Energy consumption and economic development: a semiparametric panel analysis[§]

Phu Nguyen Van*

THEMA-CNRS, Université de Cergy-Pontoise

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Abstract

This paper proposes a semiparametric analysis for the study of the relationship between energy consumption per capita and income per capita for an international panel data. It shows little evidence for the existence of an environmental Kuznets curve for energy consumption. Energy consumption increases with income at an increasing rate for low income levels and then stabilizes for higher income levels. Changes in energy structure have no significant effect on energy consumption.

Key words: Energy consumption, environmental Kuznets curve, semiparametric panel model, nonparametric tests

JEL classification: C14, C23, Q40

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* Correspondence: P. Nguyen Van, THEMA, CNRS and Université de Cergy-Pontoise, 33 boulevard du Port, F-95011 Cergy-Pontoise cedex, France; phone: +33 (0)1 34 25 60 82; fax: +33 (0)1 34 25 62 33; e-mail: `Phu.Nguyen-Van@u-cergy.fr`

1 Introduction

The Environmental Kuznets Curve (EKC) hypothesis, which suggests an inverted U-shaped relationship between environmental degradation and income, has been extensively investigated in the literature. Various environmental degradation indicators have been examined: emissions or concentrations of pollutants (CO, CO_2, SO_2, NO_x,...), deforestation rate, water quality, etc. Results on the existence of an EKC are mix and much of them depend largely on the econometric methodology.

Energy constitutes of course an important subject as it is considered as a source of many serious environmental problems. The literature on the relationship between economic growth and energy consumption is dominated by parametric cross-country modeling and time series analysis. For example, Suri and Chapman (1998) used parametric panel models and showed that the relationship between energy consumption and income displays an increasing pattern (and the turning point is outside the data sample). Richmond and Kaufmann (2006a,b), by using parametric specifications for panel data, found little evidence for an EKC for energy consumption. They showed that energy consumption increases with income at a decreasing rate. Existing time series studies include Stern (2000), Altinay and Karagol (2005), Lee (2005), Lee and Chang (2005), Richmond and Kaufmann (2006b), and papers from a recent issue of *Energy Economics* (volume 29(6), 2007). They investigated nonstationarity, cointegration and causality between energy and economic series. Causality has been found to be uni- or bi-directional between income and energy consumption, depending on the country considered.

This paper aims to provide a robust estimation of the profile of the relationship between energy consumption and income, which would help us to intervene convincingly in the discussion for the existence of an EKC for energy.[1] For this purpose, we use a semiparametric partially linear panel model, which has the advantage to avoid the misspecification problem that may arise in parametric EKC studies as pointed out by Taskin and Zaim (2000), Roy and van Kooten (2004), Bertinelli and Strobl (2005), Millimet

[1] In this respect, the paper is more related to cross-countries parametric studies than time serie ones. Indeed, we are more concerned by correlation between energy consumption and income than by the causality relationship between them. Furthermore, incorporating nonstationarity in a nonparametric cross-country framework is very complex but may constitute an interesting question to be investigated in the future.

et al. (2003), and Azomahou et al. (2006).

Moreover, this modeling enable us to control for other variables that enter parametrically in the regression. We follow Richmond and Kaufmann (2006b) by accounting for changes in the structure of final energy consumption (or changes in energy mix as called by these authors). The authors argue that structural changes (e.g. from coal to oil/natural gas and from oil/natural gas to hydro and nuclear electricity) allows for higher energy efficiency (i.e. lower energy consumption for a given level of economic activity). They also showed that the presence of these structural changes in regressions reduces the size of the turning point.

The next section presents the data and the econometric model. Section 3 discusses estimation results and Section 4 concludes.

