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World energy intensity revisited: a cluster analysis

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The aim of this article is to empirically identify convergence clubs in energy intensity among 109 countries from 1971 to 2010 by using a recently developed methodology, i.e., a new regression-based convergence test, introduced by Phillips and Sul (2007). This log *t* test allows us to endogenously identify the groups of countries that converge to different equilibriums and those that do not converge to any convergence clubs. We mainly find that, first, world countries do not seem to converge at the same steady-state level; instead, they form four separate clubs converging to their own steady-state paths and few countries are found to converge to no group at all. In addition, although the world as a whole shows the evidence of convergence, economic and geographic groups seem to converge at different speeds. Last, estimates from an ordered-logit model reveal that initial energy intensity level and openness are mainly responsible for the formation of the world convergence clubs, whereas industry share and R&D share are not.

Keywords: energy intensity; club convergence; log *t* regression test; nonlinear time-varying factor model

JEL Classification: C15; C23; Q53; Q54

I. Introduction

The decline in the world's energy intensity (i.e., the ratio of total primary energy supply (TPES) to gross domestic product) has received increasing attention from scholars, politicians and society as a whole over the past two decades. The empirical literature on energy intensity has mainly followed two strands. The first strand aims to examine the determinants of energy intensity or driving forces behind the decline in energy intensity by using data at the national, regional or sectoral levels via different econometric estimation methods. These factors, among others, include economic structure, technological progress, sectoral composition of energy use, fuel mix and efficiency in the conversion and end-use of energy (Liddle, 2010). The second strand, often attributed to the economic growth and environmental literature, is concerned primarily with cross-country or cross-region energy intensity convergence, which in

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general focuses on three different types of convergences, namely sigma (σ) convergence, beta (β) convergence and stochastic convergence. Sigma convergence, going back to Barro and Sala-i-Martin (1990), holds when the cross-sectional dispersion (usually the sample SD) of the variable of interest (energy intensity in our case) decreases over time. Beta convergence, introduced by Baumol (1986), suggests a negative relationship between energy intensity over time and its initial level; in other words, countries with a high initial level of energy intensity grow more slowly than countries with a lower initial level of energy intensity given that they all have the same steady-state growth path for energy intensity. Stochastic convergence, introduced by Quah (1990), states that the shocks to energy intensity relative to the sample average are temporary, which implies that econometrically the relative variable can be found to be trend stationary by using standard (panel) unit root tests.

Among the first to examine convergence in energy intensity was Nilsson (1993), who used a graphical analysis to examine 31 developed and developing countries over 1950–1988 and showed the evidence of a convergence process for most countries in the full sample. On the other hand, Mielnik and Goldemberg (2000) performed a descriptive analysis of energy intensity across several developing and industrialized countries and showed that these countries are converging to a common pattern of energy use. In particular, developing countries have an increasing trajectory and developed countries a decreasing trajectory over time. Recent studies of energy intensity convergence have applied more advanced techniques. While Markandya *et al.* (2006) used a panel estimation method and found that 12 countries in Eastern Europe converged (in the form of beta convergence) towards the European Union (EU) average, Le Pen and Sévi (2010) tested for stochastic convergence among a group of 97 countries over the period from 1971 to 2003 by using a pairwise econometric approach proposed by Pesaran (2007). They found no evidence of global convergence, but found some evidence of regional-based convergence (in the Middle East and OECD). By using a global sample of 98 countries over 1971–2001, Ezcurra (2007) found convergence (in the form of sigma convergence) in the spatial distribution of energy intensity by using nonparametric methods (specifically, distribution dynamic approaches). The recent paper by Liddle (2010) extended Ezcurra's study to include a larger data-set that allows for the analysis of 134 countries over 1990–2006. In the paper, he also considered energy intensity convergence across different groups of countries and different convergence measures, namely sigma convergence, beta convergence and so-called 'gamma (γ) convergence' (Boyle and McCarthy, 1997).[1] In the most recent paper, Herrerias (2012) used a similar distribution dynamics approach to that used by Ezcurra (2007) to examine world energy intensity, but took into consideration the weighting vector (i.e., population) in the kernel estimates. The objective was to explain the distributional changes of energy intensity under different scenarios for the convergence behaviour of 83 countries in terms of total energy intensity, 73 countries for fossil fuel and 71 for alternative and nuclear intensity. In addition, she differentiated between developed and developing economies in the sample of countries, and found that developing countries converge at higher energy intensity ratios, while developed countries converge at different paths of energy intensity.

In brief, the empirical studies mentioned above use a variety of econometric methodologies to examine cross-country convergences in energy intensity, and each methodology examines the existence of a different type of convergence, such as sigma convergence, beta convergence, stochastic convergence, gamma convergence or some combination of these.

