Towards a sustainable energy scenario? A worldwide analysis

María A. González-Álvarez* Antonio Montañés*† Lorena Olmos*

Abstract

This paper studies the worldwide evolution of energy intensity for a large sample of countries during the period 1990-2015, differentiating between non-renewable, non-clean and total energy intensity. This division allows us to establish more precise policy recommendations which, along with the use of the Phillips and Sul (2009) methodology, provides the novelty of the analysis. Our results refute recent evidence favouring the hypothesis of global convergence for all types of energy intensity. Grouping countries either by regions or by income level, the evidence against this hypothesis is remains overwhelming, with very few exceptions. Nonetheless, we can observe the presence of several convergence clubs, whose creation strongly depends on energy prices as well as on external energetic dependency. In any event, results relating to the different types of energy intensity are varied, suggesting that previous policy recommendations aimed at tackling climate change based on total energy intensity analyses are questionable.

JEL codes: Q4, O47, C22

Keywords: energy intensity; convergence; clubs; Phillips-Sul; sustainability.

* Department of Economic Analysis, University of Zaragoza, Gran Vía 2, 50005, Zaragoza (Spain).
† Corresponding author. E-mail: amontane@unizar.es
The paper has benefited from the comments of an anonymous referee. The usual disclaimer applies. The authors acknowledge the financial support of the Spanish Ministry of Science, Innovation and Universities (project ECO2015-65967-R) and that of the Aragonese Government (LMP71_18)

1. Introduction

Nowadays, one of the most decisive global challenges is climate change. As the use of fossil fuels, strongly associated with greenhouse gas emissions, is still predominant, the efficiency in the use of this energy source plays an important role. Furthermore, the promotion of renewable energy, free of carbon dioxide emissions, is also a crucial matter. In fact, in its seventh Sustainable Development Goal the United Nations includes the objectives of doubling the global rate of improvement in energy efficiency and raising substantially the share of renewable energy in the global energy mix by 2030 (United Nations General Assembly, 2015). This search for a more rational and sustainable use of energy has led to an increase in the interest of businessmen, technicians and policymakers in this field, which poses a two-fold dilemma: how to enhance the weight of alternative sources and energy productivity, particularly if non-renewable sources are involved, whilst assuring the level of competitiveness, which should not be jeopardized by the search for efficiency.

One of the best proxies for energy efficiency, as the World Bank recognizes, is energy intensity, measured as the ratio between energy use and GDP. Energy intensity has been declining over recent decades at global and regional levels, but the patterns among countries have not been uniform, especially if we focus on different energy sources. The observed differences, in the context of the considerable relevance of supranational environmental commitments and an increasing scarcity of fossil fuels, have encouraged a number of researchers to analyse whether energy intensity converges across countries or not. Nevertheless, the real issue should be the efficiency generated from non-renewable resources or, at least, from non-clean resources, since these are the origin of harmful emissions to the environment and other collateral damage.

Accordingly, the performance of countries according to these indicators are the appropriate basis on which global environmental agreements should be drafted. If the hypothesis of convergence is supported, policies aimed at augmenting energy efficiency should be the same for all countries (perhaps after a time lapse, when less developed countries move forward or catch up with more advanced countries). At the very least, the long-term objectives of high efficiency and low emissions should be common across countries. In contrast, if there is evidence in favour of the divergence hypothesis, international agreements should be adapted to individual countries according to their energy situations.

In this regard, the literature generally supports the hypothesis of convergence in total energy intensity. While the conclusions are not always totally robust, the results of previous analyses are more favourable to the convergence hypothesis. Among the international analyses, we can cite Nilsson (1993), who observes a certain degree of convergence with a sample that includes 31 countries for 1950-1988. The data considered in Ezcurra (2007), relating to 98 countries throughout the period 1971-2001, supports the hypothesis of convergence, though he states that the reduction in disparities will not be maintained in the long run. Mielnik and Goldemberg (2000) also assert the convergence process for developing and industrialized countries from 1971 to 1992. Miketa and Mulder (2005) investigate the energy productivity (the inverse of energy intensity) in the manufacturing sectors of 56 countries during 1971-1995, and their outcome shows that cross-country differences tend to decline in that period. Liddle (2010) considers two datasets: 111 countries during 1971-2006, and 134 countries from 1990 to 2006. Both datasets confirm the convergence process for the global sample, whilst conclusions for geographical groups of countries are varied, showing different speeds of convergence. The results of Le Pen and Sévi (2010) are the opposite: they consider 97 countries for the period 1971-2003 and reject the hypothesis of convergence at the global level and at some regional levels too. Other studies focus on specific country groups. Markandya et al. (2006) analyse whether 12 transition countries of Eastern Europe converged to the EU15 level during 1992-2002, finding evidence of convergence which, according to their forecasts, would continue during subsequent years. In contrast, the sample of Le Pen (2011) covers 195 European regions spanning 1980-2006 and his findings go against the convergence hypothesis. Mulder and De Groot (2012) examine the energy intensity paths for 18 OECD countries during 1970-2005, observing a convergence process from 1995. Sun (2002) studies 27 OECD countries from 1971 to 1998, finding that disparities in energy intensity decreased due to some transmission mechanism of energy efficiency.

Thus, the majority of studies reported in the literature have analysed the total energy intensity and therefore their findings do not provide truly relevant guides for international commitments. However, some exceptions can be found. Herrerias (2012) covers the period 1971-2008 for 83 countries, differentiating between fossil fuel, alternative and nuclear intensities, obtaining evidence supporting a convergence process only within groups of countries: developing countries converging to higher levels of energy intensity and two clusters of developed countries if the analysis includes population weights. In addition, clean energy intensity (from nuclear and renewable sources) exhibits a higher level of convergence among countries. Goldemberg and Prado (2011) assert that, whilst total energy intensity has been reduced, the efficiency of electricity generation from coal (the main source) remained practically constant from 1990 to 2007. Related to energy intensity, some authors explore the country's trajectories of carbon dioxide emissions. Aldy (2006) only finds convergence for the OECD countries, whilst for the entire sample (88 countries), he obtains evidence in favour of the divergence hypothesis. Jakob et al. (2012) examine the evolution of energy use in 51 countries, linking it to economic growth stages, and showing the differences between developing and developed countries.

Nonetheless, the above-mentioned papers do not take into account the recent design of new and more powerful methods of directly testing the null hypothesis of convergence. It seems appropriate to take advantage of these new statistical advances to analyse whether the different kinds of worldwide energy intensities converge or, by contrast, whether several convergence clubs exist, which would imply the presence of various patterns of behaviour among countries. The recent approach developed by Phillips and Sul (2007, 2009) goes beyond previous methodologies, since it allows for the presence of transitional heterogeneity, avoids the handicaps of unit root and cointegration tests, and does not impose any particular assumption about time properties of the variables. These advantages have led some researchers to revisit the analysis of convergence in total energy intensity (Yu et al., 2015) or in carbon dioxide emissions (Camarero et al., 2013), whose outcomes point to the formation of several convergence clubs, instead of pure convergence or divergence processes.

In this context, we aim at determining whether a wide sample of countries converges to the same steady state in two different measures of energy intensity, non-renewable and non-clean energy intensities. As previously mentioned, this differentiation would generate more appropriate policy guidelines, since the focus is on damage-inducing sources of energy, which should be the main concern for international agreements. In order to make comparisons with studies reported in the literature, we also analyse convergence in total energy intensity. We use a sample of 109, 157 and 182 countries (depending on the availability of data for the different types of energy intensity) during the period 1990-2015. This exceeds most previous samples in terms of sample size and, consequently, the results are less prone to suffer from sample bias.

Our findings show that there is clear evidence against the hypothesis of convergence for the three types of energy intensity in terms of global ratios, groups according to geographical regions and income-level classification. The exceptions are Sub-Saharan countries and low-income countries, which converge to their own long-run equilibria for non-renewable energy intensity, and Latin American and Caribbean States for total energy intensity. A subsequent cluster analysis reveals that two (non-renewable energy intensity) or three (non-clean and total energy intensity) clubs are formed. Besides, we go further and analyse the drivers of different countries' behaviours. The reasons behind the formation of clubs are crucial not only for understanding countries' trajectories, but also for proposing reform policies aimed at slowing down climatic change. According to the estimation results of our probit models, countries' trajectories in terms of non-renewable and non-clean energy intensities are affected by other factors than the total energy intensity. Whilst the drivers of the formation of the clubs common to all kinds of energy intensities are restricted to external energy dependence and energy prices, the analysis of the alternative energy-intensity measures adds new factors to these drivers such as research expenditure or the weight of the industry sector in the economy. Therefore, it is worth noting that the analyses of convergence, clustering, and the drivers responsible point to different outcomes depending on the type of energy efficiency taken into account, which could call into question the suitability of guidelines based on total energy intensity.

The paper is organized as follows. Section 2 presents the data and introduces the methodology employed. Section 3 shows the results of the convergence analysis and examines the main determinants of the cluster configuration. Finally, Section 4 draws the most important conclusions and some policy implications.

