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Modelling economic policy issues

Are greenhouse gas emissions converging in Latin America? Implications for environmental policies ☆

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ABSTRACT

This paper investigates greenhouse gas emissions convergence among nineteen Latin American countries, for the period 1970 to 2018. To that end, we use the Phillips–Sul methodology to examine whether these countries have followed an absolute convergence process, or whether there has been a club convergence process. Our results offer important insights into the greenhouse gas emissions catch-up exhibited by several countries, and do not support the hypothesis that all countries of the Latin American region, taken together, converge to a single equilibrium in greenhouse gas emissions intensity. We find strong evidence of subgroups that converge to different steady states. An iterative testing procedure reveals the existence of different patterns of behavior and shows that such emissions are not uniform across these countries. We also estimate an Ordered Logit Model to identify the forces underlying the creation of clubs and the likelihood that any given country will be a member of any convergence club. Estimates from an Ordered Logit Model reveal that income, population density, openness, natural resources rents, and – particularly – the level of corruption, play a crucial role in explaining the formation of convergence clubs. The existence of clubs means that the climate policies aimed at reducing emissions should consider the specific characteristics of the countries, according to the club convergence results.

1. Introduction

Climate change, resulting from growing concentrations of greenhouse gases (GHG) in the atmosphere, is a major global challenge in the twenty-first century, increasing concerns – in both developed and developing countries – about the environmental impacts of emissions. The distribution of global emissions per-capita has implications in terms of fairness and equity and is hotly debated. Specifically, many developing countries, with lower per-capita emissions, expect developed countries, with much higher per-capita emissions, to reduce their outputs (Apergis and Payne, 2017). Several

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authors have pointed out that if emissions were to converge over time, there would be less concern regarding any per-capita allocation scheme, with this becoming a key assumption in the climate change literature (Stegman and McKibbin, 2005; Aldy, 2006; Barassi et al., 2011; Payne et al., 2014) and for international commitments such as the Kyoto Protocol and the Paris Climate Agreement.

The analysis of the dynamics of greenhouse gas emissions is important for policymakers to evaluate environmental impacts or current mitigation policies and design efficient proposals to combat climate change and achieve emissions targets. More specifically, how a country's emissions performance evolves over time, and whether it converges to or diverges from that of others, are questions with important policy implications. Hence, any group of countries that follows a similar steady-state equilibrium can adopt common environmental policies to jointly cope with environmental deterioration, and the convergence of air pollutants among regions implies that they will share a common level of emissions in the long run.

In this paper, our specific aim is to investigate and test whether convergence in greenhouse gas emissions has occurred among a group of Latin American countries, using recent datasets and the club convergence technique. Convergence occurs when countries with higher initial rates of emissions intensity reduce their emissions intensity at a greater rate than countries with lower initial rates of emissions intensity, hence catching-up with the higher-emission countries in the long run. Following Apergis and Payne (2017), we use the Phillips–Sul methodology (Phillips and Sul, 2007, 2009), but in this paper we conduct our analysis by disaggregating the intensity of greenhouse gas emissions by population and GDP. Our detailed analysis also includes the disaggregation of the phenomenon by type of gas and polluting sector. This secondary analysis is important because convergence in aggregate greenhouse gas emissions can mask gas and sector differences. We assess the process of regional convergence in emissions for nineteen Latin American countries over the period 1970–2018 and, rather than simply describing any observed convergence clubs, we carry out a deeper analysis of the factors underlying the formation of such clubs. Prior studies in Latin America have failed to identify the possible determinants of club formation and, for this purpose, we employ an ordered regression model.

The contributions of this paper are then threefold. To the best of our knowledge, our study investigates, for the first time in the literature, whether differences in greenhouse gas emissions intensity decrease across Latin American countries. That is, we analyze the greenhouse gas emissions convergence process in Latin America, where the empirical evidence remains scarce. In our view, this is a remarkable contribution since policies that are suitable for high-income countries (e.g., the US or the European Union) may not be suitable for other nations, due to differences in the composition and characteristics of their greenhouse gas emissions. Besides, traditional analyses of emissions convergence concentrate principally on carbon dioxide emissions, and there is limited attention to the convergence of greenhouse gas emissions (Bello et al., 2022; Erdogan and Okumus, 2021; Payne et al., 2022; Ulucak et al., 2020). Thus, the findings of this study may be helpful to implement efficient environmental policies in the Latin American region.

Second, we explore the convergence of different greenhouse gas emissions indicators at the pollutant (carbon dioxide, methane, nitrous oxide) and sectoral level (buildings, non-combustion, other industrial combustion, transport, and power industry), rather than focusing only on the total amount of greenhouse gas emissions. It is not rational to take into account only one indicator on environmental pressure, and such disaggregated analyses produce more accurate policy conclusions to meet environmental targets by pollutant gas as well as by sector. It is highly likely that the pattern of greenhouse gas emissions varies by gas and sector and the validity of environmental policies could differ. Thus, our analysis takes into account the heterogeneities among Latin American countries in terms of greenhouse gas emissions sources, providing useful information for policymakers about which emissions are worth targeting (Solarin et al., 2021, 2022b). In addition to carbon dioxide (CO2), we also examine convergence in methane (CH4) and nitrous oxide (N2O), pollutants that have not received the same degree of attention in the literature (Ivanovski and Churchill, 2020; Solarin et al., 2021).

Third, to provide additional policy insights, we try to identify the main forces behind the club convergence results and we carry out an in-depth analysis of the different patterns of behavior observed, in contrast to the majority of works on emissions convergence (Bhattacharya et al., 2020). To do this, we use ordinal models and introduce several explanatory variables, combining the club convergence analysis with an analysis of the structural characteristics that predict the club membership. This is critical for policymakers to enhance productive efficiency, despite the lack of evidence. In particular, no prior work has studied the determinants of greenhouse gas emissions in a club convergence framework.

Some similar research has been carried out in Rodríguez-Benavides et al. (2014), Martin and Vazquez (2015), and Barrios et al. (2019), investigating whether certain Latin American countries are catching-up in terms of GDP per-capita. In the context of emissions convergence, Robalino-López et al. (2016) investigate per-capita carbon dioxide emissions convergence in 10 South American countries from 1980 to 2010. More recently, Apergis et al. (2020) analyze the carbon dioxide emissions intensity convergence for six Central American countries, from 1971 to 2014, and Tillaguango et al. (2021) study the convergence process of per-capita ecological footprint in the period 1990 to 2016 in 16 Latin American countries.

Our results suggest evidence supporting overall convergence of greenhouse gas emissions per-capita, and we identify club convergence with three distinct convergence clubs for greenhouse gas emissions per-GDP. The first club, the most numerous, is formed by 12 countries, whereas the second and third clubs consist of 4 and 3 countries, respectively. Although club members are not necessarily geographic neighbors and the estimated clusters consist of countries in quite distinct regions of Latin America, we find some common geographical characteristics in the clubs identified. In terms of emissions intensity, these clubs are ordered from the worst performing club (Club 1) to the best performing club (Club

3). Thus, most of the Latin American countries are grouped in the worst performing club. Depending on the gas pollutant or sectoral emissions indicator, from two to three clubs are identified. These findings carry important implications for policymakers, as suggest that a common or single policy to reduce greenhouse gas emissions intensity will have only limited effects, due to the different patterns of behavior observed. In addition, we try to identify the potential drivers of club formation and find that economic activity, population density, trade openness, natural resources rents, and the corruption level are key factors to explain the convergence process of greenhouse gas emissions intensity across Latin American countries.