This study makes a clear contribution to the existing literature as none of the existing studies have explored the club convergence in energy intensity. Particularly, this study examines energy intensity by using the recently developed and regression-based convergence test by Phillips and Sul (2007), referred to below as the log t test. This is based on the cross-sectional variance ratio of the variable of interest over time and a nonlinear time-varying factor model that incorporates the possibility of transitional heterogeneity or even transitional divergence. The advantage of such an approach is that it does not require the time series under study to be trend stationary or stochastic nonstationary. More importantly, this methodology allows us to *endogenously* identify the groups of countries that converge to different equilibriums and those that do not converge

[1] Gamma convergence, or intra-distribution mobility, examines whether the individual countries with the highest intensity and lowest intensity remain the same (Liddle, 2009, 2010).

to any convergence clubs by means of a clustering algorithm (see Section II for a detailed description).

The rest of the article is organized as follows. Section II presents the methodology used to examine convergence clubs in energy intensity among 109 countries. Section III describes the data-set, and Section IV reports the empirical results. Section V concludes the article.

II. Methods

Club identification: the log t test

In order to study the convergence behaviour of energy intensity among 109 countries over the period from 1971 to 2010, we adopt the log t test proposed by Phillips and Sul (2007). The test is based on a time-varying factor representation of the variable of interest. Assume that panel data X_{it} can be decomposed as

$$X_{it} = g_{it} + \varepsilon_{it} \tag{1}$$

where g_{it} represents systematic components, including permanent common components that cause cross-sectional dependence, and ε_{it} are transitory components. No particular parametric functional forms are imposed on g_{it} and ε_{it}, and thus they can be linear, nonlinear, stationary or nonstationary processes. The specification in Equation 1 also allows for both common and idiosyncratic components in the elements g_{it} and ε_{it}.

To separate the common component from idiosyncratic components, Phillips and Sul (2007) adopted the following transformation:

$$X_{it} = \left(\frac{g_{it} + \varepsilon_{it}}{\mu_t}\right)\mu_t = \delta_{it}\mu_t \quad \text{for all } i \text{ and } t \tag{2}$$

where μ_t is a single common component that is assumed to have some deterministic or stochastically trending behaviour that dominates the transitive component ε_{it} as $t \to \infty$, while δ_{it} is the time-varying idiosyncratic element that measures the relative share in μ_t of individual i at time t. Removing the common factor μ_t by rescaling the data X_{it} cross-sectionally gives the relative transition coefficients, h_{it}:

$$h_{it} = \frac{X_{it}}{\frac{1}{N}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum_{i=1}^{N} \delta_{it}} \tag{3}$$

which measures the transition element for economy i in period t in relation to a cross-sectional average. We assume that the panel average $N^{-1}\sum_{i=1}^{N}\delta_{it}$ and its limit as $N \to \infty$ both exist and differ from 0; hence, h_{it} is well defined. Then, in the case of convergence, all economies move towards the same transition path. Thus, the factor loading coefficient δ_{it} converges to δ and $h_{it} \to 1$ as $t \to \infty$ for all i, which implies that the cross-sectional variance of h_{it} is denoted by

$$H_t = \frac{1}{N}\sum_i (h_{it} - 1)^2 \to 0 \text{ as } t \to \infty$$

This simple property is used to test for convergence and to group economies into convergence clusters.

In order to design a statistical test for convergence, Phillips and Sul (2007) assumed that the factor loading coefficient δ_{it} has the following transition form:

$$\delta_{it} = \delta_i + \sigma_i \xi_{it} L(t)^{-1} t^{-\alpha} \tag{4}$$

where δ_i is fixed, $\sigma_i > 0$ is an idiosyncratic scale parameter, ξ_{it} is iid (0, 1) with finite fourth moment over i, $L(t)$ is a slowly varying function and α is the decay rate.[2] Then, the conditions for convergence in the model can be characterized as

$$\operatorname*{plim}_{k\to\infty} \delta_{i,t+k} = \delta \quad \text{for all } i$$

which holds if and only if $\delta_i = \delta$ for all i and $\alpha \geq 0$, and the conditions for divergence are

$$\operatorname*{plim}_{k\to\infty} \delta_{i,t+k} \neq \delta \quad \text{for some } i$$

which holds if and only if $\delta_i \neq \delta$ for some i or $\alpha < 0$. We are particularly interested in the case of divergence when $\delta_i \neq \delta$ and $\alpha \geq 0$. In this case, there is the possibility of local convergence to multiple steady states in Equation 4 for $\{\delta_{it}\}$.

