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Spatial spillovers and world energy intensity convergence

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ABSTRACT

This paper studies the influence of spatial spillovers on energy intensity growth and convergence across 153 countries from 1999 to 2018. The inclusion of spatially lagged variables allows the study of the influence of trade, technological diffusion and policy mimicry on these two processes. Contrary to previous literature, we consider different spatial specifications and weight matrices to test whether spatial spillovers are exogenous or endogenous, as well as their range of influence. Our study finds the spatial lag of X model (SLX), with local spatial weight matrices, fits better to the data. Convergence is found for the world as a whole, conditional to the spatial distribution of countries and several long-term economic characteristics. In this sense, clusters of nearby countries present higher rates of convergence. Besides, domestic capital accumulation, total factor productivity growth and renewable energy consumption significantly determine the characteristics of clubs of convergence. Furthermore, spatial spillovers associated to capital accumulation, population growth and renewable energy consumption also contribute to the definition of these clubs.

1. Introduction

The last sixth assessment report on climate change of the IPCC (IPCC, 2021) calls again for immediate action to avoid the excessive long-term costs associated with unpredictable and extreme natural phenomena. Human action relates to global warming through anthropogenic GHG emissions, which have likely increased the global temperature by >1 °C with respect to the 1850–1900 period, and under all scenarios, the temperature reaches the level of a 2 °C increase by the end of the XXI century. Moreover, climate change seems to have accelerated in recent decades, likely due to a feedback effect existing between the short-term effects of global warming, which seem to diminish the effectiveness of land and ocean carbon sinks, and the global temperature. One of the major conclusions is the need for net zero CO2 emissions, and to reach this goal, policymakers must pay attention to energy consumption, since it is the major driver of carbon emissions (The World Bank, 2021).

To achieve the objective of net zero CO2 emissions related to energy consumption, two possibilities emerge: substitution by nonpolluting sources and improvements in energy efficiency levels. At an aggregate level, the latter measures technical innovations in the quality of energy flows and/or more efficient production processes in other sectors that lead to lower gross energy consumption. Moreover, endogenous changes in productivity can be linked to shifts in the demand for substitute goods, and vice versa, as posed by models such as those of "directed technical change" (e.g., Acemoglu, 2002; Eriksson, 2018), thus studying the evolution of energy intensity (a proxy for energy inefficiency) is very likely to explain the long-term sustainability of modern economies. Besides, previous works have also found a strong and positive correlation between levels of energy intensity and CO2 emissions (Cole and Neumayer, 2004; Poumanyvong and Kaneko, 2010; Du et al., 2012; Liu et al., 2015; Wang et al., 2017; Balado-Naves et al., 2018; Danish, 2020).

According to the available data from the World Development Indicators Database (The World Bank, 2021) and the Energy Statistics Database (United Nations Statistics Division, 2018), the 1999–2018 period presents a steady decrease in worldwide energy intensity levels (see Fig. 1). Knowing whether this pattern is driven only by "clubs" of countries is important for long-term sustainability and supranational policies, such as the EU Emissions Trading System, given that it might change as less developed countries intensify their energy consumption due to strong industrialization processes. Herrerias (2012), for instance, stresses the importance of achieving international agreements between developing and developed countries that will foster environmentally friendly institutions and technological diffusion.

Moreover, the existence of convergent paths in energy intensity levels allows the use of energy intensity growth as a proxy variable of how well the world as a whole is dealing with climate change (Mielnik

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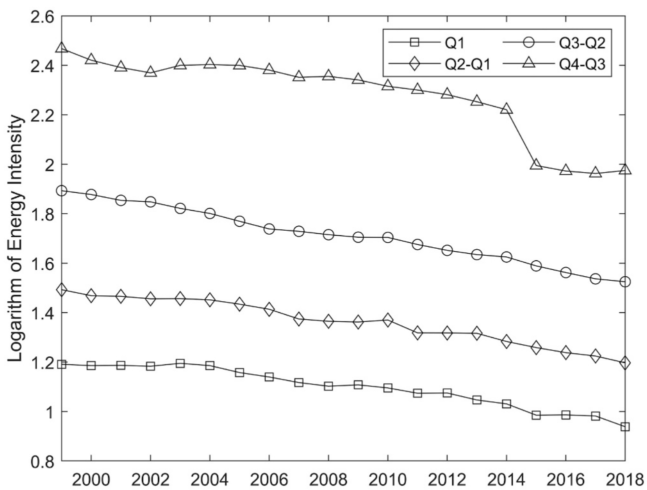

Fig. 1. Evolution of interquartile average energy intensity (logarithm of MJ/$2011 PPP GDP): 1999–2018.
Notes: Q1, Q2 and Q3 are the first, second and third quartiles respectively. Data sources: see Section 2.4. Elaborated by the authors.

and Goldemberg, 2000). In this sense, Duro et al. (2010) find strong evidence that energy intensity convergence drives energy consumption convergence for OECD countries. Therefore, if countries converge in their patterns of energy consumption, forecasts on the effect of new regulations or public policies directed to control excessive consumption will gain superior accuracy. For all these reasons, the study of worldwide energy intensity convergence is crucial for policymaking aimed at environmental sustainability.

Energy intensity convergence studies can be divided into two major branches. The first one stems from seminal works on per capita income β-convergence (Barro, 1991; Barro and Sala-i-Martin, 1992), which tests the existence of a "catch-up" phenomenon across countries in terms of energy intensity growth rates. That is, countries presenting initial low levels of energy intensity are expected to grow faster (at a decreasing rate) than energy-intensive economies. Most of these studies focused on OECD countries, considering periods of time within the interval 1970–2010, and finding favorable and strong support in favor of conditional β-convergence (Miketa and Mulder, 2005; Markandya et al., 2006; Mulder and De Groot, 2007; Mulder and De Groot, 2012; Liddle, 2010, 2012; Voigt et al., 2014; Csereklyei et al., 2016).

The second branch focuses on σ-convergence and time-series analyses, as well as nonparametric techniques aimed at tackling Galton's Fallacy, which is likely to appear in β-convergence analyses given the expected emergence of multimodal distributions, as emphasized in Quah (1993, 1996). These works find mixed results compared to β-convergence estimations (Le Pen and Sévi, 2010; Kiran, 2013; Apergis and Christou, 2016; Bulut and Durusu-Ciftci, 2018), absolute convergence between developing and developed countries (Nielsson, 1993; Goldemberg, 1996), and conditional convergence towards different clubs (Ezcurra, 2007; Duro et al., 2010; Herrerias, 2012).

As aforementioned, previous works have already found strong evidence of the existence of clubs of convergence on energy intensity. Nevertheless, the spatial dimension of this issue has been widely ignored. For instance, Miketa and Mulder (2005) comment on the need to explore worldwide technological diffusion since technological change is a major source of energy-productivity growth, while Liddle (2010) detects geographical barriers determining convergence in energy intensity within clubs of countries. In addition, Mussini (2020) poses that policymakers may be interested in the geographical space where energy intensity convergence takes place, which ``is especially true for countries that are members of an international organization, such as the EU, in which regional groups of countries with initially different levels of energy intensity are present".

Spatial clubs of convergence may emerge due to different reasons. Since trade profits are strongly constrained by distance costs (e.g., Hummels, 1999; Nitsch, 2000; Head and Mayer, 2002; Berthelon and Freund, 2008), bordering countries are expected to present more intensive trade relationships. In this sense, trade may foster productivity in domestic firms due to harsher international competition (Eaton and Kortum, 2002; Melitz, 2003), as well as incentivize the specialization in energy-intensive industries (Mulder and De Groot, 2012), leading to changes in country energy intensity levels (e.g., Adom and Kwakwa, 2014; Pan et al., 2019; Chen et al., 2022). Furthermore, geographical proximity increases the likelihood of receiving and adopting foreign technological spillovers due to capital accumulation externalities (Ertur and Koch, 2007), as well as adopting new regulation and policies affecting energy efficiency (Sun et al., 2022).

To our knowledge, there are few works of energy intensity β-convergence controlling for spatial spillovers. Yu (2012), Huang et al. (2017), and Jiang et al. (2018) focus their analysis on Chinese provinces, while Adhikari and Chen (2014) consider several Asian countries, and Wan et al. (2015) analyze energy productivity convergence for EU countries. All these works find strong evidence in favor of spatial correlation.