2 Data and method

2.1 Data

The data, collected from the Energy Information Administration (EIA), cover a balanced panel of 158 countries and territories for the period 1980–2004 (3950 observations). Variables are total primary energy consumption per capita (measured in millions British thermal units, Btu) and GDP per capita (in thousands real 2000 U.S. dollars). Total primary energy consumption includes consumptions of petroleum, natural gas, coal, hydroelectric power, nuclear power and renewable electric power (geothermal, solar, wind, wood and waste). It also includes net electricity imports (i.e. imports minus exports). GDP distribution shows that most of observations correspond to low income countries (about 2800 observations corresponding to incomes per capita lower than 10,000 dollars).

Table 1 here

Insert Figure 1 here

We calculate the shares of coal, petroleum and gas, and hydroelectric, nuclear and renewable electric power in total energy consumption. Note that the sum of these three shares, measured in percentage, might not be equal to 100 due to independent rounding.

2.2 Econometric model

We propose the following semiparametric partially linear panel model

$$\begin{aligned} y_{it} &= m(x_{it}) + z_{it}'\gamma + \delta t + u_{it}, \quad i = 1, ..., N, \; t = 1, ..., T, && (1) \\ &= m(x_{it}) + w_{it}'\eta + u_{it}, \quad w_{it} \equiv (z_{it}', t)', && (2) \end{aligned}$$

where y_{it} is energy consumption per capita of country i at year t, x_{it} is GDP per capita, m is an unknown function, identifiable up to an additive constant, z_{it} contains other observed time-varying regressors, t is the time trend, u_{it} is the error term that includes unobserved factors. The unknown form of m avoids the use of a pre-specified parametric functional form (polynomial or other parametric forms) as in existing studies on the relationship between energy consumption and income, which is source of possible misspecification.

We assume for instance that u_{it} is i.i.d. in the i index and there is no restriction in the t index. This assumption includes the case of the one-way error component model with $u_{it} = \mu_i + \varepsilon_{it}$ where μ_i is the individual effect and ε_{it} is the standard error term, both of them are uncorrelated with x_{it} and w_{it}, i.e. $E(\varepsilon_{it}|x_{i1}, ..., x_{iT}, w_{i1}', ..., w_{iT}') = E(\mu_i|x_{i1}, ..., x_{iT}, w_{i1}', ..., w_{iT}') = 0$. In fact, the model discussed here is more general than this well-known random effects model as it allows for ε_{it} being serially correlated and condionally heteroskedastic (Li and Stengos, 1996). Moreover, it also includes the usual fixed effect specification, $u_{it} = \mu_i + \varepsilon_{it}$, where $E(u_{it}|x_{i1}, ..., x_{iT}, w_{i1}', ..., w_{iT}') = E(\mu_i|x_{i1}, ..., x_{iT}, w_{i1}', ..., w_{iT}') \neq 0$.

Regressors included in z correspond to the share of coal consumption and the share of petroleum and natural gas consumption. The share of hydro-electric, nuclear, and renewable electric power is considered as the reference category. These variables capture structural changes in energy consumption. Time trend variable t is used to account for the macroeconomic effect common to all countries. It is an interesting variable because it may represent the effect of energy prices in the international market. However, this variable does not distinguish the price effect with other macroeconomic effects (international economic cycle, etc.).[2]

[2]Another variable that would be interesting to be controlled for is energy prices observed at the country level. However, such a variable is not available for all countries, and using it will considerably reduce the sample size. It will make our nonparametric method few attractive as it requires a large sample.

Consider the case $E(\mu_i|x_{i1},...,x_{iT},w'_{i1},...,w'_{iT}) = 0$ (random effects models included). Li and Stengos (1996) proposed an instrumental semiparametric estimator for this model. Firstly, taking the expectation of (1) conditional on x_{it} and then calculating the difference of it with (1), we obtain

$$y_{it} - E(y_{it}|x_{it}) = (w_{it} - E(w_{it}|x_{it}))'\,\eta + u_{it}. \qquad (3)$$