The rest of the paper is organized as follows. Section 2 summarizes and provides an overview of the related literature on emissions convergence. Section 3 describes the data and contains an initial descriptive analysis of convergence of the variables used in this study. Our methodology is presented in Section 4, and Section 5 discusses the main empirical results. We conclude the paper in Section 6, drawing the most important conclusions and policy implications.

2. Literature review

Convergence is a widely discussed issue in macroeconomic theory and empirical research, particularly since the pioneering work of Baumol (1986) and Barro and Sala-i Martin (1992). The concept of convergence comes from the economic growth literature, referring to a decrease in differences in economic growth across regions over time.[1] Convergence occurs when a negative correlation is observed between the average growth rate and initial income (i.e., a negative relationship between the growth rate of the variable of interest and its initial level). The presence of this negative correlation indicates that countries with lower income per-capita tend to grow at higher rates than those with greater levels of development, catching up in the long-run. However, convergence is an imprecise concept and is not restricted to the economic growth literature alone. At this point, recent attention has been paid to environmental behaviors given the current context of climate change, and its importance in achieving sustainable development.[2] Research on environmental convergence has been the subject of many empirical studies that have followed a variety of methodologies.

Several studies have indicated an inverted U-shaped relationship between carbon dioxide emissions and income, also known as the Environmental Kuznets Curve (EKC), but the EKC alone cannot explain whether cross-country emissions converge. Cross-sectional, time series, and panel methodologies have all been used to examine convergence, using a wide range of concepts. The cross-sectional approach of beta-convergence consists of regressing the growth rate of the variable of interest (emissions per-capita, emissions intensity) over the period in question on its initial lagged levels, and testing whether the slope coefficient is negative.[3] The cross-sectional sigma-convergence concept can be assessed by testing whether the cross-sectional dispersion of the variable of interest (emissions per-capita, emissions intensity) decreases over time.

The time series approach can be found in the seminal papers of Carlino and Mills (1993) and Bernard and Durlauf (1995, 1996) in their examination of income convergence. These authors developed the concept of stochastic convergence, based upon the stationarity properties of the variables under analysis. Hence, two non-stationary variables converge when there is a co-integrating relationship between them. For example, emissions convergence would require that shocks to emissions relative to the panel average (or relative to another reference region) are temporary, implying that the relative emissions series are stationary. On the other hand, the existence of a unit root in the series would imply that shocks are permanent, and that emissions are not converging over time. In this case, authors such as Strazicich and List (2003), Chang and Lee (2008), Romero-Ávila (2008), Westerlund and Basher (2008), and Christidou et al. (2013) find support for stochastic convergence of emissions, whereas Barassi et al. (2008) and Barros et al. (2016) find no support for the stochastic convergence of emissions. Nevertheless, the procedure testing for stochastic convergence using unit root tests is not flawless and, as Perron (1989) and Bulte et al. (2007) point out, unit root tests that do not allow for structural breaks could lead to a bias against rejecting a false unit root null hypothesis.

In two seminal papers, Phillips and Sul (2007, 2009) maintain that traditional convergence tests are inadequate when technology is heterogeneous across countries and the speed of convergence is time-varying. In the stochastic convergence analysis, we do not test any convergence hypothesis, but we do test the unit root hypothesis. To account for temporal transitional heterogeneity, Phillips and Sul (2007, 2009) introduce cross-sectional and time series heterogeneity within the parameters of a neoclassical growth model. This convergence approach, based on a non-linear time-varying factor model, has given rise to a substantial convergence literature in general, and in the environmental convergence literature in particular.

Panopoulou and Pantelidis (2009) were the first to apply the Phillips–Sul club convergence approach to per-capita carbon dioxide emissions, for the period 1960 to 2003, in 128 countries. Wang et al. (2014) follow the same procedure and identify three convergence clubs for carbon dioxide emissions intensity in China for the period 1995–2011, while

[1] The concept of convergence originates from Solow's Neoclassical Growth Model, indicating that a backward area will keep developing faster than a developed area until the gap between the two regions vanishes (Li and Lin, 2013).

[2] The issue of convergence has recently attracted attention in the energy and environmental literature. See Pettersson et al. (2014), Acar et al. (2018), Payne (2020) and Menegaki et al. (2021) for detailed surveys of the literature.

[3] By including several exogenous covariates in the regression, this concept is converted to conditional beta-convergence, which implies the existence of multiple equilibria across countries.

Burnett (2016) and Apergis and Payne (2017) provide substantial evidence of convergence in carbon dioxide emissions across all fifty states of the US. More recently, Haider and Akram (2019a) use data on carbon dioxide emissions per-capita for 53 countries over the period 1980–2016 and obtain evidence of two convergence clubs in total emissions and emissions from gas and petroleum consumption, while three clubs are identified in per-capita carbon dioxide emissions from coal.

Table 1 presents an extensive literature review of 40 recent studies, from 2018 to 2022, assessing emissions convergence among different countries, greenhouse gas emissions, and econometric techniques.

3. Data

The regional convergence process considers greenhouse gas emissions for 19 Latin American countries for the period 1970–2018. The data are taken from the Emissions Database for Global Atmospheric Research (EDGAR), measured in annual tons per-capita and per-GDP, respectively.[4] Additionally, we disaggregate the total greenhouse gas emissions intensity in its components, by pollutant gas and polluting sector.

The data follow a structure of annual time series for the period 1970–2018, collected for all Latin American countries. The countries we consider are: Argentina (ARG), Bolivia (BOL), Brazil (BRA), Chile (CHL), Colombia (COL), Costa Rica (CRI), Cuba (CUB), Dominican Republic (DOM), Ecuador (ECU), Salvador (SLV), Guatemala (GTM), Haiti (HTI), Honduras (HND), Mexico (MEX), Nicaragua (NIC), Panama (PAN), Paraguay (PRY), Peru (PER), and Uruguay (URY).

Given that the measure of greenhouse gas emissions intensity to analyze convergence is a matter of debate, we will define greenhouse gas emissions intensity as the ratio of emissions (in tons) per-capita and per unit of GDP. In most studies, emissions per-capita are used (Huang and Meng, 2013; Persson et al., 2007; Zhuang, 2008), with this indicator providing information about household consumption. Nevertheless, the applicability of greenhouse gas emissions per-GDP has also been examined extensively (Fan et al., 2007), since it reflects the productive efficiency of a given country (the lower the ratio of greenhouse gas emissions per unit of GDP, the lower the emissions needed to produce a unit of output, and the more environmentally efficient the country is). Consequently, our study defines intensity as the ratio of greenhouse gas emissions to population and GDP, respectively.[5]

Table 2 displays the summary statistics associated with each measure of greenhouse gas emissions intensity. We observe that the mean value of greenhouse gas emissions per-capita (per GDP) is around 4.149 (0.406). The maximum and minimum values of greenhouse gas emissions per-capita (per-GDP) are approximately 12.410 and 0.757 (0.963 and 0.124), respectively. The disaggregated analysis by type of gas shows that the mean value of greenhouse gas emissions intensity is higher from CH4 and non-combustion. Furthermore, these series are also more volatile.