Moreover, we have only found three studies applying this methodology for a large set of countries. On the one hand, Mulder et al. (2011) employ a panel dataset of 102 countries between 1971 and 2001, finding a significant spatial correlation. Yet, their estimations focus on simple spatial models, such as the spatial autoregressive and error specifications, overlooking the existence of spatial spillovers associated with variables such as technical progress or saving rates. On the other hand, Csereklyei and Stern (2015) only consider a spatial filter for 93 countries between 1971 and 2010, assuming that spatial spillovers are insufficiently justified in this context. Therefore, their study does not include estimates of the impact of neighboring economic agents on domestic energy intensity growth and convergence. Finally, Lee and Park (2022) study energy intensity convergence for 61 countries between 1974 and 2019. However, their approach omits the employment of the complete set of spatial specifications, focusing only on models that assume the existence of endogenous and global spillovers.

Therefore, as Wan et al. (2015) point out for sector-based studies, there is a lack of studies at a worldwide scale analyzing the importance of spatial spillovers in the evolution of cross-country differences in energy intensity levels. The main purpose of the present paper is to fill this gap. We thus extend this empirical literature by considering both global and local spatial models, employing several spatial weights matrices to test for different degrees of spatial correlation, and using the largest available dataset of countries with explanatory variables associated with the scale, composition, and technical characteristics of economies for the period 1999–2018.

The remainder of this paper is organized as follows. Section 2 presents the methods of study, the specifications for regressions and data. Section 3 features the results from the β-convergence analyses. Section 4 presents the main conclusions.

2. Materials and methods

2.1. Energy intensity β-convergence considering spatial spillovers

As stated earlier, the β-convergence approach seeks to test whether countries with initial differences in energy intensity levels tend to reduce the gap due to initial differences in convergent growth rates (absolute convergence), or rather converge to a stable gap determined by differences in the long-term characteristics of economies (conditional convergence) (Miketa and Mulder, 2005). Furthermore, absolute β-convergence is a necessary and sufficient condition for σ-convergence (the standard deviation of energy intensity tends to zero), while conditional β-convergence is only a necessary condition (if differences in the long-term characteristics of economies remain strong, the standard deviation of energy intensity tends to a positive value).[1]

According to previous literature considering spatial spillovers (Mulder et al., 2011; Yu, 2012; Wan et al., 2015; Jiang et al., 2018), the spatial models that have been already considered are the SAR (Spatial Autoregressive Model), SEM (Spatial Error Model) and the SDEM (Spatial Durbin Error Model). The first one controls for endogenous and global spillovers, which imply that all areas will also be affected by changes in those regions that have not been defined as direct neighbors, as well as the emergence of feedback effects (LeSage, 2014); the second one only takes into account the existence of global diffusion of shocks to the model disturbances (not treated as local spillovers); and the latter controls for exogenous and local spillovers, meaning that changes in domestic explanatory variables will only impact on direct neighbors with no rebound effects.

To confirm what type of spatial spillover prevails, we decide to estimate the SARAR[2] (Spatial Autoregressive Model with Autoregressive Errors), SDM (Spatial Durbin Model) and SDEM general specifications, as well as their nested models. Due to the lack of space, in this section we only present the functional form of a general nesting spatial model for energy intensity β-convergence.

$$\begin{aligned}\frac{ln(EI_{it}/EI_{it-s})}{S} &= \mu_i + b_1 lnEI_{it-s} + b_2 \sum\nolimits_{j=1}^{N} w_{ij} lnEI_{jt-s} \\ &+ \sum\nolimits_{v=1}^{K} \xi_v x_{ivt-s} + \sum\nolimits_{v=1}^{K} \sum\nolimits_{j=1}^{N} \theta_v w_{ij} x_{jvt-s} \\ &+ \rho \sum\nolimits_{j=1}^{N} w_{ij} \frac{ln(EI_{jt-s}/EI_{jt-s})}{S} + \lambda \sum\nolimits_{j=1}^{N} w_{ij} u_{jt} + v_{it}\end{aligned} \tag{1}$$

where $ln(EI_{it}/EI_{it-s})/S$ is the growth rate of energy intensity in country i between time t and $t-s$ for interval S; μ_i are the country fixed effects; b_1 is the coefficient associated to the natural logarithm of domestic energy intensity $lnEI_{it-s}$; b_2 is the coefficient associated to the spatially lagged term of neighbors' energy intensity $w_{ij}lnEI_{jt-s}$, with $w_{ij} \in [0,1]$ as the ij element of the row-standardized W spatial weights matrix; ξ_v are the parameters associated to the K remaining exogenous variables x_{ivt-s}, and θ_v are the parameters associated to the spatial lags explanatory variables $w_{ij}x_{jvt-s}$; ρ is the parameter associated to spatially lagged neighboring growth rates of energy intensity $w_{ij}ln(EI_{jt}/EI_{jt-s})/S$. Finally, the error term is divided into two parts: the spatial autocorrelation part, with λ as the parameter controlling for the potential existence of spatial correlation among spatially lagged neighboring residuals $w_{ij}u_{jt}$, and the pure random part, with the idiosyncratic error term v_{it}.

From (1), different nested models emerge (see Halleck Vega and Elhorst, 2015). If $\theta_v = 0$, the SARAR specification is true; if $\lambda = 0$, the SDM is true; if $\rho = 0$, the SDEM is true. At a lower level, we find the additional nested spatial models: if $\theta_v = 0$ and $\lambda = 0$, the SAR is true; if $\theta_v = 0$ and $\rho = 0$, the SEM is true; and if $\lambda = 0$ and $\rho = 0$, the Spatial Lag of X model (SLX) is true.

According to LeSage and Pace (2009) and Halleck Vega and Elhorst (2015), when endogenous spatial interactions arise ($\rho \neq 0$), the total effect of an explanatory variable is computed according to the average of the row sums from the following matrix

$$\frac{\partial ln(EI_t/EI_{t-s})/S}{\partial x_{vt-s}} = (I - \rho W)^{-1}(I\xi_v + W\theta_v) \tag{2}$$

where I is an identity matrix. On the contrary, when exogenous spatial interactions are the only relevant spillovers, total effects from an explanatory variable are

$$\frac{\partial ln(EI_t/EI_{t-s})/S}{\partial x_{vt-s}} = \xi_v + \sum\nolimits_{j=1}^{N} w_{ij}\theta_v \tag{3}$$

which is a special case of (2) when $\rho = 0$.

Since the rate of convergence is implied in the estimated coefficient of $lnEI_{it-s}$, as in Mulder and De Groot (2007, 2012) and Jiang et al. (2014), conditional β-convergence regressions with spatial spillovers must present a modified rate of convergence $\beta = -ln(1+\gamma)/S$, where γ is now the total effect associated to $lnEI_{it-s}$. In the simplest case of exogenous spatial interactions (SDEM and SLX specifications), this can be written as

$$\beta = -ln\left(1 + \underbrace{b_1 + \sum\nolimits_{j=1}^{N} w_{ij} b_2}_{\gamma}\right) \Big/ S \tag{4}$$

where b_1 and b_2 are the coefficients associated with domestic and neighboring initial levels of energy intensity. When endogenous spatial interactions arise (SARAR, SDM and SAR specifications), γ then equals the average of the row sums from matrix $(I - \rho W)^{-1}(Ib_1 + Wb_2)$, similar to (2).

Having set the general nesting spatial specification for our estimations, the main hypotheses that we test are:

I. $\beta > 0$: Countries converge in terms of energy intensity.
II. For $\beta > 0$, if $\xi_v \neq 0$: Convergence is conditional to the domestic steady state or long-term equilibrium of economies.
III. For $\beta > 0$, if $\rho \neq 0$ and/or $b_2 \neq 0$ and/or $\theta_v \neq 0$: Convergence is conditional to the spatial distribution of countries. As highlighted in Wan et al. (2015), the effect of geography on convergence rates is likely to be a consequence of more intense trade relationships between nearby countries

2.2. Control variables of conditional convergence

According to (1), we include several exogenous variables to control for economic differences across countries, which are very likely to influence rates and significance of convergence.

- **Capital substitution and the embodiment hypothesis.**

  Ratio between gross investment and capital stock (*lnIK*): This ratio tries to capture the turnover rate of physical capital as in Metcalf (2008). Higher ratios are expected to imply a faster replacement of old equipment for newer and more efficient gear leading to a decay in energy intensity growth.