2. Data and methodology

2.1. Data

To measure efficiency in the use of energy we employ several measures of energy intensity. First, we define Non-Renewable Energy Intensity (NREI hereafter) as the ratio between non-renewable energy consumption and GDP. Non-renewable sources include fossil fuel sources (coal, oil, petroleum, and natural gas) and nuclear energy. We also define Non-Clean Energy Intensity (NCEI hereafter) as the ratio between energy use from fossil sources and GDP. Thus, the main difference between both measures is nuclear energy, which does not produce carbon dioxide but might generate other grave environmental damage. In our view, these are the appropriate indicators of energy efficiency that should be taken into account when formulating international policies, since efficiency of energy produced from clean and renewable sources is irrelevant in terms of the restrictions and goals outlined in the international agreements. In order to draw comparisons with previous works in the literature, total energy intensity (TEI) is also analysed. In all cases, the lower the ratio, the less energy is used to produce one unit of output, so efficiency is higher. Data for the percentages of renewable energy consumption is taken from the World Bank (SE4All, Sustainable Energy for All Database), and the source for the fossil fuel percentage use is the International Energy Agency.[1] From these variables, the total final energy consumption and the total final energy use are employed to obtain the non-renewable consumption and the non-clean

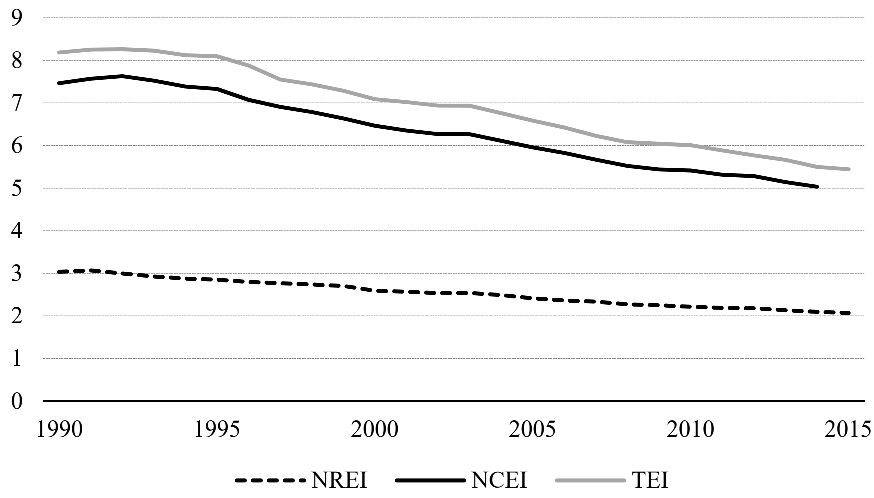
[1] All measures of energy are converted to Megajoules (MJ).

use. Meanwhile, total energy intensity is defined because of primary energy supply. NREI, NCEI and TEI are the ratios with respect to the GDP measured at purchasing power parity.

We have followed a strategy of broadening our sample subject to the availability of the data. The balanced sample for the NREI is composed of 157 countries, that for the NCEI of 109 countries, and that for the TEI of 182 countries. NREI and TEI samples cover the period 1990-2015, whilst the sample for the NCEI ends in 2014.[2] Thus, the period covered is shorter than in previous studies, but the number of countries is higher. This choice prioritizes information from recent decades and maximizes the number of observations. **We should also take into account the results of Mulder and de Groot (2012) or Bulut and Durusu-Ciftci (2018), which provide evidence that that TEI seems to show a break in the trend around 1990s. Then, the use of the post 1990 sample should not alter the results on convergence. In any event, the table A.1. compares the samples previously employed in similar works. We can observe that the obtained results depend more on the econometric technique employed rather than on the sample size considered.**

[2] The list of countries included in each sample is detailed in Appendix A.

Figure 1: NREI, NCEI and TEI. Total sample.

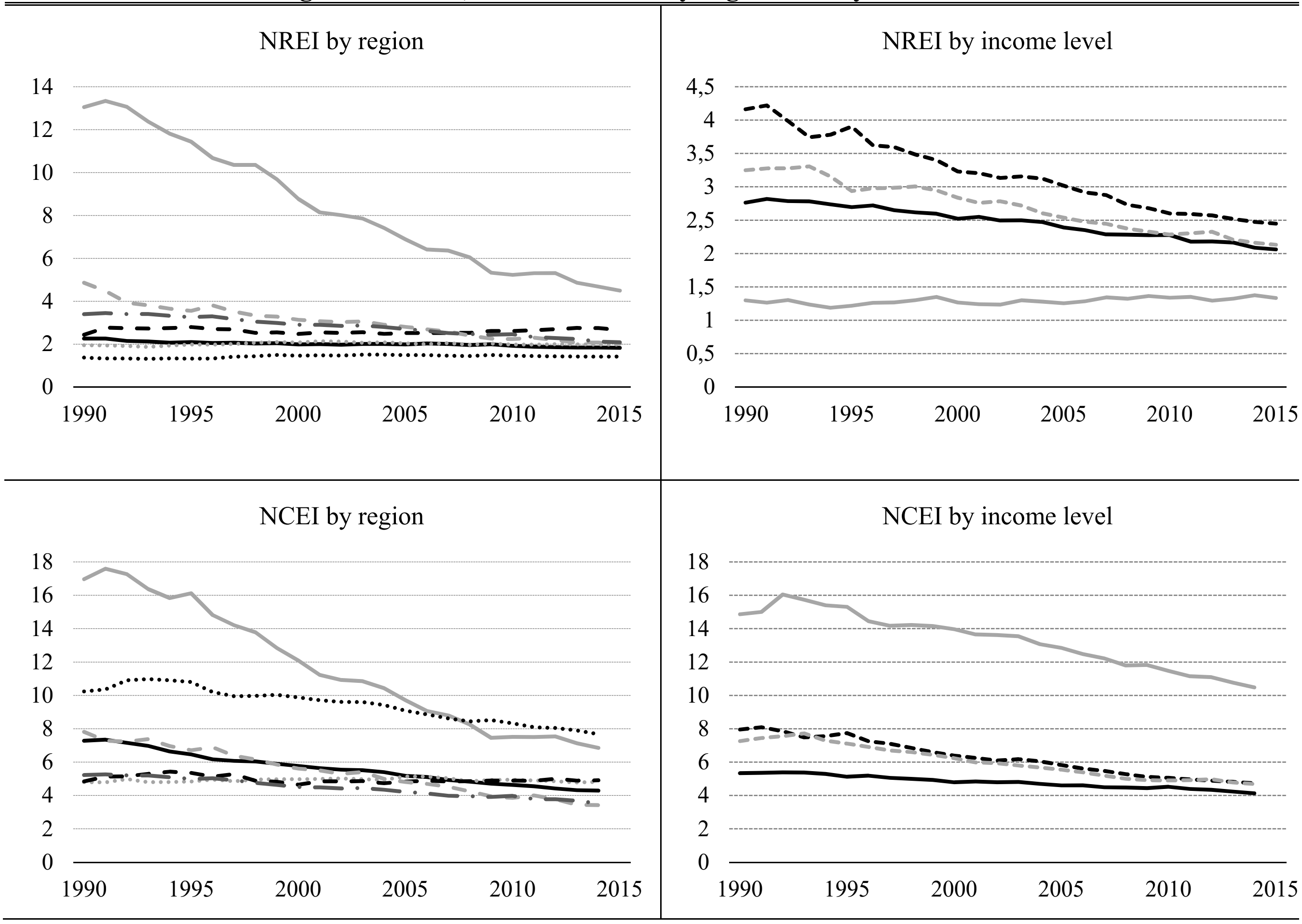


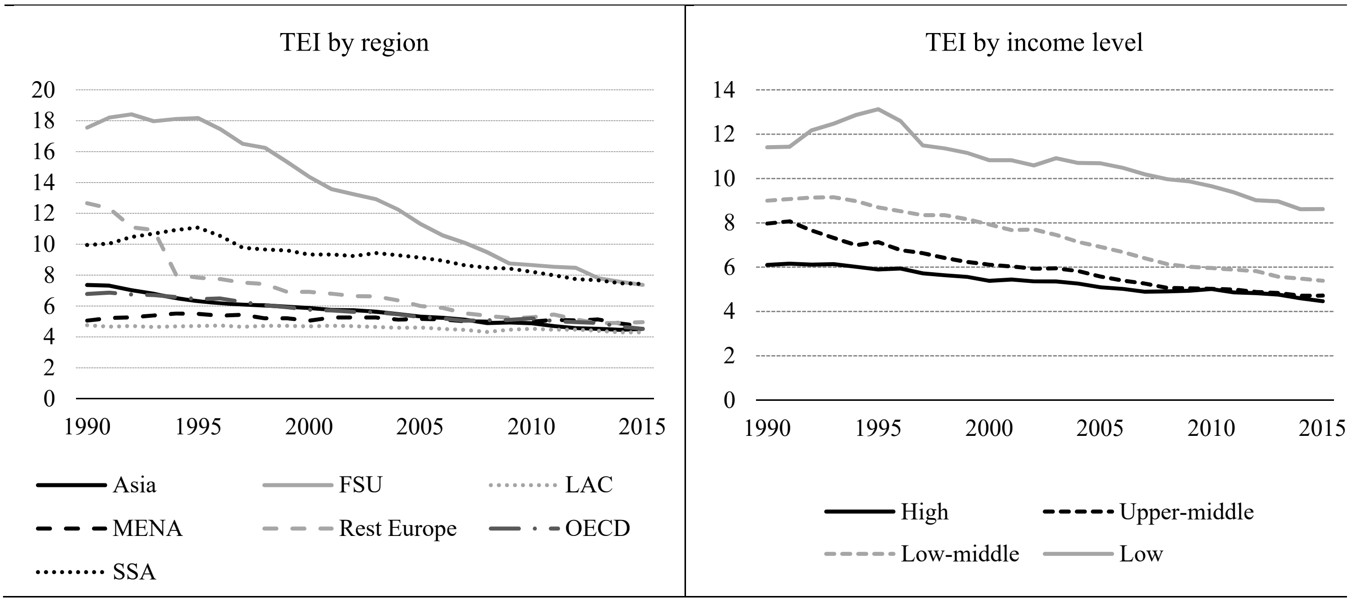
Note: this figure shows the evolution of the averages of Non-Renewable Energy Intensity (NREI), Non-Clean Energy Intensity (NCEI) and Total Energy Intensity (TEI) for the total sample.