Table 3 displays the summary statistics associated with each measure of greenhouse gas emissions intensity for each of the 19 Latin American countries. The average for greenhouse gas emissions per-capita ranges from 1.029 (Haiti) to 10.756 (Uruguay), whereas the average for greenhouse gas emissions per-GDP ranges from 0.212 (Panama) to 0.699 (Bolivia). The standard deviation (volatility) in greenhouse gas emissions per-capita ranges from 0.132 (Colombia) to 0.964 (Chile) and the standard deviation in greenhouse gas emissions per-GDP ranges from 0.009 (Guatemala) to 0.165 (Cuba). Argentina, Colombia, Ecuador, Salvador, Haiti, and Mexico (Brazil, Dominican Republic, Ecuador, Salvador, Guatemala, Haiti, Mexico, Panama, Paraguay, and Uruguay) all exhibit negative skewness in greenhouse gas emissions per-capita (greenhouse gas emissions per-GDP). Finally, kurtosis is above 3 in Ecuador in greenhouse gas emissions per-capita, and the kurtosis of greenhouse gas emissions per-GDP is higher than 3 in Bolivia, Honduras, Mexico, and Paraguay.

To provide a visual context of the time series behavior, Fig. 1 shows the evolution of the greenhouse gas emissions intensity (per-capita and per-GDP, respectively) between 1970 and 2018. We can claim that greenhouse gas emissions per-capita have historically been higher in Uruguay and Argentina. A similar pattern emerges with respect to greenhouse gas emissions over GDP, with Bolivia, Uruguay, and Nicaragua having the highest levels per-GDP.

Alternatively, drawing from the work of Barro and Sala-i Martin (1992), Fig. 2 depicts the coefficient of variation (defined as the ratio of the standard deviation to the mean) of greenhouse gas emissions per-capita and per-GDP, respectively. According to Delagard and Vastrup (2001) and Rey and Dev (2006), sigma-convergence is measured by an index of dispersion, such as the variance or the coefficient of variation, and occurs when the measure of dispersion displays a tendency to decline through time.

The coefficient of variation in Fig. 2 shows a decreasing trend in greenhouse gas emissions per-capita, which can be interpreted as evidence in favor of sigma-convergence. Nevertheless, no decreasing trend is found in greenhouse gas emissions per-GDP, particularly since 1998, indicating no evidence of sigma-convergence and suggesting the possibility of divergence. This is an initial approach to testing convergence and in the following sections we will make a more in-depth analysis of the convergence behavior of these series, using a much more powerful econometric method.

[4] More information about this database can be found in: https://edgar.jrc.ec.europa.eu/. The choice of time span is based on data availability. Consequently, we use the time span 1970–2018 for greenhouse gas emissions per-capita and the time span 1990–2018 for greenhouse gas emissions per-GDP.

[5] It is difficult to compare total greenhouse gas emissions across countries because of variations in size and economic activity, so we instead analyze country-level emissions intensities.

Table 1
Literature review.

Author(s)	Period	Countries	Variables	Methodology	Key findings
Bilgili and Ulucak (2018)	1961–2014	G20 countries	Ecological footprint and its components	Stochastic and club convergence	No stochastic convergence, two convergence clubs
Churchill et al. (2018)	1900–2014	44 countries	CO_2 emissions per-capita	Stochastic convergence	97.73% of the sample is stochastic convergent
Liu et al. (2018)	2003–2015	285 Chinese cities	SO_2 and industrial soot emissions	Club convergence test	Four and three convergence clubs
Ulucak and Apergis (2018)	1961–2013	20 EU countries	Ecological footprint per-capita	Club convergence test	Two convergence clubs
Emir et al. (2019)	1990–2016	28 EU countries	CO_2 emissions intensity	Club convergence test	Multiple convergence clubs
Haider and Akram (2019b)	1961–2014	77 countries	Ecological and carbon footprint per-capita	Club convergence test	Two convergence clubs
Hamit-Haggar (2019)	1990–2014	Canadian provinces and territories	GHG emissions per-capita	Club convergence test	Multiple convergence clubs
Morales-Lage et al. (2019)	1971–2018	27 EU countries	Sectoral CO_2 emissions per-capita	Club convergence test	Mixed results
Solarin (2019)	1961–2013	27 OECD countries	Ecological and carbon footprint per-capita, CO_2 emissions per-capita	Stochastic convergence	Mixed results
Solarin et al. (2019)	1961–2014	92 countries	Ecological footprint and its components	Club convergence test	Multiple convergence clubs
Ozcan et al. (2019)	1961–2013	113 countries	Ecological footprint per-capita	Stochastic convergence	Stochastic convergence for all high-income countries, and for the half of the low-income and upper-middle income countries, stochastic divergence for the lower-middle income countries
Apergis and Garzón (2020)	1990–2017	Spanish regions	GHG emissions per-capita	Club convergence test	Four convergence clubs
Apergis and Payne (2020)	1971–2014	NAFTA	CO_2 emissions intensity, energy intensity, the carbonization index	Stochastic convergence, sigma-convergence, club convergence test	NAFTA has not changed the convergence behavior
Bhattacharya et al. (2020)	1990–2014	70 countries	Consumption-based and territory-based carbon emissions	Club convergence test	Two and three convergence clubs
Churchill et al. (2020)	1921–2014	17 emerging countries	CO_2 emissions per-capita	Stochastic convergence	64.71% of the sample is stochastic convergent
Ivanovski and Churchill (2020)	1990–2017	Australian regions	CO_2, CH_4, N_2O emissions per-capita	Club convergence test	Multiple convergence clubs
Solarin and Tiwari (2020)	1850–2005	32 OECD countries	Sulphur dioxide emissions	Stochastic convergence	Stochastic convergence
Ulucak et al. (2020)	1961–2014	23 Sub-Saharan African countries	Ecological footprint and its components	Club convergence test	Multiple convergence clubs
Yilanci and Pata (2020)	1961–2016	ASEAN-5	Ecological footprint per-capita	Stochastic convergence	80.77% of the sample is stochastic convergent
Akram and Ali (2021)	1980–2017	93 countries	GHG emissions of agriculture	Club convergence test	Five convergence clubs
Apaydin et al. (2021)	1980–2016	130 countries	Ecological footprint per-capita	Club convergence test	Five convergence clubs
Cialani and Mortazavi (2021)	1970–2018	28 EU countries	CO_2 emissions per-capita	Club convergence test	Five convergence clubs
Erdogan and Okumus (2021)	1961–2016	89 countries	Ecological footprint per-capita	Stochastic convergence, club convergence test	Stochastic divergence, multiple convergence clubs
Erdogan and Solarin (2021)	1960–2016	151 countries	CO_2 emissions per-capita	Stochastic convergence	Mixed results in different income levels
Haider et al. (2021)	1990–2017	172 countries	Biomass material footprint	Club convergence test	Six convergence clubs
Işık et al. (2021)	1961–2016	NAFTA/USMCA countries	Ecological footprint per-capita	Stochastic convergence	48.08% of the sample is stochastic convergent
Nazlioglu et al. (2021)	1960–2016	31 countries	CO_2 emissions per-capita	Stochastic convergence	Stochastic divergence
Payne and Apergis (2021)	1972–2014	65 developing countries	CO_2 emissions per-capita	Stochastic convergence, club convergence test	Stochastic convergence, multiple convergence clubs
Solarin et al. (2021)	1750–2019	G7 countries	NO_X emissions at the aggregate and sectoral level	Stochastic convergence	Mixed results

(*continued on next page*)

Table 1 (*continued*).