  Saving rates (*s*): Related to the former, and as in Miketa and Mulder (2005) and Mulder and De Groot (2007), the share of gross investment over aggregate GDP is included to test the *embodiment hypothesis*, which poses that the role of technical progress is partially considered in the value of new vintages of capital stock (Mulder et al., 2003). If new vintages of capital stock foster more efficient production processes, then we should expect a negative relationship between saving rates and energy intensity growth in the case of good possibilities of substitution.

  Capital stock per capita (*lnk*): Capital stock has been argued to be a likely substitute for energy (Thompson and Taylor, 1995; Metcalf, 2008), thus we expect that higher capital per person can lead to slower or even negative growth rates of energy intensity.
- **Scale effects.**

  Population growth (*gL*): According to Metcalf (2008), countries with fast population growth rates can "be less efficient in their use of energy if their capital investment does not keep pace with growth (e.g., traffic congestion)". Additionally, Herrerias (2012) finds that energy intensity convergence is more significant after controlling for

[1] See Barro and Sala-i-Martin (2004) for a comprehensive theoretical and empirical justification.

[2] See Kelejian and Prucha, 2010.

population. Therefore, we include this variable to test whether its inclusion leads to faster or slower growth rates of energy intensity.

- **Technical progress, composition and structural change effects.**

Total factor productivity (TFP) growth (g_A): If TFP can be measured as a composite of different innovations at a micro level, as assumed in some models of endogenous growth (e.g., Romer, 1990; Howitt and Aghion, 1998), both aggregate and disaggregated technological progress should be correlated. If aggregate technical change is driven by efficiency-improving ideas, we must expect a negative relationship between aggregate technical progress and energy intensity growth.

Renewable energy share (*RE*): Changes in the energy mix have previously been observed to be a strong determinant for reductions in energy intensity levels (Cleveland et al., 2000; Kaufmann, 2004). Moreover, Miketa and Mulder (2005) employ this factor as a control variable to test the existence of conditional β-convergence in the energy intensity for manufacturing industries, finding contradictory results in terms of the sign and statistical significance for a few sectors. We include this variable to control for specific technical change in the energy sector. If renewable sources are more efficient, shifts in the energy mix are expected to lead to lower energy intensity growth rates.

Services sector share (*SVC*): According to Schäfer (2005), the net contribution of sectoral shifts to changes in worldwide energy intensity levels accounts for a scarce 5%. Nevertheless, it is still significant and negative as economies progress towards the tertiary sector. In addition, despite Mulder and De Groot (2012) find strong evidence in OECD countries of the services sector facing sustained decreases in energy intensity levels, they show that aggregate convergence patterns are weakly related to convergent structural transformations across countries. Therefore, we include the share of the added value of the services sector with respect to GDP as a control variable for β-convergence regressions.

- **Institutional quality.**

Rule of Law perception (*ROL*): Past developments in economic growth modeling have hypothesized the importance of efficient institutional frameworks (inclusive political and economic rules) in the long-term accumulation of capital stock per effective worker as well as in the generation of new ideas and techniques (e.g., Acemoglu, 2005, 2006). Nevertheless, among empirical researchers (e.g., Gyimah-Brempong and Dapaah, 1996; Acemoglu et al., 2001; Knutsen, 2013), there is no strong consensus that supports the existence of the aforementioned negative correlation. Glaeser et al. (2004) find this relationship weak, as well as detect likely causality in the opposite direction. Regarding studies of β-convergence in energy intensity, we only find that Markandya et al. (2006) takes into consideration the role of institutions in analyzing the correlation between the estimated speed of convergence of European transition countries with respect to the EU average, here controlling for institutional variables such as the quality of the competition policy enforced on markets or the degree of privatization among firms. Their results point towards a positive and statistically significant relationship; thus, better institutions proxied through the quality of the rule of law should imply faster convergence.

- **Spatial spillovers: technical spillovers and policy mimicry.**

The inclusion of spatial lags on explanatory variables seeks to capture the different sources of technical spillovers that have previously been argued to be potential determinants of domestic development on energy-saving improvements (Bosetti et al., 2008; Hall and Helmers, 2013; Verdolini and Galeotti, 2011). These spillovers may arrive embodied in imported capital goods (*WlnIK*, *Wlnk*), foreign investment (*Ws*), changes in the transboundary movement of the labor force (*WgL*) or disembodied in patents associated with more efficient productive processes at an aggregate level (*WgA*) and the energy mix (*WRE*). Moreover, changes in worldwide patterns of trade and sectoral specialization (*WSVC*) can also lead to shifts in energy productivity levels across firms. According to Keller (2002, 2004), geographical space is a relevant constraint for technology adoption or goods trade, acting as a strong discount factor on neighborhood relationships. Regarding institutional quality, studies such as Maddison (2006) or Shipan and Volden (2012) have posed the point that regulations depend on policy-mimicking across neighboring countries. Therefore, we also include the effect of spatial spillovers associated to institutional quality (*WROL*) as likely constraints to the evolution of domestic energy intensity.

2.3. Spatial weights

Similar to Wan et al. (2015), we consider three spatial weights matrices according to the chosen neighborhood criterion: the 5-nearest neighbors matrix (W5N), the first-order rook contiguity matrix (WCont) and the geographic distance matrices (WDist). All matrices are row-standardized.

The first two matrices consider binary spatial relationships according to the following rule

$$w_{ij} = \begin{cases} 1/N_{ij} & \textit{if } j \textit{ is neighbor of } i \\ 0 & \textit{if else} \end{cases} \tag{5}$$

where N_{ij} is the number of j neighbors associated to the i country. The geographic distance spatial weights are constructed according to

$$w_{ij} = \begin{cases} \dfrac{1/d_{ij}}{\sum_{j=1}^{N} 1 \Big/ d_{ij}} & \textit{if } j \neq i \\ 0 \quad \textit{if } j = i \end{cases} \tag{6}$$

where d_{ij} is the existing Euclidean distance between i and j centroids.

2.4. Data sources

Table 1 shows the employed variables and their definition, while Table 2 presents the main statistics. Based on data availability, the data

Table 1
Variables and their definitions.

Variable	Name	Definition
EI	Energy intensity	Megajoules of primary energy supply divided by GDP in constant 2017 international dollars
gEI	Energy intensity growth	Natural logarithm of the ratio of energy intensity at t and t-s
IK	Capital stock turnover	Gross capital formation divided by gross capital stock
k	Per capita capital stock	Private and public capital stock in constant 2017 international dollars divided by total population
s	Saving rate	Gross capital formation divided by GDP
gA	Technical progress	Natural logarithm of the ratio of total productivity at t-s and t-s-1
gL	Population growth	Natural logarithm of the ratio of population at t-s and t-s-1
RE	Share of renewable energy	Renewable energy consumption divided by energy consumption
SVC	Share of services sector	Added value of services (ISIC divisions 50–99) divided by GDP
ROL	Rule of law quality	Perceptions of the extent to which agents have confidence in and abide by the rules of society and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. (0% no confidence. 100% absolute confidence)

Notes: Data sources: Energy Statistics Database (United Nations Statistics Division, 2018); World Development Indicators (World Bank, 2021); IMF Investment and Capital Stock Dataset, 1960–2019 (International Monetary Fund, 2021); Worldwide Governance Indicators Dataset (United Nations Statistics Division, 2018).

Table 2
Main statistics.

Variable	Mean	SD	Min	Max
gEI	−0.016	0.038	−0.337	0.250
lnEI	1.636	0.608	−0.208	5.252
lnIK	−2.482	0.417	−4.332	−0.951
Lnk	9.85	1.446	6.237	12.252
s	0.191	0.080	0.017	0.604
gA	0.014	0.012	−0.020	0.069
gL	0.027	0.074	−0.687	0.365
RE	0.344	0.308	0	0.978
SVC	0.571	0.147	0.126	0.927
ROL	0.502	0.199	0.096	0.925

span the period 1999–2018 for 153 countries.[3] Data for primary energy supply is obtained from the *Energy Statistics Database* (United Nations Statistics Division, 2018). Population growth rates, the share of renewable energy over aggregate energy consumption and the added value of the services sector with respect to gross GDP are obtained from the *World Development Indicators Database* (The World Bank, 2021). The share of gross capital formation, capital stock and gross domestic product come from the *IMF Investment and Capital Stock Dataset, 1960–2019* (International Monetary Fund, 2021). The data on perception of the rule of law quality are obtained from the *Worldwide Governance Indicators Dataset* (United Nations Statistics Division, 2018), which we standardize between zero and one. The lowest value represents the weakest perceived governance performance, while higher values are associated with a strong performance.

