and standard deviations of income elasticities are given by:

$$\overline{e}_{i}^{q} = \frac{1}{T}\sum_{t=1}^{T} e_{it}^{q} = \beta + 2\lambda \overline{y}_{i} \qquad s_{e,i}^{q} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(e_{it}^{q} - \overline{e}_{i}^{q}\right)^{2}} \qquad \forall i = 1,...N \qquad [5.21]$$

It is important to note that in the FEM approach the cross-country variance (and time variability) of the income elasticities is only due to the variance in the level of *per capita* GDP. Since, the parameters β and λ are common to all countries, the international differences in income elasticities are only due to the international difference in the averages of *per capita* GDP. The richer the country, the more its income elasticity is important and the relationship between average income and income elasticity is strictly linear. On the other hand, in a PSTR model, the income elasticities are cross-country and specific for more subtle reasons. The smooth threshold effect allows a ‘continuum’ of income elasticity, given the threshold variable, the level of income. Consequently, the formal relationship between income and income elasticity is strongly non-linear as shown in our estimates (equation [5.17]). It does not necessarily imply that the average elasticities (PSTR versus FEM) are strongly different. But, for some particular countries, the PSTR elasticities may be different from the FEM elasticities. For these countries, the energetic demand model is very different from that observed for the other countries; for the same *per capita* GDP, these countries would not have the same income elasticity of their energy demand.

In Table 4, the means and standard errors of the PSTR and FEM estimates of income elasticities are reported. Recall that, in both cases, the estimated income elasticities are time varying, so these values correspond to the averages (and standard deviations) of the national elasticities estimated over the period 1950-99. We can see that, when the level of *per capita* GDP is used, a threshold variable (columns 4 and 5, Table 4), the PSTR model gives approximately the same average estimates as those obtained with an FEM quadratic model at the average point (columns 2 and 3, Table 4). This result confirms the fact that, for most countries, the quadratic FEM can be viewed as a second order Taylor approximation of a PSTR model. This result is generally true when average elasticities are considered. However, it does not imply that the time varying elasticities have identical dynamics in both models. Indeed, the estimated income elasticities derived from the FEM quadratic model and the PSTR model A are reported in Figure 3 for a list of selected countries (the others are available on request). For most of the 44 countries, the time profile of FEM and PSTR estimated elasticities are similar. This implies that for these countries, a quadratic homogenous model is sufficient to approximate the elasticity dynamics derived from a heterogeneous model. On the other hand, for some countries of our panel, this result is not valid. It is, for example, the case at least for China, Egypt, India, Indonesia, Nigeria and Thailand. For instance, for Taiwan, Galli (1998) found an estimated long-run elasticity equal to 1.18 in 1973 and equal to 0.63 in 1990. In our sample, the FEM gives an average elasticity over 1950-99 equal to 1.23. If the PSTR model is used, we find a similar profile as that observed by Galli; the estimated elasticity for Taiwan is equal to 1.58 in 1973 and 1.22 in 1990. However, with a PSTR model, we show that this decrease of the elasticity is considerably less important in our estimates than in the FEM estimates. Such heterogeneity would not have been taken into account with a homogenous quadratic model. In our opinion, it is one of the main advantages of our threshold approach.

Table 4

Individual Estimated Income Elasticities

Model	Quadratic Fixed		PSTR Model A		PSTR Model B	
	Average	Std	Average	Std	Average	Std
Argentina	1.036	7.01	1.110	9.80	1.202	2.18
Australia	0.802	12.0	0.719	21.0	1.183	0.61
Austria	0.871	18.4	0.824	29.6	1.189	1.55
Belgium	0.840	15.5	0.780	26.5	1.185	0.88
Brazil	1.295	15.5	1.367	10.5	1.194	1.74
Bulgaria	1.213	14.9	1.299	11.8	1.202	2.17
Canada	0.778	12.8	0.678	22.4	1.186	1.06
Chile	1.128	9.77	1.223	12.8	1.198	1.99
China	1.764	21.7	1.537	4.22	1.207	2.18
Colombia	1.295	11.6	1.378	8.51	1.183	0.95
EX Czechoslovakia	1.059	10.8	1.132	13.5	1.187	1.38
Denmark	0.781	13.7	0.683	23.7	1.185	1.17
Egypt	1.607	15.9	1.516	3.83	1.189	1.66
Finland	0.883	17.1	0.847	27.8	1.192	1.77
France	0.818	15.5	0.743	26.4	1.184	0.76
Germany	0.848	15.8	0.790	26.1	1.19	1.67
Hungary	1.157	11.4	1.252	11.1	1.192	1.80
India	1.801	11.3	1.553	1.36	1.191	1.48
Indonesia	1.608	17.4	1.513	5.05	1.200	2.09
Iran	1.314	16.1	1.380	10.4	1.212	2.32
Italy	0.888	18.4	0.849	29.1	1.190	1.41
Japan	0.924	27.9	0.870	38.8	1.201	2.36
South Korea	1.345	35.8	1.299	29.2	1.211	2.25
Malaysia	1.371	21.8	1.394	15.2	1.199	1.75