Author(s)	Period	Countries	Variables	Methodology	Key findings
Tiwari et al. (2021)	1976–2014	50 states of the US	CO2 emissions	Stochastic convergence, club convergence test	Stochastic divergence, four convergence clubs
Arogundade et al. (2022)	1990–2017	181 countries	Ecological footprint per-capita	Club convergence test	Multiple convergence clubs
Belloc and Molina (2022)	1970–2018	39 African countries	Ecological footprint per-capita	Club convergence test	Two convergence clubs
Bello et al. (2022)	1973–2018	49 African countries	Ecological footprint per-capita	Stochastic convergence	77.55% of the sample is stochastic convergent
Çelik et al. (2022)	1961–2017	ECCAS and ECOWAS countries	Ecological footprint per-capita	Stochastic convergence	Stochastic convergence
Dogah and Churchill (2022)	1960–2018	7 ASEAN member states	CO2 emissions per-capita from coal, oil, natural gas and cement production	Club convergence test	Multiple convergence clubs
Payne et al. (2022)	1990–2018	183 countries	GHG emissions per-capita	Stochastic convergence	No convergence
Solarin et al. (2022a)	1871–2014	37 countries	Methane emissions	Stochastic convergence	Most of the OECD countries fail to convergence
Solarin et al. (2022b)	1750–2019	37 OECD countries	Ammonia emissions at the aggregate level, by sector, and by fuel source	Stochastic convergence	Stochastic divergence
Yilanci et al. (2022a)	1961–2016	G7 countries	Carbon and ecological footprint per-capita	Stochastic convergence	Stochastic convergence
Yilanci et al. (2022b)	1968–2017	ECOWAS countries	Ecological footprint per-capita	Stochastic convergence	Stochastic convergence

Table 2
Summary statistics for the GHG series.

	Observations	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Panel A. GHG emissions intensity							
GHG emissions per-capita	931	4.149	2.400	0.757	12.410	1.277	4.438
GHG emissions per-GDP	551	0.406	0.156	0.124	0.963	0.838	3.569
Panel B. Gas emissions intensity							
CO2 emissions per-capita	931	1.645	1.108	0.055	4.950	0.986	3.307
CO2 emissions per-GDP	551	0.161	0.055	0.023	0.387	0.243	2.795
CH4 emissions per-capita	931	1.891	1.463	0.529	7.800	2.188	7.737
CH4 emissions per-GDP	551	0.183	0.117	0.035	0.619	1.264	4.369
N2O emissions per-capita	931	0.593	0.460	0.130	2.430	2.032	7.231
N2O emissions per-GDP	551	0.059	0.039	0.009	0.190	1.187	3.674
Panel C. Sector GHG emissions intensity							
GHG emissions per-GDP from building	551	0.023	0.011	0.006	0.065	0.772	3.408
GHG emissions per-GDP from non-combustion	551	0.256	0.152	0.054	0.789	1.152	3.859
GHG emissions per-GDP from other industrial combustion	551	0.034	0.019	0.001	0.126	1.015	5.057
GHG emissions per-GDP from power industry	551	0.037	0.027	0.000	0.139	0.989	4.008
GHG emissions per-GDP from transport	551	0.058	0.017	0.004	0.103	−0.706	4.586

4. Methodology

To examine the convergence of greenhouse gas emissions and to gain a complete view of the convergence, we use an econometric methodology developed by Phillips and Sul (2007, 2009), which allows us to test the null hypothesis of convergence for a pool of data and identify convergence club members through a clustering algorithm. In this section, we present a summary of the Phillips and Sul (2007, 2009) econometric technique.

This club convergence approach has a number of clear advantages over alternative methods used in the literature. First, the Phillips–Sul methodology identifies groups of regions converging towards the same growth path, grouping regions by unspecified factors that determine the formation of convergence clubs. This is an advantage over other methodologies, where the determination of clubs is done ex ante, based on some prior knowledge or assumptions, which greatly limit the results obtained. Second, this approach makes it possible to identify convergence clubs among regions, along with any divergent regions, although the null hypothesis of absolute convergence is rejected, by applying an iterative algorithm developed by Phillips and Sul (2007). Thus, the club convergence methodology measures a wide range of convergence possibilities: absolute convergence, relative or conditional convergence, club convergence, and divergence. These clubs are determined endogenously based on countries' transition paths using a clustering algorithm, based on the properties of the data, capturing the heterogeneity across countries within the panel. This property overcomes prior approaches of unit root and regression analysis that assume a single steady state to which all cross-sections converge, which is likely

Table 3
Summary statistics, by country.

Panel A. GHG emissions per-capita						
Latin American countries	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
ARG	8.714	0.512	7.850	9.660	−0.090	1.614
BOL	4.627	0.824	3.340	6.490	0.572	2.544
BRA	5.022	0.725	3.690	6.400	0.200	2.097
CHL	5.189	0.964	3.730	6.900	0.282	1.906
COL	3.796	0.132	3.530	4.050	−0.216	2.339
CRI	3.138	0.235	2.740	3.710	0.589	2.974
CUB	4.834	0.777	3.900	6.310	0.525	1.727
DOM	2.930	0.490	2.130	3.790	0.195	1.515
ECU	3.625	0.587	2.050	4.520	−0.788	3.373
SLV	1.719	0.261	1.250	2.190	−0.182	1.836
GTM	1.747	0.262	1.410	2.350	0.572	2.309
HTI	1.029	0.133	0.757	1.230	−0.164	1.716
HND	2.107	0.197	1.760	2.450	0.123	1.865
MEX	5.641	0.739	3.980	6.610	−0.682	2.587
NIC	2.815	0.420	2.170	3.740	0.674	2.489
PAN	3.668	0.469	2.840	4.490	0.009	1.862
PRY	5.036	0.615	4.090	6.350	0.795	2.811
PER	2.430	0.299	1.950	2.940	0.035	1.590
URY	10.756	0.822	9.160	12.410	0.092	2.037
Panel B. GHG emissions per-GDP						
Latin American countries	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
ARG	0.444	0.053	0.370	0.571	0.515	2.500
BOL	0.699	0.115	0.588	0.963	1.389	3.411
BRA	0.432	0.022	0.395	0.466	−0.344	1.686
CHL	0.325	0.046	0.261	0.435	0.474	2.267
COL	0.368	0.068	0.270	0.477	0.009	1.580
CRI	0.216	0.054	0.150	0.319	0.595	2.055
CUB	0.366	0.165	0.155	0.625	0.186	1.392
DOM	0.323	0.058	0.219	0.406	−0.359	1.715
ECU	0.415	0.038	0.343	0.496	−0.015	2.694
SLV	0.275	0.027	0.218	0.307	−0.835	2.334
GTM	0.282	0.009	0.265	0.298	−0.176	2.009
HTI	0.370	0.053	0.262	0.439	−0.439	2.081
HND	0.467	0.025	0.420	0.528	0.311	3.124
MEX	0.360	0.016	0.319	0.386	−0.960	3.373
NIC	0.620	0.066	0.504	0.744	0.011	2.202
PAN	0.212	0.043	0.124	0.266	−0.510	2.067
PRY	0.547	0.024	0.485	0.581	−0.779	3.039
PER	0.299	0.048	0.223	0.382	0.120	1.700
URY	0.693	0.116	0.492	0.851	−0.434	1.808

unrealistic.[6] Third, the pace of the convergence parameter can also be estimated. Finally, this methodology does not suffer from small-sample properties and does not depend on any assumptions concerning the stochastic non-stationarity or trend stationarity properties of the variables of interest. As detailed in Table 1, this methodology is now widely used in practice for testing emissions convergence, and we consider this econometric technique to be the most suitable for this study.