Following Aghion and Howitt (2007), who show that total factor productivity (TFP) growth accounts for almost 70% of per capita GDP growth, technical progress is constructed according to a similar three-step procedure: first, we estimate the capital-per-person elasticity of per capita GDP (α) employing a simple fixed-effects panel data specification $lny_{it} = \mu_i + \delta_t + \alpha lnk_{it} + v_{it}$. Second, we extract the natural logarithm of TFP from the Harrod-neutral Cobb-Douglas production function, that is $lnA_{it} = \frac{lny_{it} - \alpha lnk_{it}}{1-\alpha}$. Third, we compute the growth rates of total productivity according to $g_A = ln(A_{it}/A_{it-1})$.

To eliminate business cycle fluctuations and serial correlation from the error term, panel data estimations must be carried out over periods of time longer than one-year intervals (Islam, 1995; Pettersson et al., 2013). With the aim of maintaining a sufficiently large sample of data, we choose the five-year interval, as in Miketa and Mulder (2005) and Mulder and De Groot (2007); Mulder and De Groot, 2012).

3. Results and discussion

3.1. Tests for spatial dependence

As a preliminary test, we study the Moran's I spatial autocorrelation coefficient to confirm the significance of spatial proximity on energy intensity growth rates. The spatiotemporal Moran's I assuming no time autocorrelation (López et al., 2011) can be read as

$$STMI = \frac{N}{S_{00}^{*}} \frac{\sum_i^N \sum_j^N \sum_r^R (gEI_{ir} - \bar{g}EI) w_{ij} (gEI_{jr} - \bar{g}EI)}{\sum_i^N \sum_r^R (gEI_{ir} - \bar{g}EI)^2} \tag{7}$$

where $S_{00}^{*} = \sum_i^N \sum_j^N w_{ij}$, gEI_{ir} is the growth rate of energy intensity at subperiod r in country i, $R = T/S$ the number of subperiods of interval S for a number of total periods T, and $\bar{g}EI = \frac{1}{NR} \sum_i^N \sum_r^R gEI_{ir}$ the panel-data mean of energy intensity growth rates.

Results from Table 3 show a clear positive spatial autocorrelation among neighboring countries, with p-values lower than 1% regardless of the employed spatial weights matrix. This confirms that countries with similar rates of energy intensity growth tend to be clustered, which is an initial support to the idea of stronger energy intensity convergence among neighboring economies.

Table 3
Moran's I statistics of energy intensity growth rates.

Weights matrices	Moran's I	SD	*Z*-Value	p
W 5 N	0.104	0.023	4.565***	0.000
W Cont	0.152	0.036	4.217***	0.000
W Dist	0.035	0.007	4.597***	0.000

Notes: t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Fig. 2 also serves as further evidence in favor of this phenomenon.[4] As can be observed, on the one hand, the majority of countries in the areas of North America, Sub-Saharan Africa and Central-East Asia remained in the fourth and fifth quintiles of energy intensity between the years 1999–2018. On the other hand, most countries in Latin America and the Caribbean, as well as the European members of the OECD, have remained in the first and second quintiles over the same period. Other similar patterns are also observed at a lower scale.

3.2. Endogeneity

According to Caselli et al. (1996) and Islam (2003), the issue of endogeneity bias is prone to appear in the context of growth panel regressions. Variables such as investment or saving rates and GDP growth rates are very likely to be jointly determined. We therefore decide to follow a common strategy employed in economic growth convergence studies, which consists in using the time lags of explanatory variables as instruments (e.g., Caselli et al., 1996; Barro and Sala-i-Martin, 2004). The estimation procedure consists in a first-stage regression where each exogenous regressor x_{ivt-s} (without considering their spatial lags) is regressed against the complete set of their first-order time lags $x_{ivt-s-1}$ (results are presented in Appendix C). The predicted values from this first-stage regression are then considered for the estimation of each specification.[5]

Moreover, since we lack data on energy prices, endogenous regressors are also expected to arise due to the omission of relevant explanatory variables. Works such as Hang and Tu (2007) and Filipović et al. (2015) find a significant negative influence of energy prices on energy intensity levels for China and the European Union. Furthermore, Wan et al. (2015) show that high-price energy indicators are significant when explaining conditional β-convergence in the European Union. They argue that energy prices are a major determinant for a country's incentives to adopt more productive patterns of production in terms of energy usage. In this sense, they include a dummy variable identifying those countries with energy prices above the median of each period. Therefore, we consider a similar instrument equaling one for those countries with energy intensity levels above the median (*dEI*).

According to the results shown in Appendix D, the joint Hausman test leads to a rejection of the null hypothesis of exogeneity of explanatory variables for all specifications. Moreover, the Sargan test for over-identifying restrictions is not rejected for almost all specifications and spatial weight matrices.[6] Therefore, our further analysis will only consider the first-stage fitted values $\hat{x}_{ivt-s}$ for the correction of endogeneity.

[3] See Appendix A for the list of countries in the sample.

[4] See also Appendix B for the absolute and relative frequencies of countries according to their distribution by energy intensity percentile and geographical areas.

[5] The first-stage regression for capital stock per capita presents a high R2 due to the persistence of this variable.

[6] The null hypothesis is rejected for the SARAR and SEM with the distance spatial weights matrix. However, as we show in Subsection 3.3, these two specifications fit worse to data compared to the SLX.