From the above discussion, we formulate the hypotheses formally. The null hypothesis of convergence is given as follows:

$$H_0 : \delta_i = \delta \quad \text{for all } i \text{ and } \alpha \geq 0 \tag{5}$$

The alternative is $H_A : \delta_i \neq \delta$ for some i or $\alpha < 0$. Phillips and Sul (2007) showed that under the null

[2] For more details about Equation 4, see Phillips and Sul (2007, pp. 1786–1787).

hypothesis of convergence, the cross-sectional variance of h_{it} has the limiting form

$$H_t \sim \frac{A}{L(t)^2 t^{2\alpha}} \to \infty \quad \text{as } t \to \infty \quad \text{for some } A > 0 \tag{6}$$

from which a regression-based convergence test can be derived:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log L(t) = a + b\log t + u_t \quad \text{for } \; t = [rT], [rT]+1, \ldots, T \tag{7}$$

with $r > 0$ and $L(t)$ is a slowly varying function. Under the null hypothesis of convergence, $\log(H_1/H_t)$ diverges to ∞, either as $2\log L(t)$ when $\alpha = 0$ or as $2\alpha\log t$ when $\alpha > 0$. Thus, H_0 is tested in terms of testing for the null hypothesis $H_0' : \alpha \geq 0$ in the detrended linear regression. By using $\hat{b} = 2\hat{\alpha}$, a one-sided t-test robust to heteroscedasticity and autocorrelation can be applied here. H_0 is rejected if $t_{\hat{b}} < -1.65$ at the 5% significance level. In real applications, $r > 0$ is used to discard a small fraction of time-series data in order to make the test focus on what happens as the sample size grows. The limit properties of the test depend on the value of r. However, there is no theoretical guidance on how to choose the optimal value of r in the literature. Based on Monte Carlo simulations, Phillips and Sul (2007) proposed using $r = 0.3$ when $T \leq 50$. For the slowly varying function $L(t)$, it can be one of the following functions: $\log t$, $2\log t$, $\log\log t$ or $2\log\log t$. Phillips and Sul (2007) investigated the finite sample performance of difference choices by using a simulation and suggested using $L(t) = \log t$.

When convergence for the overall sample is rejected, there are still possibilities of convergence in subgroups. Examples include the convergence clusters around separate points of equilibria or steady-state transition paths as well as cases where there may be both convergence clusters and divergent individuals in the full sample. The existence of local equilibria or club convergence clusters is of substantial interest. Searching for convergence clubs has become one of the central issues in the empirical economic growth literature. Based on Equation 4, Phillips and Sul (2007) suggested a sequential log t testing procedure to detect the convergence of subgroups following a clustering algorithm. The testing procedure can be used to identify convergence clusters, determine the number of clusters and resolve individuals into respective groups (convergence club or divergent individuals).

Clustering algorithm

If the null hypothesis of overall convergence is rejected, convergence clubs can be identified via the clustering algorithm of Phillips and Sul (2007). This algorithm can be briefly summarized in the following four steps:

(1) *Step 1: Last observation ordering*. The panel is arranged in descending order according to the country with the highest level of energy intensity in the last period of the panel.
(2) *Step 2: Formation of the core group*. Calculate the convergence t-statistics, $t_{\hat{b}}$, for the sequential log t regression based on the k highest countries (Step 1) with $2 \leq k < N$. The core group size (k*) is chosen as the maximum of $t_{\hat{b}}$ with $t_{\hat{b}} > -1.65$, i.e., $k^* = \text{argmax}_k\{t_b\}$ *subject to* $\min\{t_b\} > -1.65$.
(3) *Step 3: Club membership*. Select countries to be members in the core group (Step 2) by adding one at a time. Include the new country if the associated t-statistic is greater than the critical value C, which in our empirical analysis is set to be 0 as recommended by Phillips and Sul (2007) for $T \leq 50$.
(4) *Step 4: Stopping rule*. Form a second group from all the countries outside the convergence club. Run the log t test for this set of countries to check whether it converges ($t_{\hat{b}} > -1.65$). If not, repeat Steps 1–3 on this group to determine whether the panel includes a smaller subgroup that forms a convergence club. If no core group is found (Step 2), we conclude that all the remaining countries are divergent.

III. Data

This study uses a data-set of countries from the Energy Information Administration. Energy intensity is defined as TPES divided by GDP in units of tons of oil equivalent (toe) per thousand year-2005 purchasing power parity (PPP) US dollars, converted into natural logs.[3] TPES accounts for all the energy consumed by a country, which includes energy imports and excludes energy exports (Liddle, 2010). By eliminating the countries with missing data, we end up with a balanced panel of 109 countries for the period 1971–2010. Thus, we have 4360 observations. The countries under study are available upon request. The countries are classified into various subgroups indicating whether they belong to any of the following: (1) a high-income country with \$12 616 per capita or more; (2) a middle-income country with \$1036–12 615 per capita; (3) a low-income country with \$1035 per capita or less; (4) an OECD member; (5) an Organization of the Petroleum Exporting Countries (OPEC) member and (6) an EU member. The income variable is defined according to 2012 gross national income per capita, which is taken from the World Development Indicators database.