Phillips and Sul (2007) propose a new econometric approach for testing the convergence hypothesis and the identification of convergence clubs, using a non-linear time-varying factor model, providing a framework for modeling transitional dynamics as well as long-run behavior. According to this methodology, groups of countries may converge to a steady state, which is common to all the countries of the same group but differs from other groups of countries. They start from a single factor model as follows:

$$X_{it} = \delta_i \mu_t + \varepsilon_{it} \tag{1}$$

where δ_i denotes the idiosyncratic distance between the common factor μ_t and the systematic part of X_{it}, the variable of interest. Phillips and Sul (2007) extend the previous Eq. (1) by allowing the systematic part of X_{it} to evolve over time, that is δ_{it}. They also allow this term δ_{it} to have a random component that absorbs the error term ε_{it}. Thus, the new model has the following expression:

$$X_{it} = \delta_{it} \mu_t \tag{2}$$

[6] The unit root tests for convergence require a base or reference country to test for convergence. This decision is arbitrary and is likely to condition the results.

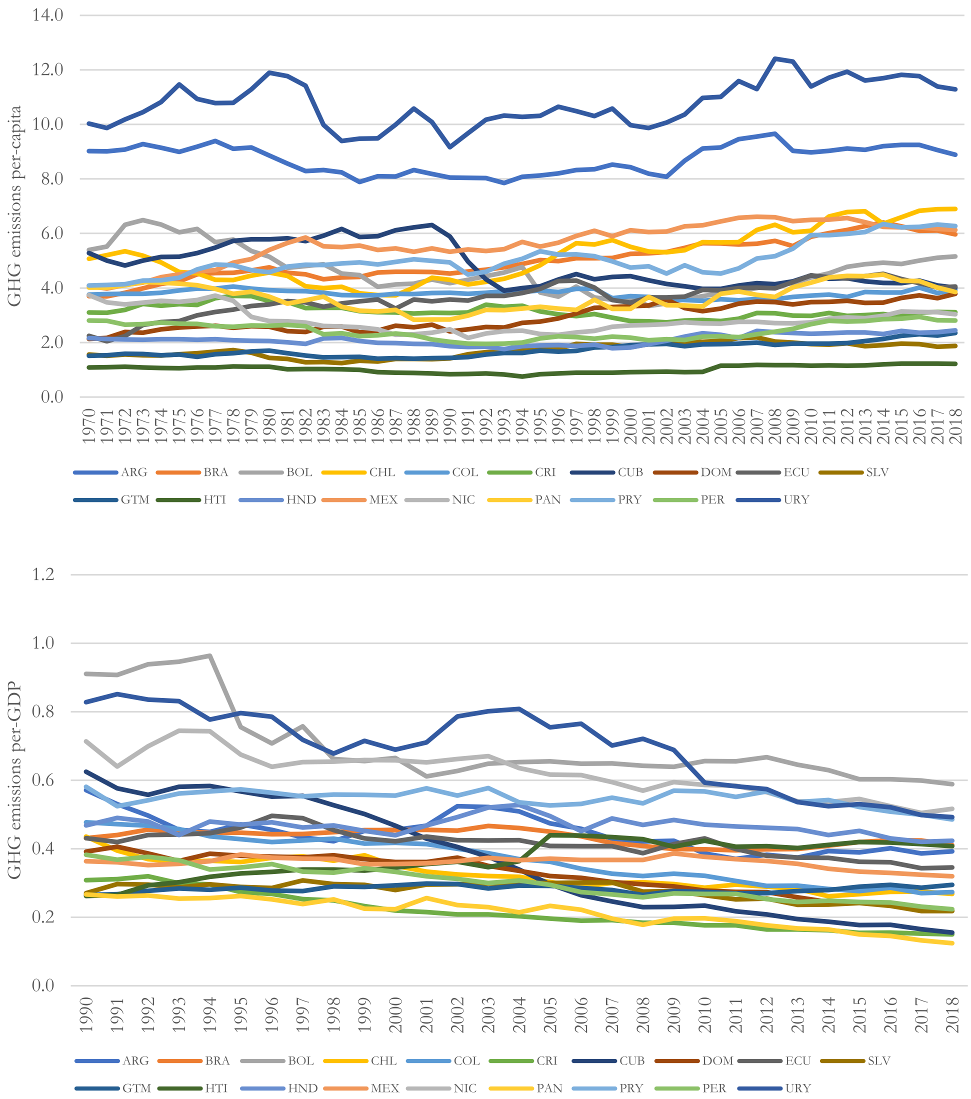

Fig. 1. Evolution of GHG emissions.

In our case, we consider X_{it} greenhouse gas emissions intensity (per-capita and per-GDP, respectively), with $i = 1, 2, \ldots, 19$ (the 19 Latin American countries considered) and t denoting the timespan. As detailed in Eq. (2), X_{it} has two components, one common, μ_t, and other idiosyncratic, δ_{it}, both of which are time-varying.

Phillips and Sul (2007) demonstrate that under this framework, testing for convergence equals to test that δ_{it} converges towards a constant δ, and they define the relative transition component, h_{it}, by eliminating the common component μ_t through rescaling by the panel average as:

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

Eq. (3) measures the transition path for greenhouse gas emissions intensity of country i relative to the panel average. It is important to note that the relative transition component h_{it} can be directly measured against δ_{it}, and the cross-sectional mean of h_{it} is unity by definition. The cross-sectional variation of h_{it} is constructed as in Eq. (4) below:

$$H_t = \frac{1}{N}\sum_{i=1}^{N} (h_{it} - 1)^2 \tag{4}$$

When convergence exists and t moves towards infinity, the dispersion H_t tends to zero. Consequently, the relative transition parameter h_{it} converges towards unity in the presence of convergence and δ_{it} moves towards δ. However, when convergence does not hold, the distance H_t remains positive as $t \to \infty$.