Assuming there exists an instrumental variable q_{it} (such that $E(u_{it}|q_{it}) = 0$) of the same dimension than w_{it}, Li and Stengos (1996) proposed an instrumental variable estimator for η, $\hat{\eta} = (Q'W)^{-1}Q'Y$, where $Q_{it} = q_{it} - E(q_{it}|x_{it})$, $Y_{it} = y_{it} - E(y_{it}|x_{it})$, and $W_{it} = w_{it} - E(w_{it}|x_{it})$. For simplicity, we choose $q_{it} = w_{it}$ as recommended by Li and Stengos (1996). Once $\hat{\eta}$ is available, m might be estimated by

$$\hat{m}(x_{it}) = E((y_{it} - w'_{it}\hat{\eta})|x_{it}) = E(y_{it}|x_{it}) - E(w_{it}|x_{it})'\hat{\eta}. \qquad (4)$$

In estimations, we use the local linear kernel method with the Epanechnikov kernel and the rule-of-thumb bandwidth (see Silverman, 1986) to calculate $E(q_{it}|x_{it})$, $E(w_{it}|x_{it})$, and $E(y_{it}|x_{it})$.[3] It is well-known that the local linear kernel estimator has a smaller bias at the data boundary, where few data points are available, than the local constant kernel (or Nadayara-Watson) estimator. Using the local liner kernel estimator will then provide more robust estimation than the local constant kernel estimator (Pagan and Ullah, 1999).

We turn now into the case of the fixed effects model where $E(\mu_i|x_{i1},...,x_{iT},$ $w'_{i1},...,w'_{iT}) \neq 0$. We can take first differences to eliminate the fixed effects μ_i:

$$y_{it} - y_{i,t-1} = \Psi(x_{it}, x_{i,t-1}) + (z_{it} - z_{i,t-1})'\gamma + \delta + u_{it} - u_{i,t-1}, \qquad (5)$$

where $\Psi(x_{it}, x_{i,t-1}) := m(x_{it}) - m(x_{i,t-1})$. As Ψ is a very general function, which may include a constant, we will not consider separately δ and Ψ in estimations (or in other words, δ is not separately identified with Ψ).

This model is the same as (1) and may be estimated by the method of Li and Stengos (1996) detailed abave, except that variables in level are replaced by their first differences, the univariate function m now replaced

[3] Oversmoothing (corresponding to a higher value of the bandwidth) and undersmoothing (smaller bandwidth) give however similar patterns as $\hat{m}$ obtained with the rule-of-thumb bandwidth.

by a bivariate function Ψ, and instrumental variables $q_{it} = w_{it}$ replaced by $q_{it} = z_{i,t-1}$. When an estimation of Ψ for this model is obtained, i.e. $\hat{\Psi}(x_{it}, x_{i,t-1}) = E((y_{it} - y_{i,t-1}) - (z_{it} - z_{i,t-1})'\hat{\gamma}|x_{it}, x_{i,t-1})$, we can use the marginal integration method to compute the univariate function m, which is identifiable up to an additive constant. This method, developed by Linton and Nielsen (1995), was applied in the case of CO_2 emissions by Azomahou et al. (2006). The main idea of marginal integration can be described as follows. For simplicity, let us rename the arguments of $\hat{\Psi}$ as u and v. We can write

$$E_v\left[\hat{\Psi}\left(u, V\right)\right] = \int \hat{\Psi}\left(u, v\right) f(v) dv \tag{6}$$

$$= m(u) - E_v\left[m\left(V\right)\right] \tag{7}$$

$$= m(u) - k, \tag{8}$$

and similarly,

$$E_u\left[\hat{\Psi}\left(U, v\right)\right] = \int \hat{\Psi}\left(u, v\right) f(u) du \tag{9}$$

$$= k - m\left(v\right). \tag{10}$$

We obtain estimators of $m\left(x_{it}\right)$ and $m\left(x_{it-1}\right)$ up to the same constant by taking the sample averages

$$\hat{m}^{(1)}\left(x_{it}\right) = \frac{1}{N\left(T-1\right)} \sum_{j=1}^{N(T-1)} \hat{\Psi}\left(x_{it}, x_j\right). \tag{11}$$