Mexico	1.191	12.9	1.283	12.0	1.190	1.68
Netherlands	0.812	13.8	0.734	23.8	1.186	1.09
New Zealand	0.826	7.62	0.762	13.6	1.190	1.79
Norway	0.819	17.4	0.749	29.3	1.185	0.72
Nigeria	1.756	7.66	1.550	0.89	1.203	2.39
Peru	1.303	6.34	1.395	4.23	1.195	2.06
Philippines	1.541	8.21	1.507	2.21	1.186	1.53
Poland	1.008	12.2	1.055	17.1	1.195	1.63
Romania	1.382	14.1	1.430	6.84	1.197	2.06
South Africa	1.276	6.12	1.375	4.33	1.185	1.24
Spain	1.042	22.0	1.063	28.1	1.195	1.97
Sweden	0.797	12.2	0.709	21.4	1.184	0.78
Switzerland	0.700	9.52	0.544	16.3	1.186	1.21
Taiwan	1.235	33.9	1.215	32.6	1.207	2.19
Thailand	1.483	25.8	1.441	13.8	1.201	2.08
Turkey	1.291	15.2	1.364	11.4	1.196	1.99
United Kingdom	0.825	11.5	0.759	20.1	1.183	0.66
USA	0.694	11.9	0.543	19.3	1.186	0.91
EX URSS	1.161	10.8	1.258	11.2	1.196	2.15
Venezuela	0.913	3.74	0.917	6.50	1.197	2.07

Notes: For each country, the average and standard deviation (in percentages) of the individual income elasticities are reported. The quadratic fixed effect model corresponds to a quadratic specification of the energy demand with individual fixed effects. For the PSTR models, Model A corresponds to the threshold variable y_{it} and Model B to Δy_{it}..

Another way to illustrate these advantages of the PSTR is to compare the estimated parameters of an FEM quadratic model for two sub-samples. In the first sample, denoted sample A, we consider 8 countries for which the PSTR and FEM models give different elasticity profiles. The second sample corresponds to the rest of the countries. As can be seen in Table 5, the homogeneous parameters estimated for both samples are substantially different, the parameter associated with the square of GDP in particular. In other words, this implies that, for the same *per capita* GDP level, these countries (samples A and B) do not have the same income elasticity of energy demand. Only a PSTR model (or a random coefficient model) is able to take into account this heterogeneity.