IV. Results

World convergence clubs

When the log t test is applied to energy intensity for a group of 109 countries for the period 1971–2010, the null hypothesis of overall convergence is rejected at the 5% significance level. Thus, we may conclude that the world as a whole does not converge to the same steady-state equilibrium in terms of energy intensity.

Next, by applying the clustering mechanism test procedure, we find four convergence clusters. Specifically, three countries are identified as being in the first club, 18 countries belong to the second club, 47 countries are in the third club and 34 countries are classified in the last convergence club. The remaining seven countries do not converge to any energy intensity club. The results of the log t test are reported in Table 1, and the club membership is mapped in Fig. 1.

Several interesting results can be summarized here. First, Club 1 has the highest level of energy intensity

Table 1. World energy intensity convergence club classification

Club	No. of countries	$\hat{b}$	t-Statistic	SE	Energy intensity
Club 1	3	−0.244	−32.066	0.008	1.285
Club 2	18	−0.179	−6.675	0.027	0.373
Club 3	47	−0.676	−88.931	0.008	0.222
Club 4	34	0.672	10.473	0.064	0.146

Note: Energy intensity is measured in units of toe divided by GDP in thousands of 2005 PPP US dollars.

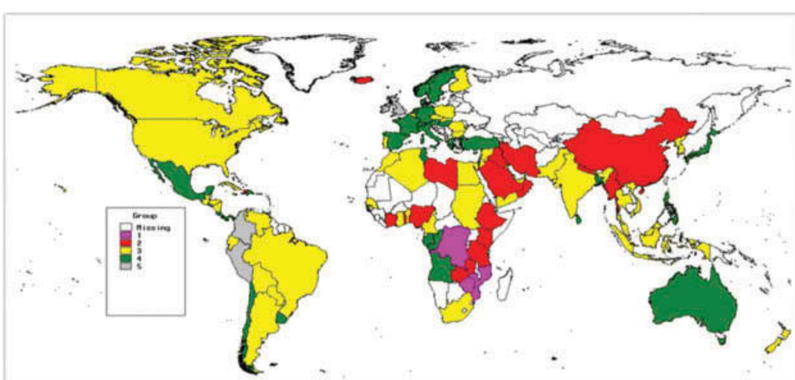

Fig. 1. World energy intensity convergence clubs
Note: Groups 1–4 represent different convergence groups, whereas Group 5 represents those countries (Albania, Colombia, Hong Kong, Ireland, Peru, Trinidad and Tobago and United Kingdom) that do not belong to any convergence group.

[3] It is typical to use both TPES and PPP-converted GDP in energy intensity studies (Mielnik and Goldemberg, 2000; Ezcurra, 2007; Jobert *et al.*, 2010; Liddle, 2010; Camarero *et al.*, 2013).

Table 2. Convergence tests by group

EU [28] (two convergence groups, one divergent group)			OECD [34] (two convergence groups, one divergent group)			OPEC [12] (two convergence groups)		
	$\hat{b}$	t-Stat		$\hat{b}$	t-Stat		$\hat{b}$	t-Stat
Club 1 [23]	1.005	16.011	Club 1 [18]	−0.86	−29.385	Club 1 [10]	0.039	1.284
Club 2 [5]			Club 2 [10]	−2.145	−17.025	Club 2 [2]		
High-income [38] (two convergence groups)			**Middle-income [55] (one convergence group)**			**Low-income [11] (two convergence groups, one divergent group)**		
	$\hat{b}$	t-Stat		$\hat{b}$	t-Stat		$\hat{b}$	t-Stat
Club 1 [11]	−0.794	−31.865	Club 1 [55]	−0.173	−11.455	Club 1 [4]	−0.165	−3.973
Club 2 [27]	−1.723	−65.649				Club 2 [6]	−0.084	−1.177

Note: The number of countries is reported in brackets.

(1.285 toe per thousand 2005 USD PPP) on average, with Club 2 ranked second (0.385), Club 3 third (0.222) and Club 4 last (0.146). In general, North American and European countries have relatively low energy intensity levels, whereas Asian and African countries (especially Zimbabwe, Mozambique, China, Myanmar and Nepal) have relatively high levels of energy intensity. Second, these clubs seem to be spatially correlated, namely countries belonging to the same club tend to cluster together. For instance, Congo (D.R.), Mozambique and Zimbabwe are all African countries and all belong to the first club, whereas Argentina, Brazil, Cuba, Paraguay and Venezuela are all located in the continent of South America and all belong to the third club. The spatial correlation characteristic can be further supported by the Moran's (1950) I test statistic.[4]

Regional convergence clubs

In this subsection, we apply the convergence test and club clustering algorithm described in Section II to examine countries with similar economic or geographic characteristics. Specifically, we test for convergence among (1) OECD countries, (2) OPEC countries, (3) EU countries, (4) high-income countries, (5) middle-income countries and (6) low-income countries. The results for these six groups are presented in Table 2. In general, the results can be summarized as follows.