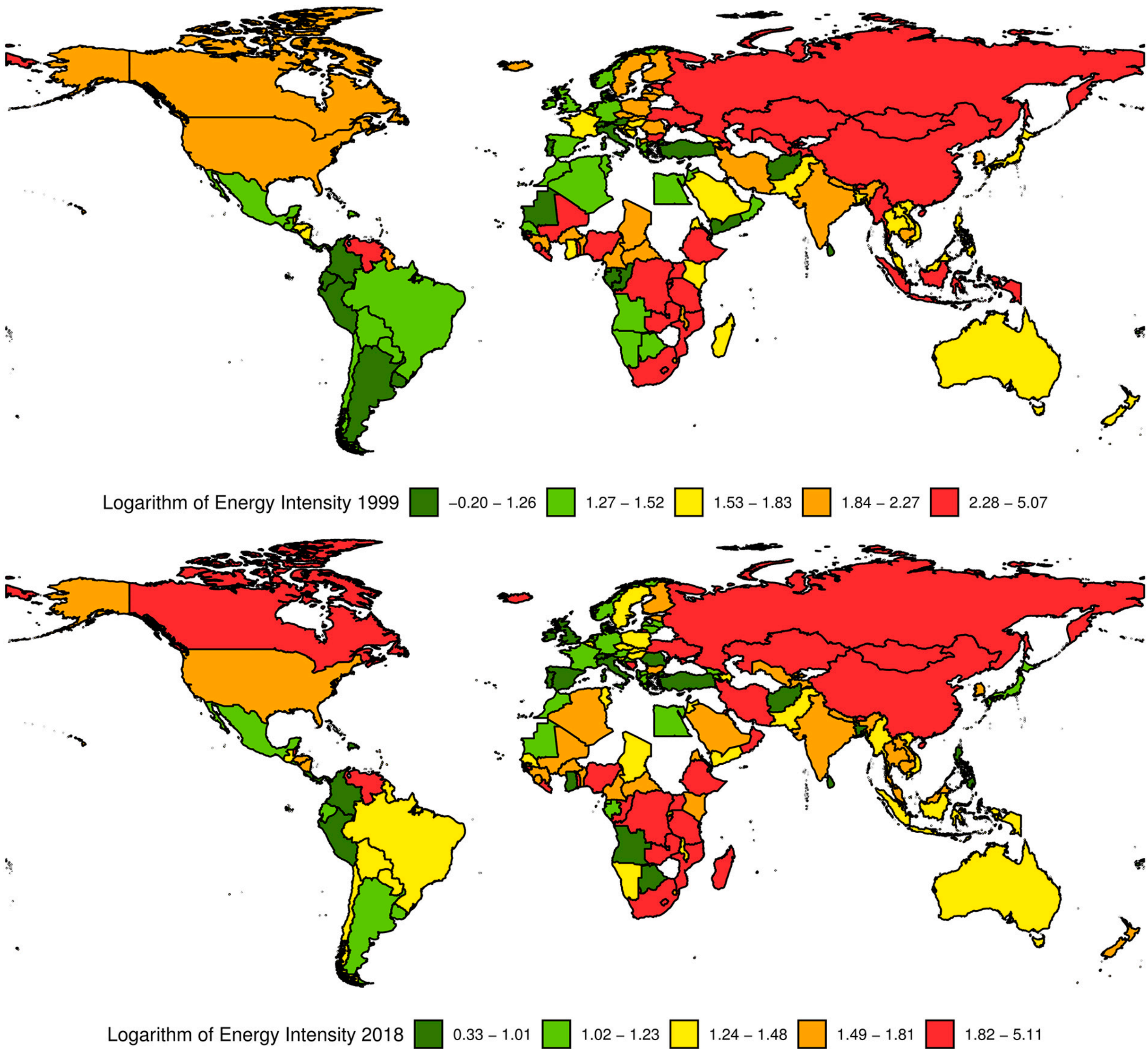

Fig. 2. Worldwide distribution of the logarithm of energy intensity distribution: 1999 and 2018.
Notes: Elaborated by the authors.

3.3. *Specification selection*

Following Snipes and Taylor (2014), we use the corrected Akaike information criterion (AICc) methodology to choose between functional specifications. This strategy requires the construction of the following associated statistics

$$AICc_q = 2\left(K_q^* - lnL_q + \frac{K_q^*\left(K_q^*+1\right)}{NT - K_q^* - 1}\right) \tag{8}$$

$$\Delta AICc_q = AICc_q - Min(AICc) \tag{9}$$

$$AIW_q = \frac{exp\left(-\frac{1}{2}\Delta AICc_q\right)}{\sum_{q=1}^{M} exp\left(-\frac{1}{2}\Delta AICc_q\right)} \tag{10}$$

$$ER_q = \frac{Max(AIW)}{AIW_q} \tag{11}$$

$$LER_q = log_{10}\left(ER_q\right) \tag{12}$$

where $AICc_q$ is the corrected AIC score, K_q^* is the number of parameters of the q model, lnL_q is the maximum log-likelihood, AIW_q is the Akaike weight of evidence in favor of a model being the actual best model for the given data, and ER_q is the evidence ratio which measures the strength of rejection of a given model opposed to the best model in terms

Table 4
β-convergence estimations of energy intensity growth without spatial spillovers.

Determinants	ABS		FE	
lnEI	−0.017***	(−7.16)	−0.164***	(−16.49)
lnIK			−0.095***	(−9.23)
lnk			−0.099***	(−10.72)
s			0.561***	(7.09)
gL			−0.582	(−1.67)
gA			−0.117**	(−2.44)
RE			−0.111***	(−3.19)
SVC			−0.065	(−1.16)
ROL			−0.024	(−0.63)
Speed of Convergence (β)	0.34		3.58	
Half-life years	231.04		19.36	
Fixed Effects	NO		YES	
Obs.	612			
R^2 (Adjusted)	0.076		0.372	
Log-likelihood	1153.6		1365.6	

Notes: t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. ABS and FE are for absolute and conditional convergence models without spatial spillovers.

Table 5
β-convergence SARAR estimations of energy intensity growth.

Determinants	SARAR WDist		SARAR WCont		SARAR W5N	
lnEI	−0.163***	(−14.95)	−0.160***	(−13.79)	−0.161***	(−14.16)
lnIK	−0.081***	(−6.37)	−0.092***	(−7.95)	−0.093***	(−7.82)
lnk	−0.074***	(−5.89)	−0.098***	(−9.02)	−0.096***	(−8.6)
s	0.481***	(5.07)	0.549***	(6.02)	0.557***	(6.12)
gL	−0.461	(−1.15)	−0.621	(−1.61)	−0.577	(−1.41)
gA	−0.109*	(−1.95)	−0.113**	(−2.13)	−0.107*	(−1.86)
RE	−0.068*	(−1.67)	−0.097**	(−2.4)	−0.097**	(−2.36)
SVC	0.020	(0.30)	−0.035	(−0.58)	−0.04	(−0.64)
ROL	−0.045	(−0.99)	−0.025	(−0.55)	−0.025	(−0.56)
WlnEI	0.036	(0.76)	−0.036	(−1.3)	−0.022	(−0.67)
WlnIK	0.018	(0.73)	−0.021	(−1.28)	−0.013	(−0.67)
Wlnk	0.016	(0.72)	−0.022	(−1.25)	−0.013	(−0.67)
Ws	−0.104	(−0.72)	0.122	(1.24)	0.074	(0.66)
WgL	0.098	(0.50)	−0.141	(−0.9)	−0.081	(−0.5)
WgA	0.025	(0.69)	−0.026	(−0.99)	−0.015	(−0.57)
WRE	0.014	(0.56)	−0.022	(−1.01)	−0.014	(−0.62)
WSVC	−0.007	(−0.29)	−0.009	(−0.45)	−0.008	(−0.43)
WROL	0.009	(0.36)	−0.006	(−0.45)	−0.004	(−0.29)
ρ	−0.385	(−1.2)	0.208	(1.63)	0.1	(0.66)
λ	0.692***	(4.8)	−0.001	(−0.01)	0.105	(0.64)
Speed of Convergence (β)	2.71		4.36		4.04	
Half-life years	25.57		15.89		17.15	
Fixed Effects	YES					
Obs.	612					
R^2 (Adjusted)	0.346		0.359		0.366	
Log-likelihood	1369.4		1371.8		1367.7	

Notes: t statistics in parentheses. * p < 0.1, ** $p < 0.05$, *** $p < 0.01$. SARAR coefficients are those of the estimated direct and indirect effects.

of the Akaike criterion. For a LER_q equal to 0, 0.5, 1 and 2, differences between models are characterized as minimal, substantial, strong and decisive.

Results from the AICc methodology (see Appendix E) show strong support in favor of the SLX specifications, regardless of the chosen spatial weight matrix. However, since differences with the SARAR specifications are not decisive ($LER_q < 2$), we will focus our analysis on both SARAR and SLX specifications for the β-convergence estimations.

3.4. Energy intensity β-convergence estimations, σ-convergence and average elasticities

In this section, we first analyze estimations on the β-convergence of the world's energy intensity. Tables 4, 5 and 6 show estimation results considering absolute convergence, as well as the non-spatial and spatial specifications of conditional convergence. All regressions are estimated according to the 2SLS procedure described in Subsection 3.2. Spatial specifications follow the SLX and SARAR models according to Subsection 3.3. We also explore the evolution of the σ-convergence process between the years 1999–2018, as well as carry out several ex-post forecasts to analyze which spatial weights matrix captures better the evolution of worldwide energy intensity dispersion.

The estimated b_1 which contains the implicit rate of convergence is negative and statistically significant for any specification. The relatively low explanatory capacity of the absolute convergence model (R^2= 0.076), and the significance of many regressors in conditional specifications point towards the existence of strong differences regarding the scale, structure, and composition of economies, as proven in studies such as Miketa and Mulder (2005), Markandya et al. (2006) and Mulder and De Groot (2012). Moreover, as pointed out in Mulder and De Groot (2012), Yu (2012) and Jiang et al. (2018), overlooking the existence of spatial spillovers, seems to reduce the explanatory capacity of energy intensity convergence models in terms of the log-likelihood.

In the light of these results, we cannot reject the hypothesis of clubs of convergence conditional to domestic and neighboring economic steady states. This implies that as long as differences in variables determining long-term growth in energy intensity remain strong, worldwide differences in the distribution of energy intensity across countries will persist. Depending on the specification and the chosen spatial weight matrix, we observe substantial changes in the implicit speeds of convergence. The SLX specification with distance matrix yields the highest rate of conditional convergence of 9.1% (>2.5 times that of the non-spatial conditional specification), while the SARAR with the distance matrix presents the lowest conditional rate of 2.71%. Therefore, our estimations show that convergence to the steady state levels of energy intensity of each economy is expected to take between 15 and 50 years (twice the half-life years required for convergence to the steady state[7]).