Similarly, we can obtain an estimator for $m\left(x_{it-1}\right)$, i.e.

$$\hat{m}^{(2)}\left(x_{it-1}\right) = -\frac{1}{N\left(T-1\right)} \sum_{j=1}^{N(T-1)} \hat{\Psi}\left(x_j, x_{it-1}\right). \tag{12}$$

A more precise estimator of m can be obtained by a weighted average between $\hat{m}^{(1)}$ and $\hat{m}^{(2)}$, and a simple estimator is given by $\hat{m}(x) = \left[\hat{m}^{(1)}\left(x\right) + \hat{m}^{(2)}\left(x\right)\right]/2$.

3 Estimation results

We consider the *parametric version* of (1) with

$$m(x_{it}) = b_0 + b_1 x_{it} + b_2 x_{it}^2 + b_3 x_{it}^3 \quad \text{and} \quad u_{it} = \mu_i + \varepsilon_{it}. \tag{13}$$

We estimate this model by GLS (random effects model), within and first-difference estimators (fixed effects model) and estimation results are reported in Table 2.

As noted previously, the underlying assumption behind the GLS and within estimators is $E(\varepsilon_{it}|x_{i1},...,x_{iT},w'_{i1},...,w'_{iT})=0$, which is known as the strict exogeneity assumption. However, compared to the within estimator, the GLS estimator has the additional assumption $E(\mu_i|x_{i1},...,x_{iT},w'_{i1},...,w'_{iT}) = 0$ which may be tested by a Hausman test. The computed statistic, equal to $35.91 > 12.59$ (value of $\chi^2(6)$ at the 5% level), allows us to reject the GLS estimator (i.e. rejecting the random effects model) in favor of the within estimator.

A Hausman test is also used to compare the within and the first-difference estimators of the fixed effects model. First-difference of the parametric model in (13) is

$$
\begin{aligned}
y_{it} - y_{i,t-1} &= b_1(x_{it} - x_{i,t-1}) + b_2(x_{it} - x_{i,t-1})^2 + b_3(x_{it} - x_{i,t-1})^3 \\
&\quad + (z_{it} - z_{i,t-1})'\gamma + \delta + (u_{it} - u_{i,t-1}) \qquad (14)
\end{aligned}
$$

We remark that the new constant of this model is δ while b_0 is eliminated from the regression. In fact, we always have the strict exogeneity assumption with the within estimator (the null hypothesis) whereas we have a much weaker assumption with the first-difference estimator, called first-difference assumption, i.e. $E(\varepsilon_{it} - \varepsilon_{it-1}|x_{it},x_{i,t-1},w'_{it},w'_{i,t-1}) = 0,\ i=1,...,N,\ t=2,...,T$.[4] The Hausman test statistic, which compares estimators of b_1, b_2, b_3, and γ, is equal to $3.30 < 11.07$ (value of $\chi^2(5)$ at the 5% level). We can conclude that the within estimator is not rejected. Therefore, the within estimator is the best estimator for the parametric case.

Insert Table 2 here

Concerning the semiparametric modeling, we use the Hausman-type test proposed by Li and Stengos (1992) to compare the estimator of γ obtained under the null (obtained from equation (5)) and that under the alternative (equation (1)). The coefficient related to the time trend is excluded. The reason is that δ is, as underlined previously, not separately identified with

[4] As pointed out by Azomahou et al. (2006), an extension of the predeterminedness assumption $E(\varepsilon_{it}|x_{i1},...,x_{it},w'_{i1},...,w'_{it})=0$ that yields this first-difference assumption is $E(\varepsilon_{it}|x_{i1},...,x_{i,t+1},w'_{i1},...,w'_{i,t+1})=0,\ i=1,...,N,\ t=1,...,T-1$.

the nonparametric component Ψ. The test statistic follows a $\chi^2(k)$, with $k = \dim(\gamma)$. The computed value of the statistic is equal to 0.003 much lower than 5.99, the value of $\chi^2(2)$ at the 5% level, implying that the semiparametric model given in (1) is preferred.