Figure 1 shows the global evolution for the three ratios. As can be seen, these series feature a strong inertia, and the trend is always downward and similar across the ratios: since 1990, NREI, NCEI and TEI have decreased by 32%, 33% and 34%, respectively. Non-renewable energy intensity is much lower than non-clean and total energy intensities because, though it includes two kinds of sources (fossil and nuclear energy) in contrast to NCEI (only fossil energy), NREI is constructed in terms of consumption, a more restricted aggregate than use or supply. In any event, the analysis of the evolution of these measures does not depend on the level reached by the ratios, but on their trajectories.

Splitting the sample by region and by income level, substantial disparities are revealed. Following Lidl (2010), regions are divided among Asian and Pacific (Asia), Former Soviet Union (FSU), Latin America and Caribbean (LAC), Middle East and North Africa (MENA), Non-OECD and Non-FSU European (Rest of Europe), OECD, and Sub-Saharan (SSA) countries. Besides, following the World Bank classification, countries are categorized into high, upper-middle, lower-middle and low-income levels. Figure 2 displays the evolution of the NREI, NCEI and TEI by region (left column) and by income level (right column). It can be seen that the reduction of the three kinds of energy intensity has not been homogenous across countries.

Figure 2: NREI, NCEI and TEI by region and by income level.





Note: this table shows the evolution of the averages of Non-Renewable Energy Intensity (NREI), Non-Clean Energy Intensity (NCEI) and Total Energy Intensity (TEI) according to the geographical region and the World Bank's income-level classification.

Focusing on the regional division, it is shown that FSU countries had the highest values for the three measures across almost the entire sample. However, this region has reduced the intensities by 60% since 1990, so the catching-up process is a reality for the NCEI and the TEI by 2015, in line with the findings of Markandya et al. (2006). However, the level of NREI still exceeds the value of the rest of the regions in the last year. The decreasing pattern of the Rest of Europe countries approaches that of the FSU countries (58.2%, 56.3% and 60.9% for the NREI, the NCEI and the TEI, respectively). The SSA countries show distinct trajectories among the ratios: whilst these countries have the lowest values of NREI for all the period, the average values for NCEI and the TEI are higher, even surpassing the rest of the regions at the end of the sample. In fact, NREI increases by 4.1% during the sample period. These differences probably derive from the lack of nuclear energy in SSA countries. We can also highlight the evolution of Asia, which has reduced its values of NREI, NCEI and TEI by 19.2%, 41.0% and 38.7%, respectively, since 1990. In addition, the MENA and LAC countries began the period with low values, but have increased NREI and NCEI during the sample period. OECD countries had moderate values in 1990, and have reduced the three ratios by approximately 30%.

The income level division provides different insights. Again, NCEI and TEI show analogous patterns. Low-income countries have the highest levels, upper-middle and lower-middle countries are located in intermediate positions, and high-income countries are the most efficient according to these ratios. All the groups decrease their ratios, from 24.4% for the high-income countries for TEI to 40.8% for the upper-middle countries for the same measure. Nonetheless, the groups' behaviour with respect to NREI differs from the other types of energy intensity. In this case, though the average increases by 2.6% during the sample period, low-income countries are the most efficient. In spite of the rest of the groups having significantly reduced their NREI (25.3%, 41.2% and 34.4% for the high-income, upper-middle income and lower-middle income countries, respectively), the gap had not been closed in 2015.

In sum, it is clear that total energy intensity, a measure that has been extensively analysed in previous studies, has not experienced the same evolution as other ratios such as non-renewable energy intensity. This could lead to inappropriate policy guidelines, since political targets have to be designed according to adequate objectives. After presenting the methodology approach in the next section, we will discuss the implications of differentiating among sources of energy when carrying out the convergence analysis.

2.2. Methodology

There are three main approaches to examining the hypothesis of convergence, apart from descriptive evaluations (for example, Nilsson, 1993). First, the classic analysis of β or/and σ-convergence introduced by Baumol (1986) and Barro and Sala-i-Martin (1990, 1992). Variations of this approach are followed by Miketa and Mulder (2005), Markandya et al. (2006) and Mulder and De Groot (2012), and include the stochastic convergence procedure of Le Pen and Sévi (2010) and Le Pen (2011). Second, the non-parametric technique proposed by Quah (1993), which is employed in Ezcurra (2007), Herrerías (2012) and Liddle (2010). Third, a relatively novel approach developed by Phillips and Sul (2007, 2009). This framework allows us not only to test the convergence hypothesis but, if the hypothesis is rejected, to define convergence clubs that share a common steady state.

Phillips and Sul's methodology (PS hereafter), also followed by Yu et al. (2015) and Herrerias et al. (2017), is framed within the σ-convergence background, since it relies on an analysis of the cross-sectional dispersion of the variable over time. Specifically, it supposes a nonlinear time-varying factor model, so does not impose any particular assumption about the data. This advantage is reinforced by the consideration of transitional heterogeneity. This overcomes some drawbacks of the standard methods, because the presence of transitional heterogeneity invalidates the traditional unit root and cointegration approach. In addition, other critical points of the analysis of the partial correlation of the variable of interest (β-convergence) highlighted in De Long (1988) and Quah (1993) are solved.

We now briefly outline the Phillips and Sul (2007) framework. We define X_{it} as the variable under analysis (NREI, NCEI or TEI), i and t being the indicators of country and time, respectively. We can decompose X_{it} into the common component across countries (μ_t) and the idiosyncratic component (δ_{it}) as follows: $X_{it} = \delta_{it}\mu_t$. This methodology proposes an analysis of the time evolution of the idiosyncratic component; if δ_{it} converges towards δ, there is evidence in favor of the hypothesis of convergence. In order to remove the common factor, the relative transition component (h_{it}) and its cross-sectional variation (H_{it}) are defined:

$$h_{it} = \frac{X_{it}}{N^{-1}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N} \delta_{it}} \qquad (1)$$

$$H_{it} = N^{-1}\sum_{i=1}^{N}(h_{it} - 1)^2 \overset{as}{\rightarrow} 0, as\ T \overset{as}{\rightarrow} \infty \qquad (2)$$

In the presence of convergence, h_{it} would tend to 1 and H_{it} to 0 when time moves towards infinite. Formally, the hypothesis of convergence is tested by defining the log-t regression:

$$log\frac{H_1}{H_t} - 2log[\log(t)] = \alpha + \beta\log(t) + u_t, t = [rT] + 1, \dots, T \qquad (3)$$

where r takes value 0.3 according to the suggestion of Phillips and Sul (2007) for this type of dataset. The null hypothesis of convergence ($\beta = 0$) is rejected if the t-statistic takes values lower than -1.65.

As mentioned above, if the hypothesis of convergence is rejected, the PS methodology develops a clustering algorithm that groups countries that converge into the same steady state.[3] In order to extract the long-run trend and remove the short-run

[3] We follow the proposal of Schnurbus et al. (2017), who slightly amend the PS algorithm, according to Du (2018).

erratic behavior, following the recommendation of Phillips and Sul (2007) we have detrended X_{it} by the use of the Hodrick and Prescott (1997) filter.[4]

3. Results

3.1. Convergence results

The values of the PS statistics for the different measures of energy efficiency are presented in Table 1. When the total sample is considered, we can clearly reject the null hypothesis of convergence for the three ratios, which comes as no surprise taking into account the heterogeneity of the total sample and the fact that it is in line with the findings of Yu et al. (2015).[5] Nonetheless, the evidence against the convergence hypothesis is much more emphatic when NREI and NCEI are analyzed, which could conciliate our results with previous findings focused on TEI.