First, two convergence clubs (using the clustering mechanism) are found within OECD countries. The first club consists of 18 OECD members (Austria, Belgium, Canada, Chile, Finland, France, Greece, Israel, Italy, Japan, Korea (D.R.), Mexico, New Zealand, Poland, Portugal, Slovak Republic, Spain and Turkey), whereas the second convergence club consists of 10 members (Australia, Czech Republic, Denmark, Germany, Hungary, Netherlands, Norway, Sweden, Switzerland and the United States). The next six OECD members do not form a club. They are Estonia, Iceland, Ireland, Luxembourg, Slovenia and the United Kingdom. Figure 2 (left panel) presents the relative transition paths for the two convergence clubs within OECD countries.

Second, similar results are found for the 28 EU members. Two energy intensity convergence clubs are identified as revealed by the log t test. While Croatia, Estonia, Latvia, Liechtenstein and Lithuania form one club, the remaining 23 EU members form the second club. Figure 2 (middle panel) presents the relative transition paths for the two convergence clubs within EU countries. It can be seen that the convergence speed is relatively fast compared with the OECD case.

[4] Moran (1950) proposed a test statistic to assess the degree of spatial autocorrelation between adjacent locations. It is defined in a matrix form as $I = (Z'WZ)/(Z'Z)$, where Z is the variable of interest (energy intensity in this study) and W is a symmetric matrix that can take several forms. In this study, the spatial weight matrix is based on the centroid distance between each pair of country i and country j.

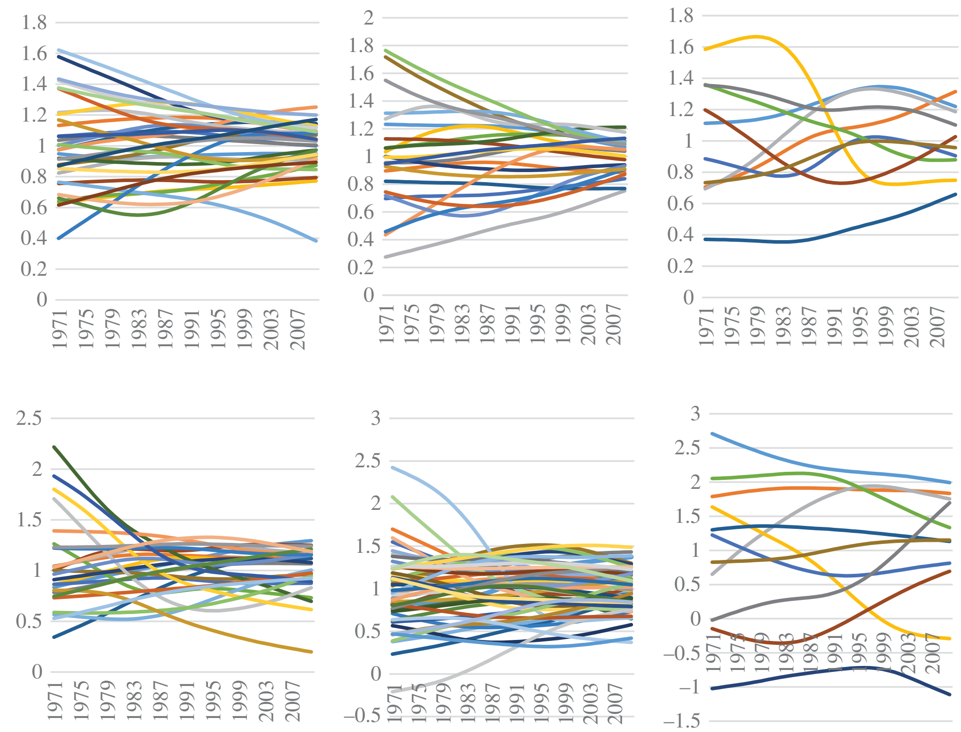

Fig. 2. Relative transition paths for different groups: OECD (top left), EU (top middle), OPEC (top right), high-income (bottom left), middle-income (bottom middle) and low-income (bottom right) members

Third, two convergence groups are found among OPEC members. While Iran and Saudi Arabia form one group, the remaining 10 members form the second one. From Fig. 1, we clearly see that Iran and Saudi Arabia fall into the second club (relatively high level of energy intensity), whereas the other 10 countries fall into the third club (relatively low level of energy intensity). Hence, the transition paths for OPEC members (Fig. 2, top right) show that the pattern of convergence is rather irregular and nonlinear and that their convergence speed is relatively slow compared with the OECD and EU groups.