Finally, we implement the nonparametric test of Li and Wang (1998). The null hypothesis is the parametric model given in (13) and the associated within estimator and the alternative is the semiparametric model in level given in (1). The test is based on the residuals of the 'mixed' regressions under the null and the alternative hypotheses. The statistic is given by

$$I = \frac{1}{n^2 h^\kappa} \sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} \hat{u}_i \hat{u}_j K_{ij} \tag{15}$$

with $n = NT$ and $\hat{u}$ corresponding to the parametric residuals of the 'mixed' regressions, i.e. $\hat{u} = y - \hat{m}(x) - w'\hat{\eta}$ where $\hat{m}(x) = \hat{b}_0 + \hat{b}_1 x_{it} + \hat{b}_2 x_{it}^2 + \hat{b}_3 x_{it}^3$ obtained under the null (given by the within estimator) and $\hat{\eta}$ obtained under the alternative. Remark also that κ is the dimension of x and in our case $\kappa = 1$ as x is univariate. $K_{ij} = K\left(\frac{x_i - x_j}{h}\right)$ where K is the kernel function (we use the Epanechnikov kernel) and h is the smoothing parameter (obtained by the rule of thumb). Under the null, $nh^{\kappa/2} I \rightarrow N(0, \Omega)$, as $n \rightarrow \infty$, where $\Omega = 2\left[\int K^2(v)\,\mathrm{d}v\right] E\left[f(x)\left(E(\sigma^2(x,z)|x)\right)^2\right]$ with $\sigma^2(x,z)|x) = E(u^2|x,z)$, $u = y - m(x) - w'\eta$. Ω is consistently estimated by $\hat{\Omega} = \left(2/n^2 h^q\right) \sum_i \sum_{j\neq i} \hat{u}_i^2 \hat{u}_j^2 K_{ij}^2$. It follows that $J := nh^{\kappa/2} I \sqrt{\hat{\Omega}} \rightarrow N(0,1)$. The computed value of the Li and Wang test statistic is 152.33 much higher than 1.96, implying the rejection of the parametric model at the 5% level. We can conclude that the more suitable model for our data is the semiparametric model in (1).

Differences between the parametric model (within estimation) and the semiparametric model given in (1) in terms of estimations of m might be viewed graphically in Figure 2. The parametric curve, based on the within estimator, has an inverted-U shape. The downward part corresponds to incomes per capita higher than 35,000 dollars. As too few observations are available for this income interval we do not have enough confidence on the existence of this decreasing part. We can conclude that the parametric relationship is increasing at a decreasing rate, as obtained by existing studies (Suri and Chapman, 1998, Richmond and Kaufmann, 2006a,b). The nonparametric confidence interval does not include the parametric curve. The nonparametric curve presents interesting patterns. Energy consumption increases with income for income levels lower than about 10,000 dollars, strongly increases for income interval 10,000–15,000 dollars, and then stabilizes for incomes higher than 15,000 dollars. Again, as few observations are available for income levels higher than 35,000 dollars, the estimated curve is not enough smooth and therefore we prefer not to interpret the results for this income interval. The stable part of the curve represents an improvement of energy efficiency (higher production for a given level of energy consumption) which might be assigned to past policies and energy-saving technologies in high income countries.