Now, it seems appropriate to analyze the potential convergence processes using more homogeneous groups. Therefore, following Liddle (2010), we consider the geographical regions specified in the above section. The evidence against the null hypothesis is still overwhelming. In terms of degree of divergence, we find that this depends on the examined ratio: NREI shows that Asia, LAC, OECD, and lower-middle income countries diverge more among themselves, NCEI points to LAC, FSU, and low-

---

[4] The smoothing parameter of the Hodrick-Prescott method can condition the results of the filtering, as noted in Ravn and Uhlig (2002). Following Phillips and Sul (2009), we have defined $\lambda = 400$. Results do not change if we change λ to 100, a standard value for annual data.

[5] Following Lidl (2010), we have replicated the estimations by removing Iraq from the sample, since the behaviour of this country follows a very special path during 1991-1998 caused by the First Gulf War. t-stat reaches the values -44.92 for NREI, -43.23 for NCEI and -24.21 for TEI. Values for the subgroups are also very similar to those obtained for the total sample. Thus, the main results do not change and baseline estimations will include this country. In addition, we have conducted the analysis for a common sample of countries and time: 109 countries during 1990-2014, and the main findings are also maintained.

income countries, and TEI to SSA and low-income countries. Then, it is rejected for the three measures and for most of the considered groups of countries, thus contradicting the results of Liddle (2010). However, there are two exceptions: the NREI for Sub-Saharan and low-income countries and the TEI for Latin American and Caribbean countries converge to the same long-run equilibrium, exhibiting a unique pattern of behavior.

In this regard, we should note that the dimension of the cross-sectional sample conditions some of these results. For instance, we have 44 countries in the SSA group when TEI is considered. The sample is quite similar for NREI (41 countries), but it is clearly reduced when we analyze NCEI (just 19 countries). Furthermore, one of the missing countries is Liberia, which exhibits the highest TEI at the end of the sample, with this fact being important given that its omission remarkably reduces the cross-sectional dispersion (16%) of the TEI. Then, if we assume that the NREI behavior of this country is similar to the TEI one, the lack of NREI data for this country is probably affecting the convergence results, helping us to explain the contradiction found between the results of the NREI and the TEI. Something similar occurs with the analysis of the low-income countries. The sample of the TEI includes 30 low-income countries, the cross-sectional dimension of NREI is similar (26 countries), whereas the sample size is again reduced for NCEI, given that we have information for only 10 countries. The lack of data for Liberia is again quite relevant to understand the different results obtained for NREI and TEI. Finally, the case of the LAC countries is clearly influenced by the cross-section sample too. One should take into account that the sample of the NCEI group only includes 18 countries, whilst those of TEI and NREI are clearly

larger (34 and 30 countries, respectively). Therefore, the different size of the cross-sectional samples is very important to interpret the results of the NCEI.

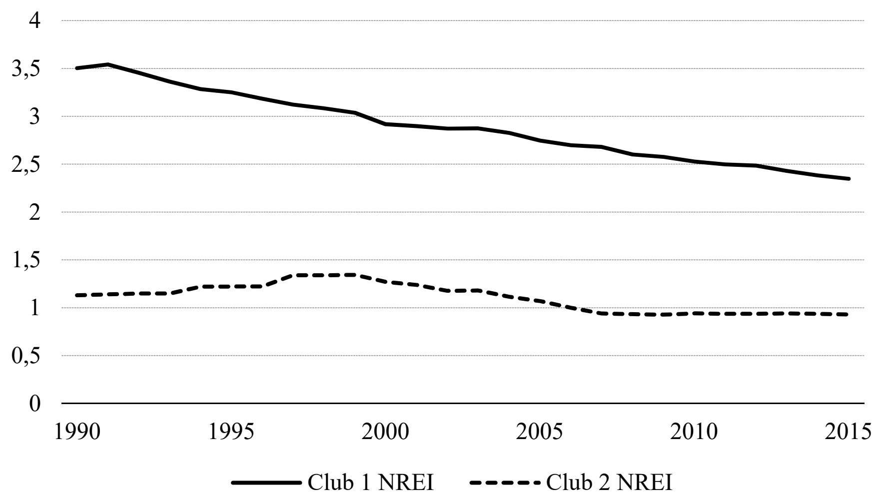
Table 1. Testing for convergence.

	NREI		NCEI		TEI	
	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat
Total sample	-0.619	-44.26	-0.923	-44.50	-0.465	-24.75
By region						
Asia	-1.153	-26.03	-1.196	-17.911	-0.999	-30.81
FSU	-1.409	-18.24	-1.871	-50.90	-1.456	-40.45
LAC	-0.931	-25.48	-1.313	-88.79	0.477	44.92
MENA	-0.977	-11.55	-1.061	-30.00	-0.782	-20.47
Rest Europe	-0.515	-8.10	-1.189	-41.62	-1.182	-19.70
OECD	-1.220	-23.05	-0.968	-41.82	-1.295	-26.79
SSA	*0.655*	*19.95*	-0.562	-44.62	-0.866	-58.57
By income						
High	-1.233	-29.33	-1.272	-40.70	-0.197	-5.83
Upper-middle	-0.400	-24.56	-0.686	-32.73	-0.486	-37.77
Lower-middle	-0.534	-72.62	-0.736	-15.78	-0.410	-42.52
Low	*3.070*	*10.11*	-0.697	-66.95	-0.769	-62.51

This table shows the statistics proposed by Phillips and Sul (2007): the estimated coefficient of the log-t ($\hat{\beta}$) specified in Equation (3) and the t-stat, the convergence test statistic, which is asymptotically distributed as a simple one-sided t-test with a critical value of -1.65. See Phillips and Sul (2007) for further details.

The disparities reflected in Table 1 reinforce our main premise: convergence analysis results change depending on the indicator of energy efficiency used, and the choice of this indicator could be decisive for policy recommendations. Besides, if we compare our outcome with the findings obtained in previous studies reported in the literature, the overall conclusion is that the use of the PS methodology allows us to mostly reject the null hypothesis of convergence, in contrast to the conclusions of previous papers. In fact, our results differ from the outcome of Le Pen and Sévi (2010), who find more evidence of divergence for the Middle East, OECD and Europe sub-groups, and also from the findings in favor of the convergence hypothesis of Markandya et al. (2006) for the EU15 countries, and those of Mulder and De Groot (2012) and Sun (2002) for the OECD countries.

Figure 3. Clubs' average. NREI.

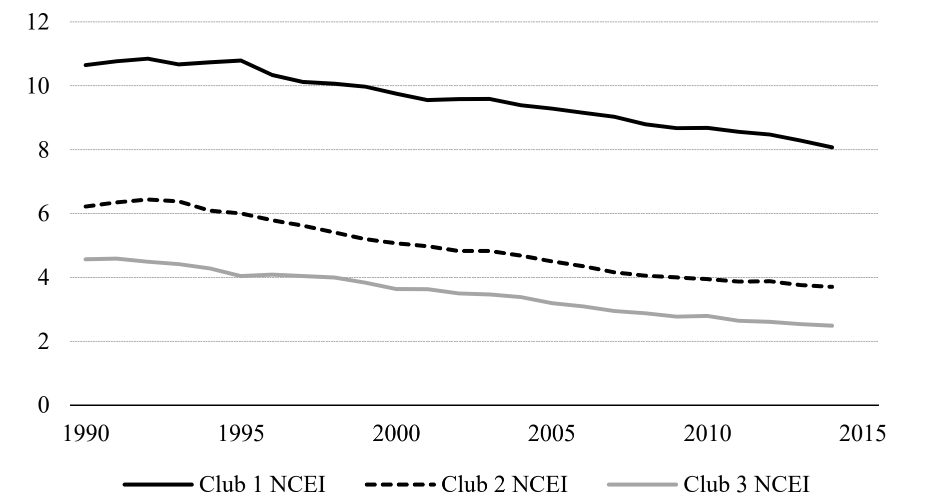


This figure shows the averages for the NREI for Club 1 and Club 2.

In order to identify some convergence clubs, we can apply the clustering algorithm designed by PS. The list of countries included in each club is detailed in table A2 of the Appendix. Clubs are ordered from higher to lower energy intensity (lower to higher efficiency). For NREI, countries are clustered in two convergence clubs: Club 1 consists of 126 countries and Club 2, the most efficient in terms of non-renewable sources, of 31 countries. Figure 3 shows the evolution of the average value of NREI during 1990-2015. The average of Club 1 exceeds the average of Club 2 by 2.4 points at the beginning of the sample period, though this gap is reduced to 1.4 points in 2015, since Club 1 has a greater decreasing pattern (33%) than Club 2 (17.7%). Although we will determine the drivers of the formation of the clubs in the next section, we can state here that Club 2 includes less economically developed countries than Club 1, as suggested by the descriptive analysis discussed in Section 2: low-income countries show the lowest values for NREI throughout the entire sample. It is also worth noting that Club 2 slows down its decreasing tendency from 2008, the outbreak of the Great Recession, whilst Club 1 continues its trajectory.

Three clubs are created for NCEI. Club 1 is composed of 39 countries, Club 2 of 51 countries and Club 3, the smallest and most efficient, of 16 countries. This method reveals that three countries do not converge to the same long-run equilibrium as other countries: Switzerland, Hong Kong and Sri Lanka. The clubs are more heterogeneous than in the previous case, since they group countries from different regions and different income levels. All clubs reduce their average value of NCEI, but the most striking fact is that the lower the NCEI was in 1990, the more the clubs decrease their values (Club 1 decreases by 24.2%, Club 2 by 40.4% and Club 3 by 45.6%). Hence, the gaps are maintained throughout the sample period. As with the NREI groupings, the clubs diminish their decreasing tendency from 2008 onwards.