Lastly, when classifying countries by income level, we find two clubs among high-income countries, one club for all middle-income countries, and two clubs among low-income countries. The transition paths for these income-level groups (Fig. 2, bottom) show that high-income countries, in general, converge the fastest followed by middle-income countries. Low-income countries seem to converge with a nonlinear pattern and the slowest speed.

Forces driving club membership

In order to explain the formation of convergence clubs across the world, we employ an ordered-logit regression model, which is designed for dependent variables that are ordinal but not interval level. The ordinal response variable, denoted by y, represents the club to which a country belongs. As there are four clubs identified, y can take on values from 1 to 4. This variable can be treated as an ordinal variable since the observed clubs can be ranked according to the steady-state energy intensity levels of the countries in the respective club. In our sample, the first club (Club 1) as identified has the highest level of energy intensity (on average), whereas the last club (Club 4) has the lowest level. Assuming that membership in a certain club is related to an unobservable (latent) continuous random variable y_i^* that indicates a country's individual steady-state energy intensity level, the ordered-logit regression model is described as

$$\begin{aligned} y_i^* &= X_i'\beta + \varepsilon_i \\ y_i &= j, \quad \text{if } \alpha_{j-1} \leq y_i^* \leq \alpha_j,\ j = 1, 2, \ldots, J \end{aligned} \tag{8}$$

where X_i is a covariate vector with $i = 1, 2, \ldots, 102$ (since there are seven countries that do not converge to any energy intensity club, 102 countries are used in this part of analysis), β is a vector of regression coefficients and ε_i is the disturbance term. α's are unknown cut-points (category boundaries) in the distribution of y^*, with $\alpha_0 = -\infty$ and $\alpha_J = \infty$. Consequently, we can observe the probabilities of belonging to a certain club depending on the level of the corresponding variable. Specifically,

$$\begin{aligned} \Pr[y_i = j] &= \Pr[y_i^* \text{ is in the } j \text{ th range}] \\ &= F\left[\alpha_j - X_i'\beta\right] - F\left[\alpha_{j-1} - X_i'\beta\right] \\ &= 1/\left[1 + \exp\left(-\alpha_j + X_i'\beta\right)\right] \\ &\quad - 1/\left[1 + \exp\left(-\alpha_{j-1} + X_i'\beta\right)\right] \end{aligned} \tag{9}$$

where $F(.) = \exp(.)/[1 + \exp(.)]$. Equation 9 can thus be used to derive a likelihood function and maximum likelihood estimates of α and β. Furthermore, we are able to examine the effect of a specific explanatory variable on the probability of membership in a specific club[5]:

$$\begin{aligned} \frac{\partial \Pr(y_i = j)}{\partial x_i^k} = -\beta_k \Bigg\{ & \frac{\exp\left(X_i'\beta - \alpha_j\right)}{\left[1 + \exp\left(X_i'\beta - \alpha_j\right)\right]^2} \\ & - \frac{\exp\left(X_i'\beta - \alpha_{j-1}\right)}{\left[1 + \exp\left(X_i'\beta - \alpha_{j-1}\right)\right]^2} \Bigg\} \end{aligned} \tag{10}$$

Turning to the selection of explanatory variables, we follow existing literature (e.g., Hübler and Keller, 2010; Bartkowska and Riedl, 2012; Herrerias *et al.*, 2013), and identify the following explanatory variables that may affect the formation of world energy intensity clubs: initial energy intensity (i.e., energy intensity during 1971), the openness, industry structure and R&D variables. All explanatory variables are taken from the World Bank's World Development Indicators database.

Initial energy intensity. The club convergence hypothesis suggests economies that are identical in their structural characteristics converge to one another in the long-run provided that they have similar initial conditions (Galor, 1996). Hence, initial conditions are expected to be responsible for the formation of convergence clubs as confirmed by the growth literature (among many others, Galor and Zeira, 1993; Durlauf and Johnson, 1995; Quah, 1996; Bartkowska and Riedl, 2012). For instance, in his theoretical paper on the empirics of economic growth and convergence, Quah (1996) states that convergence clubs are formed endogenously and that different convergence clubs are formed depending on the initial distribution of characteristics across countries, whereas Bartkowska and Riedl (2012) examined empirically the formation of convergence clubs in per capita income of European regions and found that the level of initial conditions plays a vital role. It is worth mentioning that adding initial term in the regression model reflects the dynamic and persistent feature of energy intensity, and controls for potential omitted variable bias, and other endogeneity issues from the econometric perspective.