Given the estimated ρ parameter of the SARAR specification is non-significant for all spatial weight matrices, the spillover or indirect effects associated with the explanatory regressors in these models are also non-significant (see Tables 4 and 5). This points towards the SARAR as proving to be an over specified model in this context. In this sense, Corrado and Fingleton (2012), as well as Halleck Vega and Elhorst (2015), encourage the employment of the SLX model in those instances when spatial spillovers are statistically significant but an endogenous structure cannot be theoretically or empirically defended. Additionally, Rüttenauer (2022) also proves via a Monte Carlo experiment that the SLX specification yields less biased estimates of indirect impacts (spatial spillovers) compared to other spatial models. Therefore, we decide to focus our attention on the effects derived from the SLX model, which are robust regardless of the chosen spatial weight matrix.

We firstly cannot reject the hypothesis of capital stock being a good substitute for energy inputs for the world as a whole. According to Table 6, the direct effect of an increase in domestic capital stock per capita (k) is significantly negative and reduces energy intensity growth rates between −0.073 and − 0.086 percentage points. Furthermore, neighboring capital deepening also reinforces the effect of domestic input substitution, creating trade areas for those nearby countries with lower energy intensity growth rates. In this sense, when the spatial

[7] Half-life time is derived from $H = ln(2)/\beta$ (see Barro and Sala-i-Martin, 2004; Miketa and Mulder, 2005).

Table 6
β-convergence SLX estimations of energy intensity growth.

Determinants	SLX WDist		SLX WCont		SLX W5N	
lnEI	−0.168***	(−17.03)	−0.164***	(−16.48)	−0.167***	(−16.78)
lnIK	−0.083***	(−7.53)	−0.084***	(−7.63)	−0.089***	(−8.07)
lnk	−0.073***	(−6.29)	−0.086***	(−8.19)	−0.083***	(−7.18)
s	0.486***	(5.95)	0.476***	(5.83)	0.508***	(6.19)
gL	−0.282	(−0.81)	−0.719**	(−2.04)	−0.541	(−1.56)
gA	−0.103**	(−2.12)	−0.134***	(−2.71)	−0.121**	(−2.47)
RE	−0.084**	(−2.29)	−0.104***	(−2.93)	−0.086**	(−2.38)
SVC	0.003	(0.05)	−0.065	(−1.12)	−0.013	(−0.22)
ROL	−0.039	(−0.98)	−0.018	(−0.48)	−0.039	(−0.98)
WlnEI	−0.199**	(−2.49)	−0.059***	(−2.72)	−0.055**	(−2.45)
WlnIK	−0.211**	(−2.99)	−0.069***	(−3.56)	−0.051**	(−2.18)
Wlnk	−0.183***	(−3.52)	−0.071***	(−3.48)	−0.061***	(−3.13)
Ws	1.039*	(1.74)	0.443**	(2.49)	0.301	(1.59)
WgL	5.476*	(1.74)	0.133	(0.18)	1.788**	(2.16)
WgA	0.259	(0.66)	−0.079	(−0.93)	0.079	(0.78)
WRE	−0.848***	(−2.98)	−0.279***	(−4.21)	−0.277***	(−3.79)
WSVC	−0.274	(−0.61)	−0.336***	(−2.96)	−0.231*	(−1.77)
WROL	−0.227	(−0.89)	0.046	(0.54)	−0.032	(−0.39)
Speed of Convergence (β)	9.14		5.04		5.02	
Half-life years	7.58		13.83		13.32	
Fixed Effects	YES					
Obs.	612					
R^2 (Adjusted)	0.393		0.392		0.386	
Log-likelihood	1382.4		1381.9		1378.8	

Notes: t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

weight matrix becomes laxer in the definition of neighboring countries, the indirect impact of capital deepening increases (−0.183 for the SLX WDist, and − 0.061 for the SLX W5N).

Regarding the embodiment hypothesis, we find contradictory results. The direct effect of the investment-capital ratio (*IK*) is significant and negative, showing that increasing the domestic turnover rate of capital stock by 1% reduces energy intensity growth between −0.083 and − 0.089 percentage points. However, this vintaging seems to be partially offset by the direct effect associated with higher saving rates (*s*). In this sense, increasing the domestic share of gross output devoted to capital accumulation by one percentage point leads to an acceleration in energy intensity growth between 0.476 and 0.508 percentage points. Regarding the indirect effects of the turnover and saving rates, Table 6 shows that these are usually significantly different than zero tending to reinforce the direct effects, with the largest marginal effects related to the distance spatial weight matrix (−0.211 for the turnover rate and 1.039 for the saving rates).

The scale hypothesis is rejected from a domestic viewpoint, with non-significant population growth rates (*gL*) in almost all models. Nevertheless, spatially lagged population growth (*WgL*) presents a significant and positive impact in the SLX WDist and W5N. More precisely, an increase of one percentage point in neighboring population growth rates leads to increases in domestic energy intensity growth rates higher than 1.7 points. This rejects the idea of technical spillovers embodied in neighboring human capital and might be an approximation of the increasing demand for energy associated with growing economic activity in surrounding countries. Metcalf (2008), for instance, finds a change in the pattern of energy intensity clustering across the United States from the slow-growing northern states, in terms of population, to the fast-growing and industrializing southern and southwestern regions.

The negative and significant coefficient associated with domestic technological change (*gA*) seems to support the idea of TFP moving economies towards more efficient ways of production in terms of energy usage. More precisely, an increase of one percentage point in domestic TFP growth leads to a reduction of domestic energy intensity growth rates of between −0.103 and − 0.134 points. On the contrary, we do not find a significant impact of neighboring TFP growth (*WgA*) on the domestic evolution of energy intensity, this probably being captured by the indirect effects of per capita capital stock, turnover and saving rates.

Regarding technical change associated with the energy mix, we find that increases in both the domestic and neighboring relative weights of renewable energy consumption (*RE* and *WRE*) are significant at the 5% level thereby reducing energy intensity across economies. The total effect shows that an increase of one percentage point in the share of renewable energy consumption in a given country and its neighbors leads to an overall reduction in domestic energy intensity growth ranging between −0.363 (SLX W5N) and − 0.932 (SLX WDist) points. This could serve as further evidence of renewable energy proving to be a more productive source compared to traditional fuels, with the existence of technological spillovers also being associated with their use.

Regarding structural change, the degree of tertiarization *SVC* is not significant at the domestic level. This result is in line with Mulder and De Groot (2012), who find that structural changes for OECD countries only explain a limited change in β-convergence for the 1995–2005 period; or Duro et al. (2010), who detect that structural change led to an increased disparity in energy intensity for a similar set of countries. Finally, both domestic and neighboring institutional qualities measured through perceptions of the extent of the rule of law across states (*ROL*), are statistically non-significant.

The ex-post forecasts in Fig. 3 also show that conditional convergence models estimated in Tables 4 and 6 fit well to the data.[8] Both SLX models with the 5-nearest neighbors matrix (SLX W5N), and the contiguity matrix (SLX WCont) reproduce the best approximation to the real evolution of standard deviations in energy intensity. Therefore, local, instead of global, spillovers are preferred when explaining the σ-convergence of logarithmic energy intensity over the period 1999–2018 (an average reduction of 11.48%). This implies that most economies closed the gap to the world mean, and differences between clubs of convergence also decreased as well. In this sense, works such as Liddle (2010), have also observed the existence of geographical barriers in the validation and speed of convergence. Mulder et al. (2011), Wan

[8] Ex-post forecasts of *lnEI* are constructed considering the estimated fixed effects and coefficients from final models of Tables 4 and 6. The sum of the squared residuals comparing the forecasted and observed standard deviation (σ) are 0.0058, 0.0059, and 0.0070 for the W5N, WCont, and WDist SLX models.

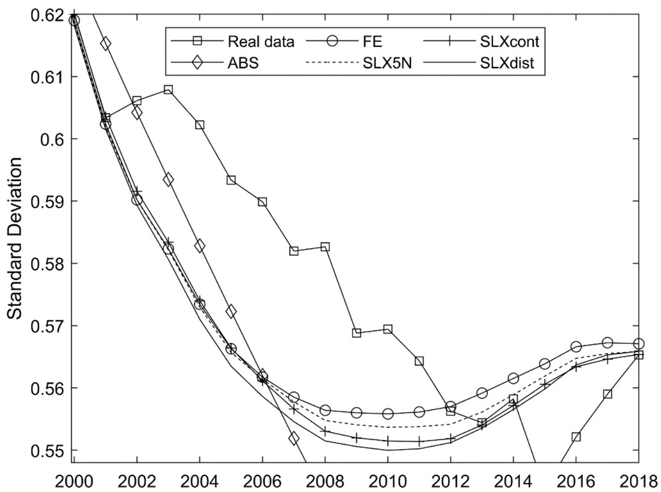

Fig. 3. Ex-post forecasts of the standard deviation (σ) of the logarithm of energy intensity: 1999–2018.
Notes: Elaborated by the authors.

et al. (2015) and Jiang et al. (2018) also found strong evidence in favor of local spillovers in the context of energy intensity convergence.