Figure 4. Clubs' average. NCEI.

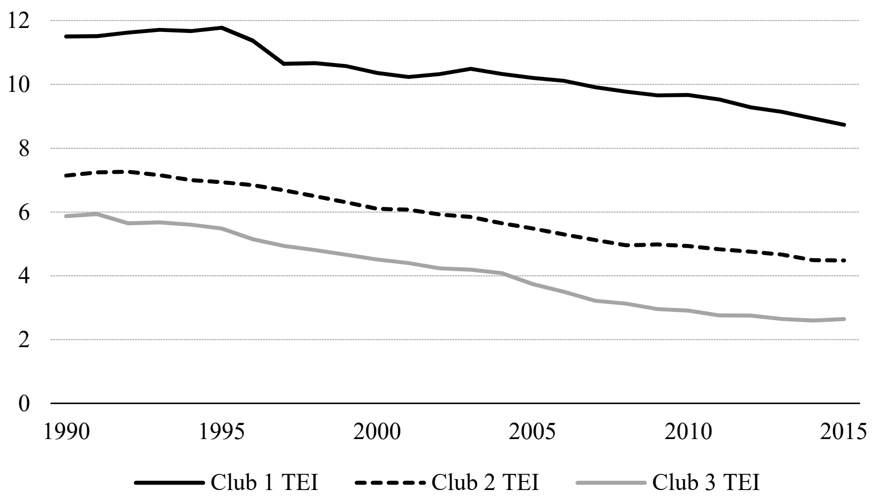


This figure shows the averages for the NCEI for Club 1, Club 2 and Club 3.

The clustering algorithm classifies countries in three clubs according to their TEI. Club 1 has 53 countries, the most numerous group is Club 2 with 103 countries, and 24 countries are included in Club 3. Two countries diverge from the rest: Hong Kong and Macao. The average values of the total energy intensity of each club are presented in

Figure 5. As we can appreciate, these values clearly decline across the sample (24.0%, 37.3% and 55.0% for Clubs 1, 2, and 3, respectively). The distance between the average values of the clubs is similar in 1990 and 2015, given that the average growth rate of Club 1 is -1.1%, whilst it is -1.8% and -3.1% for Clubs 2 and 3, respectively. Club 1 has the highest initial value, whilst Club 3 shows the lowest. The post-Great Recession period has moderated the downturn of Clubs 2 and 3, while Club 1 has accelerated its decline.

Figure 5. Clubs' average. TEI.



This figure shows the averages for the TEI for Club 1, Club 2 and Club 3.

In sum, we acquire different results depending on the measure considered for energy efficiency. On the one hand, NCEI and NREI, measures that do not include fossil or fossil and nuclear energy, respectively, show a higher degree of divergence than TEI, which could be the cause for the discrepancies with previous results reported in the literature. This finding is in line with the results of Herrerias (2012), who find that alternative and nuclear energy intensity show more symptoms of convergence. On the other hand, the outcome of the clustering analyses of the NCEI and the TEI are very similar, since three clubs are formed and 84% of the countries are included in the same cluster. In addition, the trajectories of the averages resemble each other, since the Pearson correlation coefficient of the average growth rates is 0.83. However, the findings for NREI are very different from those for TEI and, therefore, from previous results in the literature. Only two clubs are created for NREI, the percentage of countries matched to the same cluster for both measures is only 25%, and the correlation coefficient is 0.45. Thus, conclusions obtained from the examination of non-renewable sources of energy are not analogous to those obtained from the traditional analysis of the total energy intensity. The following section is devoted to ascertaining the reasons for these differences.

3.2. Factors driving the clubs

A key issue of the clustering analysis is determining the factors driving the formation of the clubs. If we can identify these factors, national and international policies aimed at improving energy efficiency could reduce energy intensity both in the short and in the long run. This is particularly relevant in developing countries, which face the possibility of shifting towards a more efficient club.

Many factors could affect energy intensity and explain the differences among regions or countries. Following the literature mentioned in the introductory section, we analyse the following variables:[6]

- Economic factors: we consider the GDP per capita (*GDPpc*) measured at PPP (thousands, constant 2011 $US) to represent the economic development, and the percentage of the value added over the GDP for the industrial sector (*Industry*),

[6] In order to assure the homogeneity of the data, the source of all variables is the World Bank.

which would capture the participation of capital in the economic structure and the so-called composition effect. Per capita income and industry weight are studied in Metcalf (2008), and Miketa and Mulder (2005), among others.

- Openness factors: we include two kinds of openness dimensions, commercial trade and financial interdependency. The former is assessed as the *Imports* or *Exports* of goods and services, and will test the existence of mechanisms of transmissions via scale, composition, and technical effects (Antweiler et al., 2001). The foreign-direct-investment dimension is included through the net *FDI inflows* and *FDI outflows*, studied in depth in Hübler and Keller (2010). All these variables are expressed as a percentage of GDP, and they have been found to be relevant in related papers (Yu et al., 2015).
- Technology factors: though a specific variable that measures a country's resources devoted to developing technologies that improve energy efficiency would be more appropriate, this data is not available. For this reason, we incorporate a proxy, the research and development expenditure over GDP (*R&D*).
- Energy trade: we include *Fuel imports* and *Fuel exports* as a percentage of merchandise imports and exports, respectively. The former captures the external energetic dependence and the latter represents fuel-producing countries.
- Energy prices: specifically, we incorporate fossil-fuel prices through *Diesel* and *Gasoline* prices (US$ per liter) in order to test a potential price effect.
- Population factors: the percentage of urban population (*Urban*) and the percentage of population with access to electricity (*Electricity*) are included to examine whether the degree of urbanization and the development of the electricity sector are determinants of the energy efficiency.

- Climate: extremely hot or cold areas are supposed to be more intense in terms of energy use, so we include the average number of heating and cooling degree days (*HDD* and *CDD*).[7]

It should be noted that the restrictions on availability of the data has led us to take into account the averages for the last 10 years of the sample. In this way, we maximize the number of observations. Firstly, we develop a descriptive analysis of the differences of these factors among groups, which consists of a comparison of means. This technique is useful to obtain a comprehensive overview, and for the identification of the variables that, in average terms, are statistically different across clubs. Table 2 presents the results. Values in bold mean that the club's average is not statistically equal to the average of the largest club (Club 1 for NREI, and Club 2 for NCEI and TEI). As we can see, per capita income barely differs for the different clubs, but the rest of the factors discriminate to a greater or lesser extent among clusters.

Table 2. Factors driving the clubs. Comparison of Means.

	NREI		NCEI			TEI		
Variable	Club 1	Club 2	Club 1	Club 2	Club 3	Club 1	Club 2	Club 3
GDPpc	17,178	18,231	17,080	20,898	25,365	14,403	17,761	**23,563**
Industry	28.4%	**24.2%**	**36.1%**	27.2%	25.3%	**31.3%**	26.6%	27.0%
FDI inflows	5.8%	**9.0%**	4.4%	5.9%	**13.8%**	4.9%	5.8%	**12.2%**
FDI outflows	2.3%	**3.6%**	**1.1%**	4.1%	4.5%	1.3%	2.4%	**4.0%**
Imports	47.3%	49.4%	42.9%	41.1%	**59.7%**	48.5%	46.4%	**53.2%**
Exports	41.2%	**46.7%**	42.4%	38.1%	**57.4%**	39.7%	40.6%	**54.2%**
R&D	0.9%	0.7%	**0.6%**	1.0%	1.0%	**0.5%**	0.9%	0.8%
Fuel imports	17.3%	**14.7%**	17.2%	17.2%	**14.5%**	16.4%	16.9%	**14.1%**
Fuel exports	18.5%	15.0%	**36.7%**	17.6%	13.0%	**24.9%**	17.0%	13.1%
Diesel	1.01	**1.21**	**0.80**	1.11	**1.30**	**0.90**	1.10	1.19
Gasoline	1.13	**1.34**	**0.89**	1.25	**1.45**	**1.00**	1.22	**1.34**
Urban	57.9%	**49.4%**	**57.4%**	67.2%	69.2%	**49.3%**	59.6%	60.4%
Electricity	82.5%	**62.7%**	**76.4%**	91.2%	**97.0%**	**65.6%**	84.6%	85.8%
HDD	1,729	**1,005**	**1,540**	2,044	2,241	**1,025**	2,104	**1,405**
CDD	1,460	1,358	**1,636**	1,129	**821**	**1,833**	1,199	**1,524**

[7] We have considered *HDD* and *CDD* based on temperature, a heat index and humidex, converted to a 1 day frequency. Database is provided by Atalla et al. (2018).

This table presents the average values (period 2006-2015) of the variables employed to analyze the drivers of the formation of the clubs. Bold values mean that the club's average is not included in the 95% confidence interval of the largest club (Club 1 for NREI, and Club 2 for NCEI and TEI).