Openness variables. Including the share of foreign direct investment, and imports of goods and services in the GDP (Heil and Selden, 2001; Cole, 2006; Peterson, 2008; Hübler and Keller, 2010). Rising FDI inflows and increasing openness to trade could affect energy intensity via a scale, a composition, and a technical effect (Grossman and Krueger, 1993; Antweiler *et al.*, 2001). The scale effect rests on the idea that expended economic activity results in higher energy use, implying the scale effect resulting from FDI inflows is positive. The composition effect is related to a structural shift in the economic activity; that is, shift from the agricultural to the (heavy) industrial sector, from the industry to the service sector or from the heavy to the lighter industry. While the former is more energy intensive, the latter is less energy intensive. This suggests that the composition effect can be either negative or positive. The technical effect is based on the idea that foreign capital is one important channel for the transfers of energy-saving technologies from developed countries by newly industrializing countries, and technology transfer, which results from openness to trade and foreign direct investment and potentially reduces energy use, can occur in two ways: first, directly via more efficient foreign firms operating in the host country and second, indirectly through technological spillovers from the foreign firms to indigenous firms (Keller, 2004; Hübler and Keller, 2010).

Industry structure. Defined as the share of industrial value added in GDP (Fisher-Vanden *et al.*, 2004;

[5] See Cameron and Trievedi (2005), Greene (2003), and Jung (1993) for more details on the ordered-logit approach.

Herrerias *et al.*, 2013), and is related to the aforementioned composition effect. It captures shifts between the agricultural sector, the industrial and service sector (Hübler and Keller, 2010). One may expect that a higher industry share raises energy intensity as industrial production requires more energy inputs than agriculture or services. It should be mentioned, though, that industry sector includes both heavy industry (i.e., energy-intensive industry) and light industry, and that energy resources consist of coal, electricity and petroleum. Hence, without detailed information on the sectoral shift from heavy industry to light industry (vice versa), and information on energy composition, the structure change effect on energy intensity or energy efficiency cannot be determined a prior.

R&D variable. Measured as R&D expenditure as a percentage share of GDP (Fisher-Vanden *et al.*, 2004; Jefferson *et al.*, 2006). There are general agreements in the existing literature that technological progress is important to explain energy intensity, just as ACEEE (American Council for an Energy-Efficient Economy) points out, 'R&D is critical to advancing energy efficiency by promoting the creation, development, and commercialization of new, energy-efficient technologies and practices', even so, the relationship between R&D expenditures and energy intensity or carbon intensity remains a controversial issue, and empirical evidence is scarce (Garrone and Grilli, 2010). On the one hand, public energy R&D is successful in improving energy efficiency at country level (Garrone and Grilli, 2010); on the other hand, Jefferson *et al.* (2006) conclude conservatively that R&D has a measurable effect on energy intensity. In brief, R&D may play a vital (at least neutral) role in the development of advanced, efficiency-related energy technologies.

Focusing on the empirical results, Table 3 presents the change in the probability of belonging to a specific club given a small change in the explanatory variables. In line with the growth empirics, the initial condition is found to play an important role in explaining a country's membership in a specific club. The negative coefficient sign (−1.735) on the initial condition variable implies that a small positive change in initial energy intensity decreases the probability (0.18) of belonging to a low-energy-intensity club (Club 3 or Club 4).[6] In other words, if a country's initial energy intensity is higher, the country is more likely to join the club with high level of energy intensity. Consistent with several country studies (e.g., Eskeland and Harrison, 2003; Fisher-Vanden *et al.*, 2004; Golder, 2011; Herrerias and Orts, 2013), openness has been a driving force in the reduction of energy intensity, as shown by the very significant and positive coefficients on both imports and FDI, confirming the idea, as mentioned above, that rising FDI inflows and increasing imports could reduce energy intensity via a technical effect. In addition, the computed probability of a country moving from its current club to a low-energy-intensity club (Club 3 or Club 4) from a rise in FDI is bigger than that from imports (3.8 versus 2.8), implying that the reduction effect appears to be stronger

Table 3. Ordered-logit regression results on club formations

	Coefficient	SE	*Z*-statistic	Odds ratio
Initial energy intensity	−1.735***	0.698	−2.49	0.18
Share of industrial value added in GDP	0.279	0.385	0.73	1.32
Imports, as a share of GDP	1.028***	0.142	7.24	2.80
Net inflows of FDI, as a share of GDP	1.336***	0.316	4.23	3.80
R&D expenditure, as a share of GDP	1.956	1.27	1.54	7.07
Continent dummies	Yes			
Pseudo R^2	0.26			
Likelihood test	57.03 [0.0000]			
Number of countries	102			

Notes: *** $p < 0.01$. Club 1 has the highest level of energy intensity on average, Club 2 the second highest level, Club 3 the third and Club 4 the lowest. The *p*-value is reported in brackets. The estimation is performed by using the command 'ologit' in Stata 13.