4. Conclusions

In this paper we study whether energy intensity has converged for the world as a whole conditioned to the existence of spatial spillovers. Previous literature lacks a comprehensive analysis of the influence of trade, technological diffusion, and policy mimicry on cross-country differences in energy intensity on a global scale. Focusing on the idea of trade being strongly correlated to geographical distance, the existence of clubs of convergence in energy intensity should be influenced by the spatial distribution of countries, as already found in previous studies for smaller sets of countries or regions (Mulder et al., 2011; Wan et al., 2015; Jiang et al., 2018). As Wan et al. (2015) highlight, further technical adoption and deeper intra-industry trade both link energy intensity convergence to commerce.

Contrary to previous work, we use different spatial specifications to test whether spatial spillovers are endogenous or exogenous for a large set of countries. If the former is true, all entities are influenced by changes in any country through a feedback process. If the latter is true, technological diffusion and policy mimicry are limited in the space, creating more defined clusters of interacting countries. Besides, different spatial weights matrices and explanatory variables are considered to analyze their influence on energy intensity growth and convergence.

We find support for conditional energy intensity convergence, as in Miketa and Mulder (2005), Markandya et al. (2006), Mulder and De Groot (2007); Mulder and De Groot, 2012), Liddle (2010, 2012), Voigt et al. (2014) and Csereklyei et al. (2016) for previous periods of time. This convergent path is described by an increasing number of countries approaching in terms of logarithmic energy intensity. As in Mulder et al. (2011), Adhikari and Chen (2014) and Wan et al. (2015), we find a positive spatial correlation for energy intensity growth. On the contrary, our results favor estimations with exogenous spatial spillovers following the SLX specification with spatially lagged explanatory variables. In addition, the 5-nearest neighbors and the contiguity matrix are preferred for ex-post forecasts on convergence. The estimated rates of conditional convergence increase by >40%, and the half-life time of convergence decreases by up to 30% after controlling for spatial spillovers, thereby supporting the idea of clubs of convergence constrained to geography.

We also detect contradictory effects regarding capital accumulation. While raising saving rates explains a large portion of increases in energy intensity growth, as well as its convergence, higher endowments of capital stock per capita and turnover ratios lead to small reductions in energy intensity growth. In this sense, we find weak support for the substitution hypothesis between capital stock and energy, while the embodiment hypothesis must be rejected. Therefore, new vintages of capital stock are not conducive to more energy-saving production processes. Moreover, these effects are bolstered among neighboring countries, indicating that, on average, fostering foreign investment seems to worsen global energy intensity levels, while trading capital goods creates energy-saving clusters of countries. Furthermore, total factor productivity growth and an energy mix based on renewable sources lead to convergence in lower energy intensity levels, with technological diffusion only proving significant when associated with renewable energy use. Furthermore, we do not find enough evidence of structural change and institutional quality as significant determinants of energy intensity growth and convergence.

Further work on worldwide energy intensity and spatial spillovers is required for a better understanding of the role of trade and technology diffusion on sustainable growth. Due to data availability for large sets of countries, the present study faces some limitations. We propose the following improvements: the consideration of disaggregated data at a sectoral level for richer estimations and policy recommendations; the construction of trade flow spatial weights matrices, as in Wan et al. (2015), to better measure the influence of trade on worldwide energy intensity convergence; and the inclusion of other relevant control variables, such as trade specialization, which has helped to explain energy intensity convergence for some sectors, as in Miketa and Mulder (2005), Markandya et al. (2006), Mulder and De Groot (2012) or Wan et al. (2015).

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CRediT authorship contribution statement

Roberto Balado-Naves: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Jose Francisco Baños-Pino:** Conceptualization, Writing – review & editing. **Matías Mayor:** Conceptualization, Writing – review & editing.

Appendix A. Appendix

Table 7
List of countries by geographical area.

North America	Canada, United States
LAC	Antigua and Barbuda, Argentina, Barbados, Bahamas, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominica, Dominican Republic, Ecuador, El Salvador, Grenada, Guatemala, Guyana, Honduras, Mexico, Nicaragua, Paraguay, Peru, Panama, Saint Kitts and Nevis, Saint Lucia, Uruguay, Saint Vincent and the Grenadines, Venezuela

(*continued on next page*)

Table 7 (*continued*)

Europe OECD	Denmark, Ireland, Estonia, Austria, Czech Republic, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Latvia, Lithuania, Slovakia, Malta, Belgium, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom
Europe No OECD	Azerbaijan, Albania, Armenia, Bosnia and Herzegovina, Bulgaria, Cyprus, Georgia, Croatia, The former Yugoslav Republic of Macedonia, Romania, Russia, Ukraine
MENA	Algeria, Bahrain, Djibouti, Egypt, Iran (Islamic Republic of), Jordan, Kuwait, Lebanon, Morocco, Oman, Saudi Arabia, Tunisia, Yemen
South Asia	Bangladesh, Sri Lanka, Afghanistan, Bhutan, India, Maldives, Nepal, Pakistan
Central-East Asia	China, Japan, Korea, Republic of, Kazakhstan, Mongolia, Hong Kong, Tajikistan, Uzbekistan
Southeast Asia-Oceania	Australia, Burma, Brunei Darussalam, Cambodia, Fiji, Lao People's Democratic Republic, Malaysia, New Zealand, Philippines, Singapore, Thailand, Vietnam, Indonesia
Sub-Saharan Africa	Angola, Benin, Congo, Democratic Republic of the Congo, Burundi, Cameroon, Chad, Central African Republic, Cape Verde, Equatorial Guinea, Eritrea, Ethiopia, Gambia, Gabon, Ghana, Guinea, Kenya, Liberia, Madagascar, Mali, Mauritius, Mauritania, Mozambique, Malawi, Nigeria, Guinea-Bissau, Rwanda, Seychelles, South Africa, Lesotho, Botswana, Senegal, Sierra Leone, Togo, Sao Tome and Principe, United Republic of Tanzania, Uganda, Burkina Faso, Namibia, Swaziland, Zambia

Appendix B. Appendix

Table 8
Distribution of countries by energy intensity percentile and geographical area.

Region/Percentile	PC20	PC40-PC20	PC60-PC40	PC80-PC60	>PC80
		Year 1999			
North America (2)	0.00% (0)	0.00% (0)	0.00% (0)	100.00% (2)	0.00% (0)
LAC (28)	39.29% (11)	32.14% (9)	17.86% (5)	7.14% (2)	3.57% (1)
Europe OECD (28)	25.00% (7)	28.57% (8)	14.29% (4)	28.57% (8)	3.57% (1)
Europe No OECD (12)	0.00% (0)	8.33% (1)	25.00% (3)	33.33% (4)	33.33% (4)
MENA (13)	7.69% (1)	53.85% (7)	15.38% (2)	15.38% (2)	7.69% (1)
South Asia (8)	37.50% (3)	0.00% (0)	25.00% (2)	25.00% (2)	12.50% (1)
Central-East Asia (8)	12.50% (1)	0.00% (0)	12.50% (1)	12.50% (1)	62.50% (5)
Southeast Asia-Oceania (13)	7.69% (1)	0.00% (0)	69.23% (9)	7.69% (1)	15.38% (2)
Sub-Saharan Africa (41)	17.07% (7)	12.20% (5)	12.20% (5)	19.51% (8)	39.02% (16)
		Year 2018			
North America (2)	0.00% (0)	0.00% (0)	0.00% (0)	0.50% (1)	0.50% (1)
LAC (28)	28.57% (8)	25.00% (7)	28.57% (8)	10.71% (3)	7.14% (2)
Europe OECD (28)	32.14% (9)	28.57% (8)	28.57% (8)	7.14% (2)	3.57% (1)
Europe No OECD (12)	8.33% (1)	25.00% (3)	33.33% (4)	8.33% (1)	25.00% (3)
MENA (13)	7.69% (1)	30.77% (4)	15.38% (2)	15.38% (2)	30.77% (4)
South Asia (8)	37.50% (3)	12.50% (1)	12.50% (1)	12.50% (1)	25.00% (2)
Central-East Asia (8)	12.50% (1)	12.50% (1)	0.00% (0)	37.50% (3)	37.50% (3)
Southeast Asia-Oceania (13)	23.08% (3)	15.38% (2)	7.69% (1)	53.85% (7)	0.00% (0)
Sub-Saharan Africa (41)	12.20% (5)	9.76% (4)	17.07% (7)	24.39% (10)	36.59% (15)

Notes: number of countries in brackets.