In order to confirm the intuition behind the comparison of means, we adopt a more suitable methodology. We estimate a probit model for each ratio, binary for NREI and ordered for NCEI and TEI, since the dependent variables in the latter cases are ordinal and ranked according to the different steady sates. Apart from the factors previously described, we have also incorporated dummy variables to capture geographical effects. For the purpose of assessing the best specification, we have followed a strategy that goes from the general to the specific, eliminating sequentially from the model the initial variables that are far from statistical significance. In addition, we have searched for any collinearity problem, finding no evidence of multicollinearity through an analysis of the variance inflation factors. The results obtained for each measure of energy intensity are presented in Table 3.

In the case of NREI, the variables included in the final model that exert a negative effect on energy intensity are the GDP per capita, the weight of the R&D expenditure, the price of diesel, and some geographic dummy variables (D_{Asia}, D_{LAC} and D_{SSA}). The higher the value of these variables, the higher the probability of belonging to Club 2 and, therefore, of being less energy-intensive. Then, the economic development and technological progress may enhance energy efficiency, which seems logical and agrees with previous findings (Garrone and Grilli, 2010). Besides, there is evidence in favour of a "price effect", since rising prices encourage efficiency gains. By contrast, the share of the industry sector, strongly associated with energy-intensive processes, and the degree of urbanization for similar reasons, increase the probability of belonging to Club

1 and, consequently, of being less efficient.[8] Thus, a composition effect is supported (Antweiler et al., 2001).

One surprising result is the negative effect of the external energetic dependence (*Fuel imports*) and the positive effect of the producing countries (*Fuel exports*) on the energy efficiency. This counterintuitive finding points to the idea that energy dependent countries do not make efforts to improve their efficiency, whilst producing countries, which generally are not capital intensive, are oriented to selling their energetic resources and to more efficient activities. We should note that the explanatory power of the model is not negligible, especially if we take into account that the number of countries in Club 1 is clearly lower than the number of countries in Club 2, and that the percentage of correctly classified cases is very high.

The number of clusters formed for NCEI is three, so the estimated model is an ordered probit model. In this framework, a higher number of clubs generates a reduced capacity of explanation of the model, though the percentage of countries correctly classified is good enough. The explanatory variables included in the final specification are quite different from the previous case. Though the share of the industry sector and the fuel imports continue to generate a negative effect on the energy efficiency, and the energy price (*Gasoline*) is a positive one, we find a new explanatory variable, the percentage of population with access to electricity. This factor captures the maturity of the electricity sector and, consequently, the impact on the efficiency is positive.

Table 3. Factors driving the clubs. Estimation results of probit models.

	NREI	NCEI	TEI
GDPpc	0.08***		

[8] See Jobert et al. (2010) for an in-depth analysis of the relationship between the share of industry in GDP and the carbon dioxide emissions.

	(2.95)		
Industry	-0.07**	-0.02*	
	(-2.14)	(-1.67)	
R&D	0.99*		-0.08
	(1.83)		(-0.49)
Fuel imports	-0.11***	-0.03**	-0.03*
	(-3.06)	(-2.01)	(-1.76)
Fuel exports	0.04**		
	(2.51)		
Diesel	7.20***		
	(3.65)		
Gasoline		1.49***	1.45***
		(3.91)	(4.23)
Urban	-0.09***		
	(-3.02)		
Electricity		0.03***	
		(3.53)	
CDD			0.00*
			(1.74)
D_{Asia}	9.47***		
	(4.33)		
D_{LAC}	9.79***		
	(3.42)		
D_{SSA}	6.84***		-1.25***
	(3.70)		(-3.26)
D_{OECD}		-0.87**	
		(-2.48)	
D_{FSU}		-1.20***	
		(-2.57)	
D_{MENA}	7.71***		
	(3.60)		
N	103	102	106
Pseudo R^2	0.58	0.23	0.15
Correctly classified cases	91%	61%	63%

This table shows the coefficient estimates of the probit models by using White-Huber standard errors. *t*-ratios in parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Finally, an ordered probit model has been estimated for TEI. The variables finally incorporated in the empirical model that stimulate efficiency gains are energy price and cooling degree days. This means that countries that have to dedicate energetic resources to warm living spaces have been successful in obtaining efficiency improvements. The value of the estimated coefficient for *Fuel imports* is inversely related to the probability of being in Club 1 so, once more, the external dependency on fossil fuels does not provide efficiency gains. Other potential drivers, such as the share of the industry sector and the expenditure on R&D activities, are not statistically significant. Though the power of explanation of this model is not high either, the capacity of correctly classifying the countries into the three clubs is acceptable.

Summing up, the drivers are similar but not the same for the three measures of energy intensity. Whilst no empirical evidence has been found to support the importance of the degree of trade openness, economic structure and research expenditure only apply a significant effect for the measures that do not take into account renewable or/and nuclear sources. Meanwhile, energy prices exert a robust positive impact on energy efficiency, and the external dependency on fossil fuels is counter-productive for efficiency gains. In the light of these results, policies aimed at harmonising the long-run trajectories of countries in terms of energy efficiency should consider the following caveats: energetic taxation could be a useful tool to fight against energy waste, and technological development represents the right path for efficiency gains if the traditional total energy intensity approach is replaced by more accurate measures such as non-renewable energy intensity.

4. Conclusions

Traditional analyses of convergence in energy efficiency have taken into consideration the total energy intensity. However, efficiency in terms of renewable sources or clean energy (nuclear sources) is not relevant for developing policies included in international environmental agreements, since these kinds of sources do not produce carbon dioxide emissions and, therefore, do not contribute to worsening climate change.

Against this backdrop, this paper aims at examining the worldwide convergence process of several measures of energy intensity. Previous literature has found evidence in favour of the convergence hypothesis for the total energy intensity, and we test the hypothesis by distinguishing among non-renewable, non-clean and total energy intensities, which produce more accurate conclusions. The sample covers a large set of countries (109, 157 and 182, depending on the measure) during the 1990-2015 period. The methodology incorporates recent techniques proposed by Phillips and Sul (2007), which improve on previous approaches in several ways. The results lead to the rejection of the convergence hypothesis for the three measures, but the evidence is stronger in the case of non-renewable and the non-clean energy intensities, a finding that could conciliate our findings with previous outcomes. In a second step, we develop a clustering analysis and, again, the results are different depending on the different measures of energy efficiency analysed. When non-renewable energy intensity is examined, two clubs are formed, while the number of clubs is three when non-clean and total energy intensities are studied. The drivers behind the formation of the clubs are mainly related to energy prices and energy dependence.

Some policy recommendations arise. First, normative guidelines should be oriented towards non-renewable or non-clean energy intensity, rather than total energy intensity. Second, in the light of our results, international agreements should not be the same across all countries, since there are several differentiated clusters. Third, the efforts of countries to improve both short- and long-run efficiency should be focused on energy (price) taxes and on the search for alternative sources to fossil fuels in non-producing countries. Besides, other factors such as technological progress and deindustrialisation processes could assure efficiency gains according to these new measures of energy intensity.

References

Aldy, J. E. (2006). Per capita carbon dioxide emissions: convergence or divergence?. *Environmental and Resource Economics*, 33, 533-555.

Atalla, T., Gualdi, S., and Lanza, A. (2018). A global degree days database for energy-related applications. *Energy*, 143, 1048-1055.

Barro, R. J., and Sala-i-Martin, X. (1990). Economic growth and convergence across the United States (No. w3419). National Bureau of Economic Research.

Barro, R. J., and Sala-i-Martin, X. (1992). Convergence. *Journal of Political Economy*, 100, 223-51.

Baumol, W. J. (1986). Productivity growth, convergence, and welfare: what the long-run data show. *American Economic Review*, 1072-1085.

Bulut, U., and Durusu-Ciftci, D. (2018). Revisiting energy intensity convergence: new evidence from OECD countries. *Environmental Science and Pollution Research*, 25, 12391-12397.

Camarero, M., Picazo-Tadeo, A. J., and Tamarit, C. (2013). Are the determinants of CO2 emissions converging among OECD countries?. *Economics Letters*, 118, 159-162.

De Long, J. B. (1988). Productivity growth, convergence, and welfare: comment. *American Economic Review*, 78, 1138-1154.

Du, K. (2018). Econometric convergence test and club clustering using Stata. *Stata Journal*, 17, 882-900.

Ezcurra, R. (2007). Distribution dynamics of energy intensities: a cross-country analysis. *Energy Policy*, 35, 5254-5259.

Filipović, S., Verbič, M., and Radovanović, M. (2015). Determinants of energy intensity in the European Union: A panel data analysis. *Energy*, 92, 547-555.

Garrone, P., and Grilli, L. (2010). Is there a relationship between public expenditures in energy R&D and carbon emissions per GDP? An empirical investigation. *Energy Policy*, 38, 5600-5613.

Goldemberg, J., and Prado, L. T. S. (2011). The decline of the world's energy intensity. *Energy Policy*, 39, 1802-1805.

Herrerias, M. J. (2012). World energy intensity convergence revisited: A weighted distribution dynamics approach. *Energy Policy*, 49, 383-399.