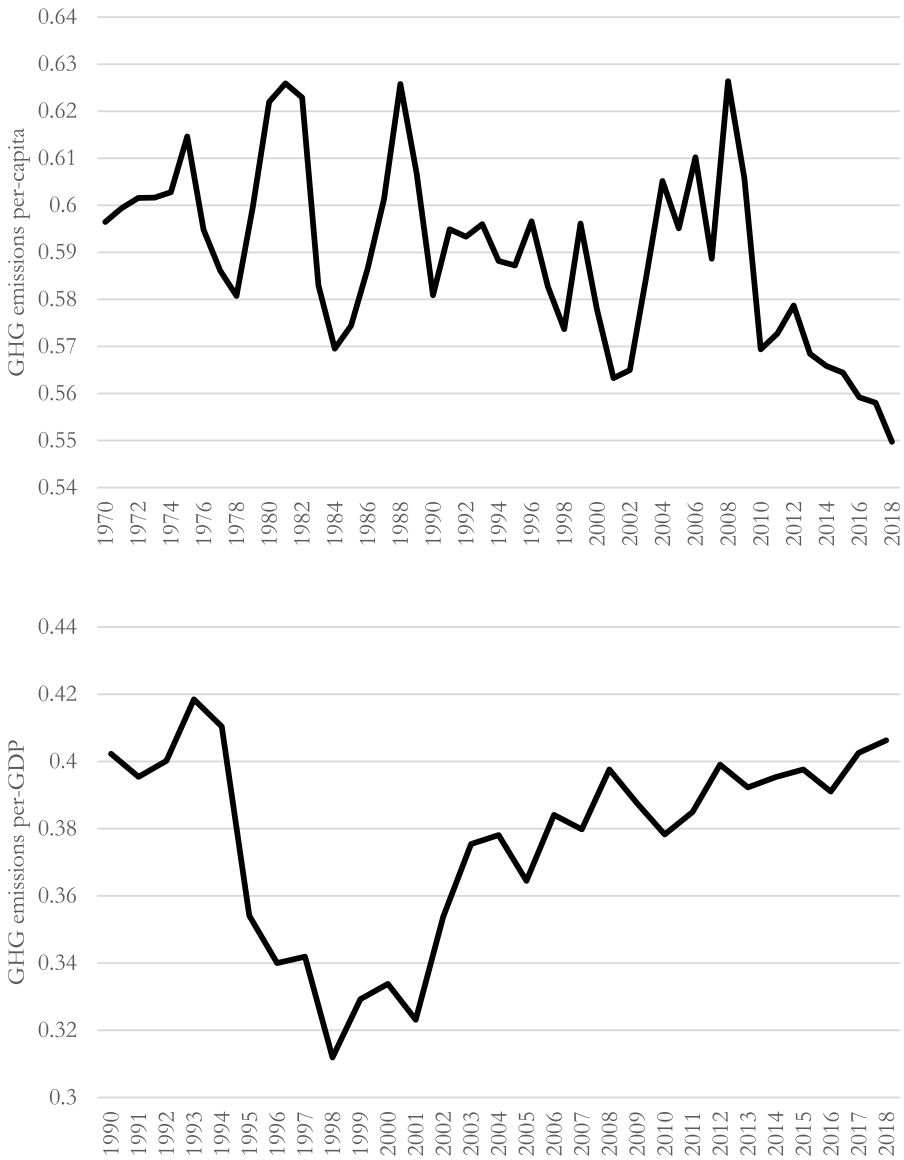

Fig. 2. Coefficient of variation GHG emissions intensity.

δ_{it} cannot be estimated due to over-parametrization problems and, in order to define an econometric test of convergence as well as an empirical algorithm for identifying the convergence clubs, the following semi-parametric specification for the time-varying coefficients δ_{it} is assumed:

$$\delta_{it} = \delta_i + \sigma_{it}\xi_{it} \tag{5}$$

where $\sigma_{it} = \frac{\sigma_i}{(L(t)t^{\alpha})}$, $\sigma_i > 0$, $t \geq 0$, and ξ_{it} is weakly dependent over t, but $iid\,(0, 1)$ over i. The size of α determines the speed of convergence and the convergence or divergent behavior of δ_{it}, and $L\,(t)$ is a gradually varying function (like $\log t$) for which $L\,(t) \to \infty$ as $t \to \infty$. Under this specification of δ_{it}, the null hypothesis of convergence for all i takes the form: $H_0 : \delta_i = \delta$, $\alpha \geq 0$, while the alternative hypothesis of the non-convergence for some i takes the form: $H_A : \delta_i \neq \delta$, $\alpha < 0$.

Phillips and Sul (2007) prove that the null hypothesis of convergence can be statistically tested estimating the following regression, commonly known as the log t regression:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log\left(\log t\right) = \hat{c} + \hat{b}logt + \hat{u}_t, \quad t = rT, rT+1, \ldots, T \tag{6}$$

The methodology tests the null hypothesis of convergence using a simple regression that includes the cross-sectional variance ratio $\frac{H_1}{H_t}$, where H_1 measures the variation at the beginning of the sample ($t = 1$), and H_t represents the variation for every point in time. Taking the log of $\frac{H_1}{H_t}$, this ratio then measures the distance of the panel from the common limit. The coefficient $\hat{b}$ provides a scaled measure of the parameter $\hat{\alpha}$ and, under the null hypothesis of convergence $\hat{b} = 2\hat{\alpha}$, where $\hat{\alpha}$ is the least square estimate of α. Thus, the null hypothesis of convergence for all i can be tested using the estimated coefficient $\hat{b}$ by a one-sided t-test of $\hat{b} \geq 0$, against $\hat{b} < 0$.

Using a heteroskedasticity and autocorrelation consistent estimator for the standard error of the residuals, the null hypothesis of convergence is rejected if the computed one-sided t-statistic for the b coefficient is lower than -1.65, as this t-statistic follows the standard normal distribution (0, 1). Note that this regression is run after discarding a fraction of the sample, r, indicating that only $(1-r)$ fraction of sample will be used for the analysis. We consider a value equal to 1/3, which is appropriate for $T \leq 50$, as suggested by Phillips and Sul (2007).

Nevertheless, rejecting the null hypothesis of convergence across the whole panel cannot rule out the existence of convergence across subgroups or clubs within the sample, and the alternative can accommodate both overall divergence and club convergence. If the convergence cannot be verified for the full sample, it should be investigated for the case of sub-groups or clubs. At this point, Phillips and Sul (2007) develop a data-based algorithm that identifies clubs based on the value of the dependent variable.

This algorithm consists of five steps. First, this algorithm sorts the N countries in descending order, according to the last observation of the time series in the panel. Second, it forms all possible core clubs C_k by selecting the first k highest countries obtained previously, for $k\,(2 \leq k \leq N)$. Then, test for convergence and repeat the log t test within each subgroup of size k to see if they can be merged in the same club. Finally, define the core club C^* of size k^* as the club with the maximum log t-statistic subject to the restriction that it is greater than -1.65 and, consequently, supports the null hypothesis of convergence. If a core group cannot be formed, then there are no convergence clubs. Third, from the remaining $N - k^*$ countries, add regions one by one to the core club C^* and run the log t test. If the test strongly supports the convergence hypothesis (the log t-statistic is greater than a chosen critical value c^*, which in practice is 0 as recommended by the authors for $T \leq 50$), include the country in the core club C^*.[7] This is accomplished by adding all countries that strongly support the convergence hypothesis, according to the log t test, and converge to the same equilibrium with C^*. These countries and the core club form the first convergence club if the log t-statistic is greater than -1.65. Otherwise, the critical value c^* is raised, so that fewer countries will be included, and the procedure of step 3 must be repeated until the log t-statistic for these countries and the core club is greater than -1.65. Fourth, for the remaining regions in the sample (if any) run the log t test to see if they are converging and form a complement club. If so, it is possible to conclude that there are two convergence clubs. If not, repeat steps 1–3 iteratively for remaining countries to determine the next convergence club. If no core club can be found, then stop the process and conclude that the remaining countries form a divergent club.