Appendix C. Appendix

Table 9
First-stage estimation of 2SLS conditional convergence (A).

Determinants	lnEI	lnIK	lnk	s
lnEI(lag)	0.793***	−0.028	−0.013***	0.008
	(40.36)	(−0.64)	(−6.04)	(0.99)
lnIK(lag)	−0.130***	1.033***	0.064***	0.045***
	(−7.20)	(25.63)	(32.08)	(6.01)
lnk(lag)	−0.091***	0.029	0.991***	0.027***
	(−5.49)	(0.79)	(535.15)	(4.01)
s(lag)	0.730***	−1.895***	0.060***	0.448***
	(6.53)	(−7.60)	(4.88)	(9.65)
gL(lag)	−1.273**	0.812	−1.074***	0.138
	(−2.20)	(0.63)	(−16.82)	(0.57)
gA(lag)	−0.050	0.897***	−0.001	0.095***
	(−1.19)	(9.62)	(−0.34)	(5.50)
RE(lag)	−0.215***	0.170	0.011*	0.050**
	(−3.69)	(1.31)	(1.69)	(2.09)
SVC(lag)	0.029	0.161	−0.059***	−0.005
	(0.38)	(0.94)	(−7.05)	(−0.18)
ROL(lag)	0.166**	0.433***	−0.004	0.069**
	(2.28)	(2.66)	(−0.53)	(2.28)
dEI	0.066***	0.047*	0.001	0.008
	(5.32)	(1.69)	(1.42)	(1.59)
Fixed Effects	YES			
Obs.	612	612	612	612
R^2 (Adjusted)	0.882	0.709	0.999	0.543

Notes: t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10
First-stage estimation of 2SLS conditional convergence (B).

Determinants	gL	gA	RE	SVC	ROL
lnEI(lag)	−0.001	−0.016	−0.001	0.004	−0.004
	(−0.06)	(−0.88)	(−0.19)	(0.39)	(−0.92)
lnIK(lag)	0.001	−0.039**	−0.012*	0.003	0.007*
	(0.01)	(−2.32)	(−1.86)	(0.33)	(1.81)
lnk(lag)	0.001	−0.046***	−0.019***	−0.032***	0.002
	(1.49)	(−2.89)	(−3.13)	(−3.39)	(0.75)
s(lag)	0.004	−0.070	0.036	0.065	−0.049*
	(0.79)	(−0.65)	(0.86)	(1.02)	(−1.92)
gL(lag)	0.727***	−0.817	0.076	−0.581*	−0.174
	(22.56)	(−1.48)	(0.35)	(−1.75)	(−1.31)
gA(lag)	0.002	0.335***	−0.032**	−0.081***	−0.013
	(1.22)	(8.43)	(−2.08)	(−3.35)	(−1.36)
RE(lag)	0.002	0.159***	0.852***	−0.154***	0.008
	(0.88)	(2.88)	(39.34)	(−4.61)	(0.64)
SVC(lag)	−0.007*	0.049	−0.057**	0.594***	−0.005
	(−1.72)	(0.67)	(−2.03)	(13.51)	(−0.29)
ROL(lag)	0.011***	−0.118*	0.033	0.073*	0.872***
	(2.90)	(−1.70)	(1.22)	(1.74)	(51.63)
dEI	0.001	0.003	−0.002	0.017**	0.002
	(0.26)	(0.25)	(−0.56)	(2.46)	(0.74)
Fixed Effects	YES				
Obs.	612	612	612	612	612
R^2 (Adjusted)	0.475	0.227	0.767	0.301	0.833

Notes: t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix D. Appendix

Table 11
Hausman and Sargan test results for second-stage 2SLS regressions.

Model - Statistic / Weights matrix	W5N	WCont	WDist
SARAR – F(9, 591)	27.801***	26.500***	26.079***
	(0.000)	(0.000)	(0.000)
SARAR – Sargan $\chi^2(1)$	1.079	1.321	4.279**
	(0.298)	(0.250)	(0.038)
SDM – F(18, 573)	15.898***	15.498***	14.347***
	(0.000)	(0.000)	(0.000)
SDM – Sargan $\chi^2(1)$	0.583	1.170	0.564
	(0.445)	(0.279)	(0.452)
SDEM – F(18, 574)	15.744***	15.428***	14.261***
	(0.000)	(0.000)	(0.000)
SDEM – Sargan $\chi^2(1)$	0.634	1.141	0.514
	(0.425)	(0.285)	(0.473)
SAR – F(9, 592)	27.643***	27.439***	27.593***
	(0.000)	(0.000)	(0.000)
SAR – Sargan $\chi^2(1)$	1.027	1.319	1.093
	(0.311)	(0.251)	(0.295)
SEM – F(9, 592)	27.405***	27.406***	27.055***
	(0.000)	(0.000)	(0.000)
SEM – Sargan $\chi^2(1)$	1.160	1.223	2.827*
	(0.281)	(0.268)	(0.092)
SLX – F(18, 575)	15.747***	15.495***	14.319***
	(0.000)	(0.000)	(0.000)
SLX – Sargan $\chi^2(1)$	0.608	1.076	0.564
	(0.435)	(0.299)	(0.452)
FE – F(9, 593)	27.496***		
	(0.000)		
FE – Sargan $\chi^2(1)$	1.112		
	(0.291)		
ABS – F(1, 608)	146.268***		
	(0.000)		
ABS – Sargan $\chi^2(1)$	0.026		
	(0.871)		

Notes: t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. ABS and FE are for the absolute and conditional convergence models without spatial spillovers.

Appendix E. Appendix

Table 12
Akaike Information Criteria for model selection.

Model	AICc	ΔAICc	AIW	ER	LER
SARAR W5N	−2716.065	4.424	0.096	9.134	0.960
SDM W5N	−2699.901	20.587	0.0002	29,546.509	4.470
SDEM W5N	−2699.304	21.184	0.0002	39,829.076	4.600
SAR W5N	−2695.438	25.051	0.00003	275,296.555	5.439
SEM W5N	−2694.506	25.982	0.00002	438,654.782	5.642
SLX W5N	−2720.489	0	0.883	1	0
FE W5N	−2712.897	7.591	0.019	44.513	1.648
ABS W5N	−2416.690	303.798	9e-67	9e+65	65.968
SARAR WCont	−2725.119	1.590	0.310	2.215	0.345
SDM WCont	−2712.958	13.752	0.0007	969.063	2.986
SDEM WCont	−2713.924	12.786	0.001	597.661	2.776
SAR WCont	−2704.202	22.507	0.000008	77,186.788	4.887
SEM WCont	−2701.820	24.890	0.000002	254,017.373	5.404
SLX WCont	−2726.710	0	0.687	1	0
FE WCont	−2712.897	13.812	0.0006	998.680	2.999
ABS WCont	−2416.690	310.019	3e-68	2e+67	67.319
SARAR WDist	−2719.065	8.670	0.012	76.362	1.882
SDM WDist	−2702.565	25.171	0.000003	292,301.948	5.465
SDEM WDist	−2703.031	24.705	0.000004	231,558.804	5.364
SAR WDist	−2692.128	35.608	0.00000001	53,981,784.190	7.732
SEM WDist	−2696.301	31.435	0.0000001	6,701,619.123	6.826
SLX WDist	−2727.736	0	0.986	1	0
FE WDist	−2712.897	14.839	0.0005	1668.276	3.222
ABS WDist	−2416.690	311.045	2e-68	3e+67	67.542

Notes: ABS and FE are for the absolute and conditional convergence models without spatial spillovers.

Appendix F. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106807.

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