Insert Figure 2 here

For a majority of countries and territories, of which observed income per capita is lower than about 10,000 dollars and observed energy consumption per capita is lower than about 100 millions Btu (see Figure 2), our estimation results suggest that their energy consumption would rapidly increase with economic development. Indeed, as shown in Figure 2, energy consumption per capita in these countries would rise by three times higher than its observed level (to attain about 300 millions Btu) if income per capita reaches for example an amount of 15,000 dollars. Taking China and India as an example, income per capita and energy consumption per capita of China are in average equal to 2,314 dollars (with the maximum value of 5,051 dollars) and 26.32 millions Btu (highest value = 45.87 millions Btu). Figures for India are respectively 2,202 dollars in average (highest value = 3,442 dollars) and 10.290 millions Btu in average (highest value = 14.475 millions Btu). We thus expect that energy consumption of these two countries will increase at an increasing rate as long as their economies grow. Our finding contrasts with existing results in the literature where the relationship between energy consumption and income is represented by a diminishing returns curve, i.e. energy use increases with income but at a decreasing rate even for low income countries (e.g., Richmond and Kaufmann, 2006a,b).

Concerning the share of coal consumption and the share of petroleum and natural gas consumption in model (1), their estimates, respectively 0.229 (standard error = 4.333) and 0.016 (3.799) are not significant compared to the share of hydroelectric, nuclear and renewable electric power. They are also insignificant in parametric models. Changes in energy structure (or energy mix) have no effect on energy consumption, contrary to the results of Richmond and Kaufmann (2006a).

Finally, the effect of the time trend is not significant in semiparametric models. It seems therefore that macroeconomic cycle does not have an impact on final energy consumption for the period of the study.

4 Concluding remarks

The EKC hypothesis is not confirmed by our analysis. Energy consumption rises with income at an increasing rate for low incomes and then stabilizes for high incomes. This finding suggests that energy consumption in developing countries would rise more rapidly than expected by parametric studies. It would result in a near future in serious economic and environmental problems in these countries like rapid augmentation of greenhouse gas emissions due to energy use, excessive pressure on the provision of energy resources, etc.

The structure of models used in this paper relies on weaker assumptions (unknown functional form, weakly exogenous regressors) than those of standard parametric panel data models (polynomial functional forms, strict exogeneity) may be applied in the study of other environmental indicators. Moreover, the instrumental variables semiparametric estimator of our model would be interesting to be extended on the case of endogenous regressors. However, our methodology has the drawback that we cannot perform a forecasting analysis as in other parametric studies.

Appendix: List of countries and territories

Antigua and Barbuda, Afghanistan, Algeria, American Samoa, Argentina, Australia, Austria, Bahrain, Barbados, Botswana, Bermuda, Belgium, The Bahamas, Bangladesh, Belize, Bolivia, Burkina Faso, Burma, Benin, Solomon Islands, Brazil, Bhutan, Brunei, Burundi, Canada, Cambodia, Chad, Congo (Brazzaville), Congo (Kinshasa), China, Chile, Cayman Islands, Cameroon, Comoros, Colombia, Costa Rica, Central African Republic, Cuba, Cape Verde, Cyprus, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, Equatorial Guinea, El Salvador, Ethiopia, Fiji, Finland, France, French Guiana, Gabon, The Gambia, Ghana, Greece, Grenada, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Kiribati, North Korea, South Korea, Kuwait, Laos, Lebanon, Lesotho, Liberia, Libya, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Martinique, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Nepal, Netherlands, Netherlands Antilles, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Portugal, Puerto Rico, Qatar, Reunion, Rwanda, Saint Kitts and Nevis, Saint Lucia, Saint Vincent/Grenadines, Samoa, Sao Tome and Principe, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Singapore, Solomon Islands, Somalia, South Africa, Spain, Sri Lanka, Sudan, Suriname, Swaziland, Sweden, Switzerland, Syria, Taiwan, Tanzania, Thailand, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey, Uganda, United Arab Emirates, United Kingdom, United States, Uruguay, Vanuatu, Venezuela, Vietnam, US. Virgin Islands, Yemen, Zambia, Zimbabwe.