Finally, Phillips and Sul (2009) note that employing a sign criterion in step 3 and increasing the critical value c^* may lead to creating more clubs than actually exist and the last fifth step of the algorithm is club merger which consists of conducting club convergence tests for all pairs of the initial clubs, to remedy the potential overestimation problem of the algorithm. If the null hypothesis is not rejected, the corresponding clubs can be merged into a larger group. This procedure is repeated until no clubs can be merged, and we can obtain in this last step a new number of convergence clubs (strictly lower than those previously identified in step 4).

In our empirical application, this methodology will be carried out for distinct indicators of greenhouse gas emissions intensity. First, we present results for the two aggregate measures of greenhouse gas emissions intensity (per-capita and per-GDP, respectively). Next, we turn to the disaggregated analysis and run the club convergence test at two disaggregation levels for greenhouse gas emissions: air pollutants emissions (carbon dioxide, methane, and nitrous oxide) and sectoral emissions (buildings, non-combustion, other industrial combustion, transport, and power industry). In the last subsection, we present the results of an Ordered Logit Model, with the aim of identifying the main determinants behind the club convergence formation, given its ordinal nature.

5. Results

For all data, we use the Hodrick and Prescott (1997) filter to extract the long-run trend component and remove the cyclical component, as suggested by Phillips and Sul (2007). We adopt this procedure because convergence is a long-run concept and only the trend component of the series is used when applying the log t test.

5.1. Convergence of total greenhouse gas emissions intensity

We first test the full panel convergence in greenhouse gas emissions intensity, with Table 4 presenting the results. When the total sample is considered, the t-statistic for the log t test of the null hypothesis of overall convergence is -0.8085 for greenhouse gas emissions per-capita, and -148.6638 for greenhouse gas emissions per-GDP, indicating that the null hypothesis of full convergence is not rejected at the 5% level for greenhouse gas emissions per-capita, but is clearly rejected for the ratio of greenhouse gas emissions over GDP, since the tabulated value (-148.6638) is clearly smaller than

[7] c^* indicates the degree of conservativeness, and the higher the c^*, the lower the risk of including a wrong country in the club. This also increases the likelihood of finding more convergence clubs than the true number.

Fig. 3. Map of Latin America: Convergence clubs for GHG emissions per-GDP.

the critical value (−1.65) suggested by Phillips and Sul (2007). We cannot reject the null hypothesis of overall convergence for the greenhouse gas emissions per-capita, indicating the presence of a single pattern of behavior. However, in the case of greenhouse gas emissions over GDP, since we reject the null hypothesis of absolute convergence, the implication is that club convergence exists and that countries considered in the analysis do not follow the same pace of convergence in terms of greenhouse gas emissions per-GDP. This result is supported by the traditional cross-sectional approach of sigma-convergence previously discussed in Fig. 2.

Phillips and Sul (2007) argue that rejection of the null hypothesis of overall convergence does not necessarily mean there are no convergence clubs, and we can apply the cluster algorithm to identify some convergence clubs. In fact, the club convergence methodology determines clubs based on statistical methods rather than any artificial definition. We reject the null hypothesis of absolute convergence at the 5% significance level in greenhouse gas emissions per-GDP but, to identify some convergence clubs and their member countries, and the possible existence of any divergent behavior in the sample, we apply the cluster algorithm (Panel B of Table 4). The results of the club-clustering algorithm illustrate the presence of three distinct convergence clubs. Club 1 consists of Argentina, Bolivia, Brazil, Chile, Ecuador, Guatemala, Haiti, Honduras, Mexico, Nicaragua, Paraguay, and Uruguay, with the coefficient b on $\log t$ equal to 0.0813 and t-stat equal to 2.1749 (>-1.65), which fails to reject the null hypothesis of convergence. This club includes the majority of the countries in the sample. Club 2 encompasses Colombia, Dominican Republic, Salvador, and Peru, with $b = 1.0206$ and t-stat $=$ 15.4492 (>-1.65), which again fails to reject the null hypothesis of convergence. Club 3 contains Costa Rica, Cuba, and Panama, with $b = 3.9819$ and t-stat $= 14.5555$ (>-1.65), again failing to reject the null hypothesis of convergence.

Fig. 3 shows the geographical distribution of the convergence clubs on a map of the Latin American continent, showing that there is a certain degree of geographical proximity. Club 1 is mostly composed of northern (Mexico), southern (Argentina, Brazil, Bolivia, Chile, Ecuador, Paraguay, and Uruguay), and Central American countries (Guatemala, Honduras, and Nicaragua). These countries have lower environmental performances.[8] Club 2 includes countries in the south (Colombia, and Peru) and center (Salvador) of Latin America, and Club 3, the best performers in greenhouse gas emissions intensity terms, is formed by three countries in the center of Latin America (Costa Rica, Cuba, and Panama).

However, the cluster algorithm may lead to over-estimation of the true number of clubs, and Phillips and Sul (2009) propose rerunning the $\log t$ test across the sub-clubs to observe the possibility of merging clubs into larger clubs. To address this potential issue, we evaluate merging adjacent numbered clubs into larger clubs by performing club merging tests and re-using the $\log t$ test between the clubs.

[8] The cluster algorithm orders the countries in a descending order according to their final values of greenhouse gas emissions intensity. Thus, Club 1, Club 2, and Club 3 are ordered from the highest to the lowest greenhouse gas emissions intensity club.

Table 4
Convergence analysis for GHG emissions intensity.

Panel A. Overall convergence			
GHG emissions per-capita		GHG emissions per-GDP	
$\hat{b}$ coefficient	t-stat	$\hat{b}$ coefficient	t-stat
−0.0507	−0.8085	−0.7395	−148.6638*
Panel B. Convergence clubs			
Club 1 [12] ARG, BOL, BRA, CHL, ECU, GTM, HTI, HND, MEX, NIC, PRY, URY			
$\hat{b}$ coefficient		t-stat	
0.0813		2.1749	
Club 2 [4] COL, DOM, SLV, PER			
$\hat{b}$ coefficient		t-stat	
1.0206		15.4492	
Club 3 [3] CRI, CUB, PAN			
$\hat{b}$ coefficient		t-stat	
3.9819		14.5555	
Panel C. Club merging convergence analysis			
		$\hat{b}$ coefficient	t-stat
Merging Clubs 1 + 2		−0.4159	−38.3752*
Merging Clubs 2 + 3		−0.0769	−1.7622*

Notes: * denotes statistical significance at the 5% level and indicates rejection of the null hypothesis of convergence at the 5% level (if the t-statistic < -1.65). The term b coefficient stands for a parameter that is twice the rate of convergence of each club towards the panel average. The t-stat is the convergence test statistic and is a simple one-sided t-test with a critical value of -1.65. Entries in square brackets represent the number of countries in a group.

Having determined 3 convergent clubs, the club-merging statistics shown in Panel C of Table 4 also reveal the presence of 3 convergence subgroups, and the results do not support the merger of any clubs as the t-statistics are lower than the critical value in both possible cases.[9]

Consequently, when we measure greenhouse gas emissions intensity as greenhouse gas emissions per-capita, we find a single pattern of behavior of greenhouse gas emissions intensity among the Latin American countries. Nevertheless, when we measure emissions intensity as the ratio of greenhouse gas emissions over GDP, we find 3 convergence subgroups, and the speed of convergence ranges from 0.04065 (0.0813/2) to 1.99095 (3.9819/2). The club-merging algorithm results do not lead to any amalgamation of clubs and the results do not support the merger of Clubs 1 and 2, or Clubs 2 and 3, so Panel B of Table 4 shows the final club classification.