Herrerias, M. J., Aller, C., and Ordóñez, J. (2017). Residential energy consumption: A convergence analysis across Chinese regions. *Energy Economics*, 62, 371-381.

Hodrick, R. J., and Prescott, E. C. (1997). Postwar US business cycles: an empirical investigation. *Journal of Money, Credit, and Banking*, 1-16.

Hübler, M., and Keller, A. (2010). Energy savings via FDI? Empirical evidence from developing countries. *Environment and Development economics*, 15, 59-80.

Jakob, M., Haller, M., and Marschinski, R. (2012). Will history repeat itself? Economic convergence and convergence in energy use patterns. *Energy Economics*, 34, 95-104.

Jobert, T., Karanfil, F., and Tykhonenko, A. (2010). Convergence of per capita carbon dioxide emissions in the EU: legend or reality?. *Energy Economics*, 32, 1364-1373.

Le Pen, Y. (2011). A pair-wise approach to output convergence between European regions. *Economic Modelling*, 28, 955-964.

Le Pen, Y., and Sévi, B. (2010). On the non-convergence of energy intensities: evidence from a pair-wise econometric approach. *Ecological Economics*, 69, 641-650.

Liddle, B. (2010). Revisiting world energy intensity convergence for regional differences. *Applied Energy*, 87, 3218-3225.

Markandya, A., Pedroso-Galinato, S., and Streimikiene, D. (2006). Energy intensity in transition economies: is there convergence towards the EU average? *Energy Economics*, 28, 121-145.

Metcalf, G. E. (2008). An empirical analysis of energy intensity and its determinants at the state level. *Energy Journal*, 29, 1-27.

Mielnik, O., and Goldemberg, J. (2000). Converging to a common pattern of energy use in developing and industrialized countries. *Energy Policy*, 28, 503-508.

Miketa, A., and Mulder, P. (2005). Energy productivity across developed and developing countries in 10 manufacturing sectors: patterns of growth and convergence. *Energy Economics*, 27, 429-453.

Mulder, P., and De Groot, H. L. (2012). Structural change and convergence of energy intensity across OECD countries, 1970–2005. *Energy Economics*, 34, 1910-1921.

Nilsson, L. J. (1993). Energy intensity trends in 31 industrial and developing countries 1950-1988. *Energy*, 18, 309-322.

Phillips, P.C., Sul, D. (2007). Transition modelling and econometric convergence tests. *Econometrica*, 75, 1771-1855.

Phillips, P.C., Sul, D. (2009). Economic transition and growth. *Journal of Applied Econometrics*, 24, 1153-1185.

Quah, D. (1993). Empirical cross-section dynamics in economic growth. *European Economic Review*, 37, 426-434.

Ravn, M. O., and Uhlig, H. (2002). On adjusting the Hodrick-Prescott filter for the frequency of observations. *Review of Economics and Statistics*, 84, 371-376.

Romero-Ávila, D. (2008). Convergence in carbon dioxide emissions among industrialised countries revisited. *Energy Economics*, 30, 2265-2282.

Schnurbus, J., Haupt, H., and Meier, V. (2017). Economic transition and growth: a replication. *Journal of Applied Econometrics*, 32, 1039-1042.

Sun, J. W. (2002). The decrease in the difference of energy intensities between OECD countries from 1971 to 1998. *Energy Policy*, 30, 631-635.

United Nations General Assembly (2015). Transforming our world: The 2030 agenda for sustainable development. Retrieved 23 April 2019 from http://www.un.org/ga/search/view_doc.asp?symbol=A/RES/70/1&Lang=E

Yu, Y., Zhang, Y., and Song, F. (2015). World energy intensity revisited: a cluster analysis. *Applied Economics Letters*, 22(14), 1158-1169.

Appendix

Table A.1. Previous results on the analysis of convergence for total energy intensity

	Countries	Sample	Findings	Methodology
Nilson (1993)	31	1950-1988	Convergence	Descriptive analysis
Ezcurra (2007)	98	1971-2001	Convergence	Non-parametric approach
Mielnik and Goldemberg (2000)	41	1971-1992	Convergence	Chart analysis
Sun (2002)	27 OECD	1971-1998	Convergence	Mean Deviation
Miketa and Mulder (2005)	56 (10 manufacturing sectors)	1971-1995	Club convergence	σ and β-convergence
Markandya et al. (2006)	12 transition countries of Eastern Europe	1992-2002	Convergence to the EU15 level	β-convergence
Liddle (2010)	111	1971-2006	Convergence	σ, β, and γ-convergence
	134	1990-2006	Convergence	
Le Pen and Sévi (2010)	97	1971-2003	Divergence	Stochastic convergence
Mulder and De Groot (2012)	18 OECD (50 sectors)	1970-2005	Convergence since 1995	σ and β-convergence
Herrerias (2012)	83	1971-2008	Convergence/ Club convergence	Weighted distribution dynamics approach
Yu et al. (2015)	109	1971-2010	Divergence	Philips-Sul
Bulut and Durusu-Ciftci (2018)	27 OECD	1980-2014	Mixed	Stochastic Convergence

Table A.2: List of countries, averages of NREI, NCEI and TEI and Clubs

Country	Income level	Region	Average NREI	Club NREI	Average NCEI	Club NCEI	Average TEI	Club TEI
Albania	U-M	Rest Europe	2.00	1	3.60	3	4.44	3
Algeria	U-M	MENA	1.98	1	3.63	1	3.65	2
Angola	L-M	SSA	1.09	1	4.26	2	4.85	2
Antigua and Barbuda	H	LAC	2.19	1	6.37	1	3.65	1
Argentina	H	LAC	2.75	1	4.28	2	4.56	2
Armenia	U-M	FSU	6.03	1	8.02	2	9.69	2
Aruba	H	LAC	1.52	1				
Australia	H	OECD	3.52	1			6.42	2
Austria	H	OECD	2.21	1	3.60	2	4.03	2
Azerbaijan	U-M	FSU	5.95	1	11.09	2	10.90	3
Bahamas, The	H	LAC	1.81	1			3.40	2
Bahrain	H	MENA	2.65	1	11.03	1	10.89	1
Bangladesh	L-M	Asia	1.13	1	3.55	2	3.54	2
Barbados	H	LAC	2.31	1			4.37	2
Belarus	U-M	FSU	7.55	1	13.16	1	13.34	2
Belgium	H	OECD	3.51	1	4.75	2	6.05	2
Belize	U-M	LAC	3.08	1			6.11	2
Benin	L	SSA	2.23	1	8.64	1	8.66	1
Bolivia	L-M	LAC	2.59	1	4.82	1	4.96	1
Botswana	U-M	SSA	1.95	1	3.96	2	3.85	2
Brazil	U-M	LAC	1.56	1	3.39	2	3.91	2
Brunei Darussalam	H	Asia	1.05	1	3.84	1	4.21	1
Bulgaria	U-M	Rest Europe	4.43	1	7.78	2	9.77	2
Burkina Faso	L	SSA	0.93	1			8.20	2
Cabo Verde	L-M	SSA	1.52	1			3.16	2
Canada	H	OECD	4.66	1	7.36	1	9.03	1
Central African Republic	L	SSA	0.94	1			8.19	1
Chile	H	OECD	2.16	1	4.14	2	4.30	2
China	U-M	Asia	5.40	1	11.16	1	11.30	2
Congo. Rep.	L-M	SSA	0.72	1	2.75	1	2.87	1
Costa Rica	U-M	LAC	1.52	1	2.71	2	3.30	2
Cote d'Ivoire	L-M	SSA	1.05	1	6.59	1	6.70	1
Cyprus	H	Rest Europe	2.56	1	4.02	2	3.99	2
Czech Republic	H	OECD	4.12	1	6.81	2	7.71	2
Denmark	H	OECD	2.29	1	3.52	3	3.67	3
Dominica	U-M	LAC	1.84	1			2.68	2
Dominican Republic	U-M	LAC	1.89	1	3.61	3	3.69	3
Ecuador	U-M	LAC	2.29	1	3.33	2	3.53	2
Egypt. Arab Rep.	L-M	MENA	2.24	1	3.73	2	3.77	2
El Salvador	L-M	LAC	1.71	1	4.50	2	4.23	2
Equatorial Guinea	U-M	SSA	1.44	1			4.33	3
Fiji	U-M	Asia	1.93	1			3.95	2
Finland	H	OECD	3.77	1	6.10	2	7.77	2
France	H	OECD	2.52	1	2.78	3	4.94	2
Gabon	U-M	SSA	0.80	1	4.40	1	4.57	1
Gambia. The	L	SSA	1.50	1			4.62	2
Georgia	L-M	FSU	4.62	1	8.45	2	9.35	2
Germany	H	OECD	2.70	1	4.04	2	4.59	2
Ghana	L-M	SSA	1.41	1	5.45	2	5.76	2
Greece	H	OECD	2.39	1	3.92	2	3.93	2
Grenada	U-M	LAC	1.98	1			2.98	2
Guatemala	U-M	LAC	1.22	1	3.95	1	4.07	1
Guinea	L	SSA	1.42	1			11.99	1