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Table 1: Descriptive statistics

Variable	Units	Mean	Std. Dev.	Min.	Max.
Energy consumption per capita	millions British thermal units (Btu)	88.904	174.09	0.12	2507.34
GDP per capita	thousands real 2000 U.S. dollars	7.89	8.04	0.07	44.07
Coal share	percent	7.67	15.86	0	84.65
Petroleum and natural gas share	percent	78.11	23.32	4.28	100.54
Hydroelectric, nuclear & renewable power	percent	14.19	18	-3.05	91.51

Notes: Balanced panel data on 158 countries and territories observed for the period 1980–2004 (3950 observations).

Data source: Energy Information Administration (EIA).

Table 2: Parametric regressions

	GLS[a]		Within[b]		First-difference[c]	
	Coef.	Std.Err	Coef.	Std.Err	Coef.	Std.Err
GDP, linear term	4.038*	1.70	1.599	1.769	-2.389	2.795
GDP, quadratic term	0.196*	0.097	0.275*	0.099	0.533*	0.148
GDP, cubic term	-0.005*	0.002	-0.006*	0.002	-0.010*	0.002
Coal share	-0.082	0.241	-0.056	0.250	0.045	0.286
Petroleum and gas share	-0.007	0.146	-0.035	0.150	-0.007	0.153
Time trend	0.377*	0.112	0.467*	0.113	0.254	0.422
Intercept	40.814*	17.386	53.182*	14.056	–	–

Notes: [a]GLS estimation of the random effects model. [b]within estimation of the fixed effects model. [c]first-difference estimation of the fixed effects model. The intercept term b_0 cannot be estimated in the first-differenced model as it is drooped from the regression. Significant coefficients at the 5% level are starred.

Table 3: Nonparametric regressions

	Level[a]		First-difference[b]	
	Coef.	Std.Err	Coef.	Std.Err
Coal share	0.229	4.333	-0.120	151.9
Petroleum and gas share	0.016	3.799	-1.084	210.0
Time trend	0.022	4.242	–	–

Notes: [a] Li and Wang' (1996) estimator for equation in level, i.e. equation (1). [b]Li and Wang' (1996) estimator for equation in first-difference, i.e. equation (5). In the first-differenced model, the coefficient of the time trend δ is note separately identified from the nonparametric component Ψ. Significant coefficients at the 5% level are starred.