Table 5

Quadratic Energy Demand Function, Fixed Effects Model

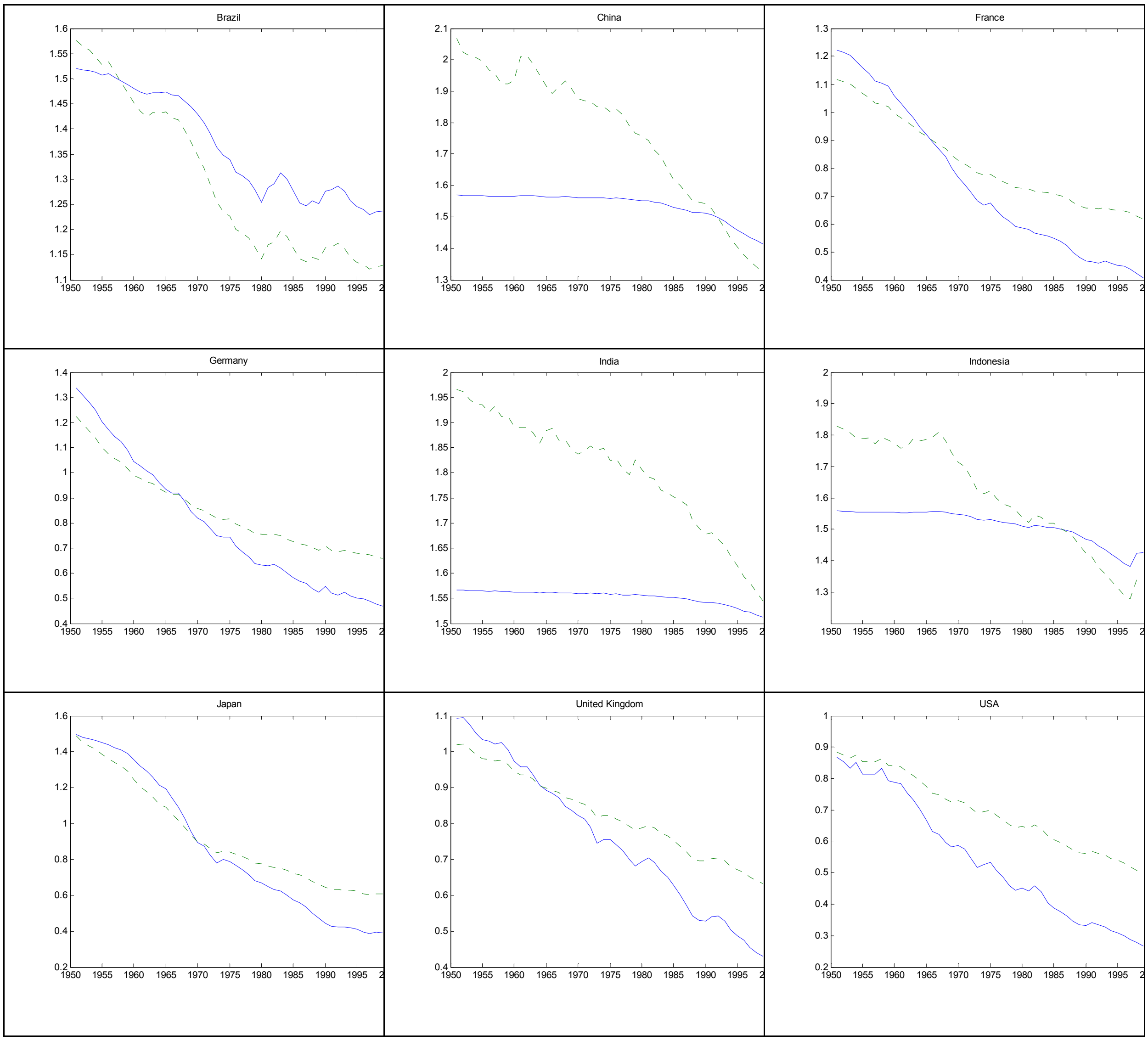
	Total Sample	Sample A	Sample B
Income Parameter β_0	1.78	1.72	1.94
	(63.6)	(26.7)	(55.9)
Squared Income	-0.194	-0.179	-0.235
Parameter $\beta 1$	(-23.4)	(-5.61)	(-24.8)
RSS	110.34	41.14	66.7

Notes: Sample A corresponds to China, Egypt, India, Indonesia, Nigeria, the Philippines and Thailand. Sample B corresponds to all others countries.

Finally, when the GDP growth rate is used as a threshold variable (columns 6 and 7, Table 4), the PSTR model gives similar average estimated elasticities. This meaningless result can be interpreted as follows. Obviously, if the transition mechanism is not well specified, that is if the threshold variable is not well chosen, the use of the PSTR model implies associating countries according to fallacious criteria. Consequently, at each date the countries are split into a small number of randomly constituted groups and associated with different slope parameters, according to the value of the fallacious threshold variable. Therefore, the estimated slope parameters obtained in this context on random groups are not different from those estimated for the whole sample. Consequently, the fact that we obtain roughly the same individual estimated elasticities as those obtained in linear panel models may be interpreted as evidence that the threshold variable is not well identified. This conclusion is reinforced by the fact that the linearity tests lead to a stronger rejection of the linearity of model A than that observed for model B (Table 3). As suggested by Gonzalez & al., it is recommended to choose the threshold variable that leads to the largest value of the linearity test statistics.

Figure 3

Individual PSTR and FEM Income Elasticities (1950-99)



Note: The blue continuous line corresponds to the estimated income elasticity obtained in the PSTR with qit=yit (model A) and the dashed line corresponds to estimated elasticity obtained in the quadratic fixed effect model.

8. Conclusion

In this chapter, we propose an original method for specifying the heterogeneity and the time variability of the income elasticity of energy demand. This method is based on panel smooth transition regression models. Indeed, the issue of heterogeneity in panel approach is deeply linked to the non-linearity of the energy demand. Therefore, an alternative to parametric threshold models would consist of using a non-parametric method to estimate the relationship between income and energy demand. In this context, Judson, Schmalensee & Stocker (1999) propose the use of local regressions (knot-spline) in order to estimate this relationship for 123 countries over the period 1950-92. In particular, they show that when the *per capita* GDP is larger than 1500 1985$, the income-elasticity is decreasing. These observations are not incompatible with our threshold representation.

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