[6] In the ordered-logit model, the probability (or odds ratio) is an exponential function of the estimated logistic coefficients and hence can be computed by exponentiating the logistic coefficients. For instance, the odds ratio of the initial energy intensity is: exp(–1.735) = 0.18.

from FDI than imports. Structural change seems to contribute little (if any) to the change in the energy intensity or to the formation of a country's membership to a new club. Though increase in the share of industry in GDP increases energy intensity, this effect is not statistically significant at any conventional significance level. This result would appear unexpected at first glance since a shift of the agricultural sector to the industrial sector should increase energy intensity given that industrial production needs more energy inputs than agriculture or services, but such result could be expected if we consider the sectoral shift or structural changes inside the industry sector, or the shift of energy resources. Specifically, the increase in the share of industry in GDP does not necessarily lead to rise in energy intensity if there were increases in light industry, or improvements in relative energy efficiency of heavy industry. However, such assumption cannot be verified further given data availability. Last, we find that R&D targeted at energy efficiency improvements has only limited effects (at 15% level of significance), suggesting that R&D plays a limited role in determining the formation of world energy intensity convergence clubs. This result seems not consistent with conventional wisdom. Some tentative explanations for this result are offered as follows: (1) there are no country-level time-series data available on energy-related R&D expenditures (i.e., expenditures on technologies related to electricity generation and use, clean and sustainable fuels, transportation, and so on), instead, we are only able to use the general R&D expenditures as proxy, which could induce measurement error and make an inaccurate inference on the R&D effect; (2) increases in energy R&D may crowd out other types of R&D by drawing away research funding and scientists from other productive sectors (Schneider and Goulder, 1997; Popp, 2006), yet, substantiating this claim is beyond the scope of this study.

V. Conclusions and Policy Implications

In this study, we examined club convergence in energy intensity among 109 countries for the 40-year period between 1971 and 2010 by using a new regression-based convergence test introduced by Phillips and Sul (2007). This log t test allows us to endogenously identify the groups of countries that converge to different equilibriums and those that do not converge to any convergence clubs. In addition, we examined the driving forces behind the formation of multiple steady states of energy intensity around the world by using an ordered-logit regression approach.

We draw the following three main findings: first, countries do not seem to converge at the same steady-state level; instead, they form four separate clubs converging to their own steady-state paths and few countries are found to converge to no group at all. Second, although the world as a whole shows the evidence of convergence, economic and geographic groups seem to converge at different speeds. OECD countries, EU countries and OPEC countries all show the evidence of two convergence clubs and one divergent group. Among converged countries, EU countries in general have a higher convergence speed compared with OECD countries, while OPEC countries have the lowest speed. Moreover, high-income countries seem to converge at a faster speed than middle-income countries, while low-income countries exhibit the evidence of two convergence clubs and one divergent group. Finally, the estimates from the ordered-logit model show that initial energy intensity level and openness are mainly responsible for the formation of world convergence clubs, whereas industry share and R&D share are not.

In the light of the study findings, we can draw the following implications: first, although our results support the convergence hypothesis, the convergence process is not achieved equally among all groups of countries, which display different time paths of energy intensity. This result indicates that the 'one size fits all' energy policy is ill-designed, which is consistent with Herrerias (2012). From this point of view, analysing the convergence process across countries is of great importance since it will help policy-makers develop differentiated policies. In addition, given that low-income countries do not form a single convergence club and to facilitate the catching up process, specific energy saving policy measures should be designed and implemented to help these countries converge to a lower level of energy intensity, or to close the gap with efficiency frontier clubs.

Second, it is true that the convergence of energy intensity is present; however, it is worth mentioning that for some groups of countries such as OPEC countries (say, Iraq, Kuwait and Saudi Arabia), the average level of energy intensity has been increasing since the 1980s, which implies an upward convergence trend (i.e., the situation there is worsening).

By contrast, a considerable number of developing or middle-income countries (say, India and China) have experienced a declining level of energy intensity and have converged to a lower energy intensity level. Hence, the implication is that while stronger economic growth and lower energy consumption may be in conflict for some countries such as OPEC members, it may not be for others (e.g., India and China).

Third, the finding of this article indicates that openness to FDI and to imports raised the probability of a country moving to a low-energy-intensity club. Hence, the openness strategies/reforms have improved energy efficiency and should be encouraged and continued.

Last, industry share seems to have limited (if any) impact on the change in the energy intensity or the formation of a country's membership to a new club. The problem of this variable is that it does not account for the sectoral shift (heavy industry to light industry, vice versa), structural changes inside the industry sector, the shift of energy resources (coal, electricity, petroleum, natural gas and other fuels) or country heterogeneity (coal-dependent or oil-dependent country). When data are available, how these factors affect energy intensity or the probability of the formation of a country's membership to a low-energy-intensity club seem to be an interesting topic for future research.

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