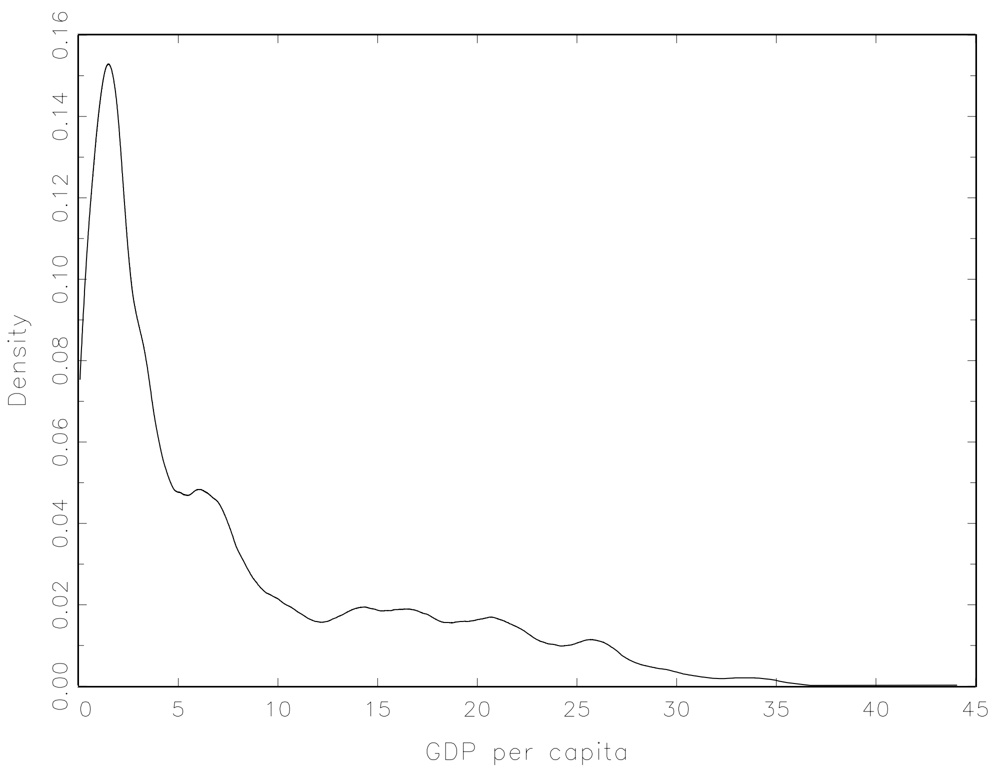

Figure 1: Kernel density estimation for GDP per capita (in thousands real 2000 US dollars).

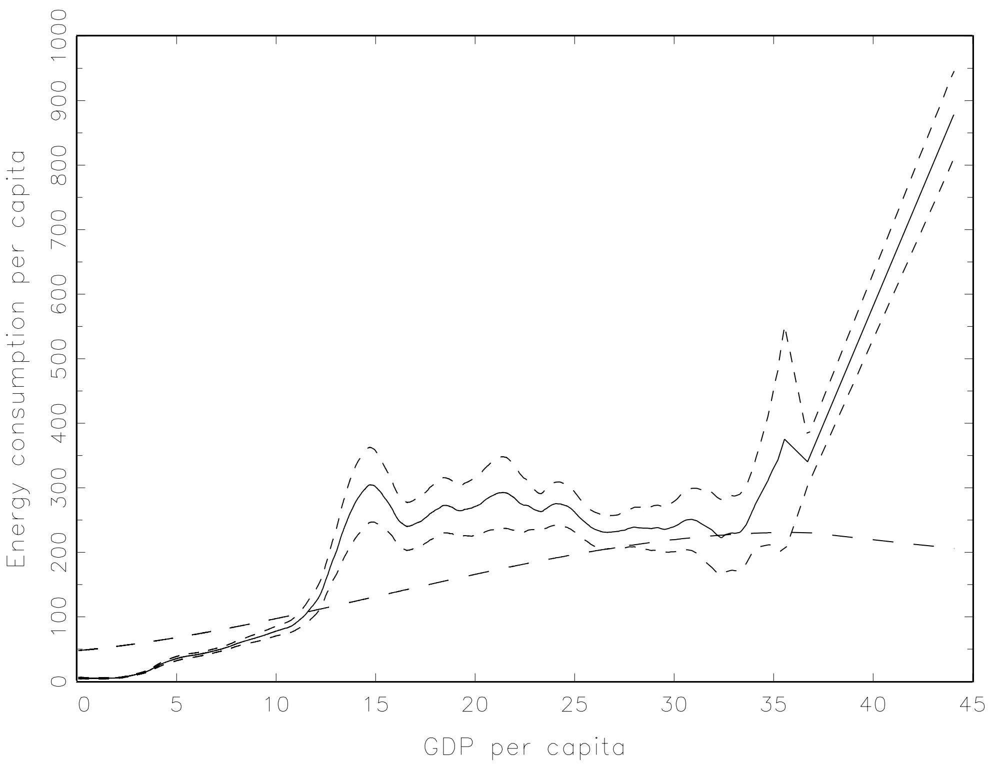

Figure 2: Relation between energy consumption per capita (in millions Btu) and GDP per capita (in thousands real 2000 US dollars). The solid curve is the nonparametric estimation of $m(x)$. The short dashes curves correspond to its 95% confidence interval. The long dashes curve corresponds to the within estimation of the parametric model with $m(x_{it}) = b_0 + b_1 x_{it} + b_2 x_{it}^2 + b_3 x_{it}^3$.