Guinea-Bissau	L	SSA	1.32	1			12.79	1
Guyana	U-M	LAC	4.29	1			8.57	2
Haiti	L	LAC	1.27	1	7.37	1	7.51	1
Honduras	L-M	LAC	2.41	1	5.95	1	6.14	1
India	L-M	Asia	2.22	1	6.54	2	6.55	2
Indonesia	L-M	Asia	1.75	1	4.59	2	4.58	2
Iran. Islamic Rep.	U-M	MENA	4.18	1	6.00	1	6.56	1
Iraq	U-M	MENA	3.17	1	5.67	2	5.62	2
Ireland	H	OECD	2.66	1	3.77	3	3.70	3
Israel	H	OECD	2.28	1	4.37	2	4.59	2
Italy	H	OECD	2.24	1	3.31	2	3.45	2
Jamaica	U-M	LAC	3.64	1	6.37	2	6.34	2
Japan	H	OECD	2.52	1	4.03	2	4.87	2
Jordan	U-M	MENA	3.36	1	5.19	2	5.25	2
Kazakhstan	U-M	FSU	7.30	1	11.32	1	10.87	1
Kiribati	L-M	Asia	2.54	1			4.03	1
Korea. Rep.	H	OECD	3.98	1	6.37	1	7.42	1
Kyrgyz Republic	L-M	FSU	6.96	1	9.24	1	11.25	1
Lao PDR	L-M	Asia	1.00	1			4.93	3
Lebanon	U-M	MENA	2.82	1	4.49	2	4.45	2
Lesotho	L-M	SSA	5.83	1			14.11	1
Luxembourg	H	OECD	3.83	1	4.37	2	4.47	2
Malaysia	U-M	Asia	2.72	1	5.27	1	5.29	2
Mali	L	SSA	0.54	1			3.99	3
Mauritania	L-M	SSA	1.78	1			3.83	2
Mexico	U-M	OECD	2.18	1	4.09	2	4.33	2
Mongolia	L-M	Asia	6.12	1	9.49	1	9.36	2
Morocco	L-M	MENA	2.13	1	3.41	2	3.44	2
Mozambique	L	SSA	1.81	1	28.30	1	28.96	1
Netherlands	H	OECD	3.02	1	4.87	2	4.89	2
New Zealand	H	OECD	2.91	1	5.28	2	6.02	2
Nicaragua	L-M	LAC	1.77	1	6.05	2	6.09	2
North Macedonia	U-M	Rest Europe	3.02	1	5.93	2	6.07	2
Oman	H	MENA	2.21	1	4.26	1	4.35	1
Pakistan	L-M	Asia	2.02	1	5.06	2	5.19	2
Panama	H	LAC	1.59	1	2.78	3	3.07	3
Papua New Guinea	L-M	Asia	2.05	1			10.14	1
Peru	U-M	LAC	1.60	1	2.58	3	2.86	3
Poland	H	OECD	4.03	1	7.17	2	7.14	2
Portugal	H	OECD	1.92	1	3.47	2	3.62	2
Romania	U-M	Rest Europe	3.21	1	5.94	2	6.28	2
Russian Federation	U-M	FSU	6.45	1	10.45	1	11.13	2
Samoa	U-M	Asia	2.10	1			4.36	2
Saudi Arabia	H	MENA	2.49	1	4.83	1	5.44	1
Senegal	L	SSA	1.39	1	4.14	1	5.18	1
Seychelles	H	SSA	2.99	1			4.01	3
Sierra Leone	L	SSA	1.08	1			9.89	2
Solomon Islands	L-M	Asia	2.10	1			6.94	2
South Africa	U-M	SSA	4.02	1	10.03	1	10.23	1
Spain	H	OECD	2.23	1	3.31	2	3.88	2
St. Kitts and Nevis	H	LAC	1.43	1			3.19	3
St. Lucia	U-M	LAC	1.66	1			3.05	2
St. Vincent and the Grenadines	U-M	LAC	2.03	1			2.96	2
Sudan	L-M	SSA	0.98	1	5.24	2	6.58	2
Tajikistan	L	FSU	3.77	1	5.29	3	9.73	2
Tanzania	L	SSA	0.73	1	10.40	1	10.42	1

Thailand	U-M	Asia	2.42	1	5.14	1	5.19	1
Togo	L	SSA	2.10	1	13.98	1	13.90	1
Tonga	U-M	Asia	2.63	1			3.29	2
Trinidad and Tobago	H	LAC	3.65	1	18.28	1	18.59	1
Tunisia	L-M	MENA	2.54	1	4.06	2	4.05	2
Turkey	U-M	OECD	1.95	1	3.26	2	3.65	2
Turkmenistan	U-M	FSU	14.87	1	22.95	1	22.60	1
Tuvalu	U-M	Asia	2.18	1			3.58	2
Ukraine	L-M	FSU	10.36	1	16.53	1	19.07	1
United Arab Emirates	H	MENA	3.30	1	4.75	1	4.73	1
United Kingdom	H	OECD	2.74	1	4.07	3	4.51	3
United States	H	OECD	4.06	1	6.38	2	7.05	2
Uzbekistan	L-M	FSU	18.07	1			26.97	1
Vanuatu	L-M	Asia	1.61	1			3.47	2
Vietnam	L-M	Asia	2.41	1			6.15	1
Yemen. Rep.	L	MENA	2.05	1			2.91	2
Zimbabwe	L	SSA	3.11	1			16.56	1
Bhutan	L-M	Asia	1.42	2			19.51	1
Burundi	L	SSA	0.51	2			12.31	1
Cameroon	L-M	SSA	0.92	2	5.74	2	6.29	2
Chad	L	SSA	0.20	2			5.05	3
Colombia	U-M	LAC	1.62	2	2.85	3	3.08	3
Comoros	L	SSA	0.91	2			4.42	1
Congo. Dem. Rep.	L	SSA	0.57	2	18.58	1	20.60	1
Eswatini	L-M	SSA	1.80	2			4.74	2
Ethiopia	L	SSA	0.99	2	27.85	1	27.43	1
Hong Kong SAR. China	H	Asia	1.29	2	2.14		2.12	
Kenya	L-M	SSA	1.14	2	8.08	1	8.22	1
Macao SAR. China	H	Asia	0.57	2			0.97	
Madagascar	L	SSA	0.80	2			5.21	1
Malawi	L	SSA	0.97	2			7.60	2
Malta	H	MENA	1.55	2	3.53	3	3.46	3
Mauritius	U-M	SSA	1.49	2	3.06	3	3.04	3
Myanmar	L-M	Asia	1.06	2	7.95	2	7.87	3
Nepal	L	Asia	0.88	2	8.81	1	8.94	1
Nigeria	L-M	SSA	0.98	2	8.08	1	8.52	2
Norway	H	OECD	1.16	2	2.77	2	4.19	2
Paraguay	U-M	LAC	1.05	2	3.29	3	4.79	2
Philippines	L-M	Asia	1.66	2	4.13	3	4.22	3
Puerto Rico	H	LAC	0.58	2			0.15	1
Rwanda	L	SSA	0.88	2			7.88	2
Singapore	H	Asia	1.07	2	4.06	3	4.00	3
Sri Lanka	L-M	Asia	0.91	2	2.86		2.92	3
Sweden	H	OECD	2.51	2	3.38	3	6.24	2
Switzerland	H	OECD	1.70	2	1.78		2.92	3
Uganda	L	SSA	0.69	2			12.66	2
Uruguay	H	LAC	1.39	2	2.54	2	2.98	2
Zambia	L-M	SSA	0.98	2			10.54	2
Afghanistan	L	Asia					1.96	1
Bermuda	H	LAC					2.48	3
Bosnia and Herzegovina	U-M	Rest Europe					12.39	1
Cambodia	L-M	Asia					8.18	2
Croatia	H	Rest Europe					4.91	2
Cuba	U-M	LAC					3.46	3
Djibouti	L-M	MENA					4.53	2
Estonia	H	OECD					10.19	2

Hungary	H	OECD					5.64	2
Iceland	H	OECD					14.26	1
Kuwait	H	MENA					5.03	1
Latvia	H	FSU					6.42	2
Liberia	L	SSA					30.34	1
Libya	U-M	MENA					5.20	2
Lithuania	H	FSU					7.27	2
Maldives	U-M	Asia					3.18	1
Moldova	L-M	FSU					13.96	2
Niger	L	SSA					7.02	1
Qatar	H	MENA					7.31	2
Sao Tome and Principe	L-M	SSA					5.43	2
Serbia	U-M	Rest Europe					8.93	2
Slovak Republic	H	OECD					8.23	2
Slovenia	H	OECD					5.92	2
Suriname	U-M	LAC					4.67	2
Syrian Arab Republic	L	MENA					7.52	2
Venezuela. RB	U-M	LAC					5.89	2

Note: this table displays the list of countries included in the three samples (for the Non-Renewable, Non-Clean and Total Energy Intensity), the geographical region, the income level (H: High, U-M: Upper-Middle, L-M: Lower-Middle and L: Low) and the club assigned to each country according to its value of Non-renewable Energy Intensity (NREI), Non-Clean Energy Intensity (NCEI) and Total Energy Intensity (TEI).