The convergence speeds α substantially differ across clubs. Countries in Club 1 converge at a rate of 4.06 per cent, whereas the convergence speed in Clubs 2 and 3 is 51.03 and 199.09 per cent, respectively.[10] The fact that the b coefficient in Club 1 is lower than the same coefficient in the rest of the clubs, but not significantly different from zero ($t > -1.65$), suggests that this is the weakest convergence club. Thus, a common policy will not yield similar outcomes in the case of greenhouse gas emissions per-GDP, unlike greenhouse gas emissions per-capita, because these ratios and these countries are not converging to a single transition path.

The evolution of the average values of greenhouse gas emissions per-GDP have been obtained for each of the estimated clubs and the results are presented in Fig. 4. According to the criteria applied by the cluster algorithm, Clubs 1, 2, and 3 are defined as the highest greenhouse gas emissions intensity club, the medium intensity club, and the lowest intensity club, respectively. Thus, more than half of the Latin American countries studied belong to the club with the greatest greenhouse gas emissions intensity. The average of Club 1 exceeds the average of Club 2 by 0.14 points at the beginning of the sample period, though this gap is increased to 0.18 points in 2018, so the distance between the emissions intensities of these two clubs has expanded over time. As can be seen, all the clubs estimated show a decreasing trend in greenhouse gas emissions per-GDP. However, the decreasing growth rate up to the end of the sample is greater for Club 3 (average growth rate of −3.555 per cent), than for Clubs 1 and 2 (−0.816 per cent and −1.716 per cent, respectively). These results are in line with the speed of convergence parameter.

9 As can be seen from Table 4, the t-statistics of the club merging tests are smaller than −1.65 and, as a result, each coefficient is statistically significant, indicating that these initial clubs fail to pass the merging test.

10 The coefficient b provides a scaled estimator of the speed of convergence parameter α, specifically $b = 2\alpha$. This coefficient reveals how fast the members of each club are converging towards the same steady-state, and the larger the b coefficient, the faster the convergence.

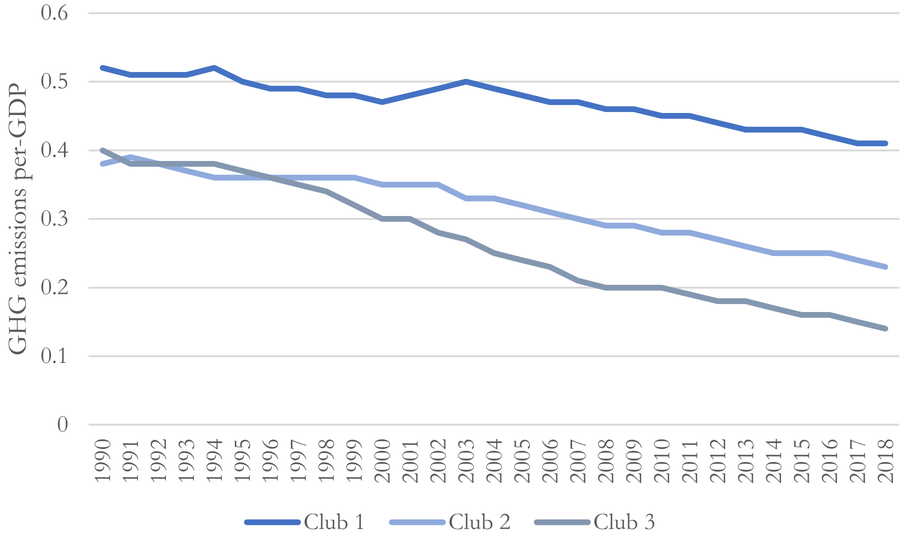

Fig. 4. Average values Clubs 1 – 3.

Following Phillips and Sul (2007, 2009), we alternatively plot the relative transition measures defined in Eq. (3), which capture the transition paths with respect to the panel average. Fig. 5 shows the relative transition paths within each club.[11] The transition paths show that clubs 2 and 3 are above one (above the cross-sectional average), whereas Club 1 displays more heterogeneous behavior, with a large number of countries below unity, except Chile and Guatemala.

To the best of our knowledge, there is no study on the convergence process of greenhouse gas emissions intensity across Latin America. Therefore, we can only compare the results of this study with prior investigations of convergence in carbon dioxide emissions or ecological footprint across Latin American countries. Our results corroborate those of Robalino-López et al. (2016), Apergis et al. (2020) and Tillaguango et al. (2021), who found evidence of club convergence in carbon dioxide emissions intensity and ecological footprint, respectively, in the Latin American context. Nevertheless, these works focus on different Latin American countries, and our study offer a more complete view of the region.

5.2. Disaggregated analysis: by type of gas and sector

As a robustness check of these results, and to gain a more complete picture of the whole region, we have applied the club convergence test for carbon dioxide gas emissions (CO2), the major component of greenhouse gases and the primary greenhouse gas responsible for global warming, and for methane (CH4) and nitrous oxide (N2O) emissions. The results are presented in Table 5. We cannot reject the null hypothesis of absolute convergence when we use CO2 emissions per-capita. Nevertheless, we find three convergence clubs and one divergent club when we measure greenhouse gas emissions intensity as the ratios between CH4 emissions and population, whereas two convergence clubs are found for N2O emissions per-capita. The first subgroup consists of Argentina, Brazil, Ecuador, Haiti, Mexico, Nicaragua, and Paraguay (Argentina, Brazil, Mexico, Nicaragua, Paraguay, and Uruguay) for CH4 emissions per-capita (N2O emissions per-capita). The second convergence club is composed of Chile, and Cuba (Bolivia, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, Salvador, Guatemala, Haiti, Honduras, Panama, and Peru). Finally, Club 3 in CH4 emissions per-capita is formed by Costa Rica, Dominican Republic, Salvador, Guatemala, Honduras, Panama, and Peru, whereas Bolivia, Colombia, and Uruguay form a diverging club.

The results for the 19 countries in CO2 emissions per-GDP are presented in the second column of Table 5. The hypothesis of overall convergence is clearly rejected. From the application of the club algorithm, we find two convergence clubs. The first consists of Argentina, Bolivia, Ecuador, Honduras, and Mexico. Club 2 has the most members, and includes Brazil, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Salvador, Guatemala, Haiti, Nicaragua, Panama, Paraguay, Peru, and Uruguay.

In the case of CH4 emissions per-GDP, the results are presented in the fourth column of Table 5. As with other gases, the null hypothesis of overall convergence is clearly rejected. Concerning club convergence, three convergence clubs are identified, along with one non-converging country. The first club – the most numerous group – corresponds to Bolivia, Brazil, Guatemala, Haiti, Honduras, Nicaragua, Paraguay, and Uruguay. Colombia, Dominican Republic, Ecuador, Salvador, Mexico and Peru form Club 2, and Club 3 contains Chile, Costa Rica, Cuba, and Panama.

[11] Under the assumption of convergence, the relative transition path should tend to unity.

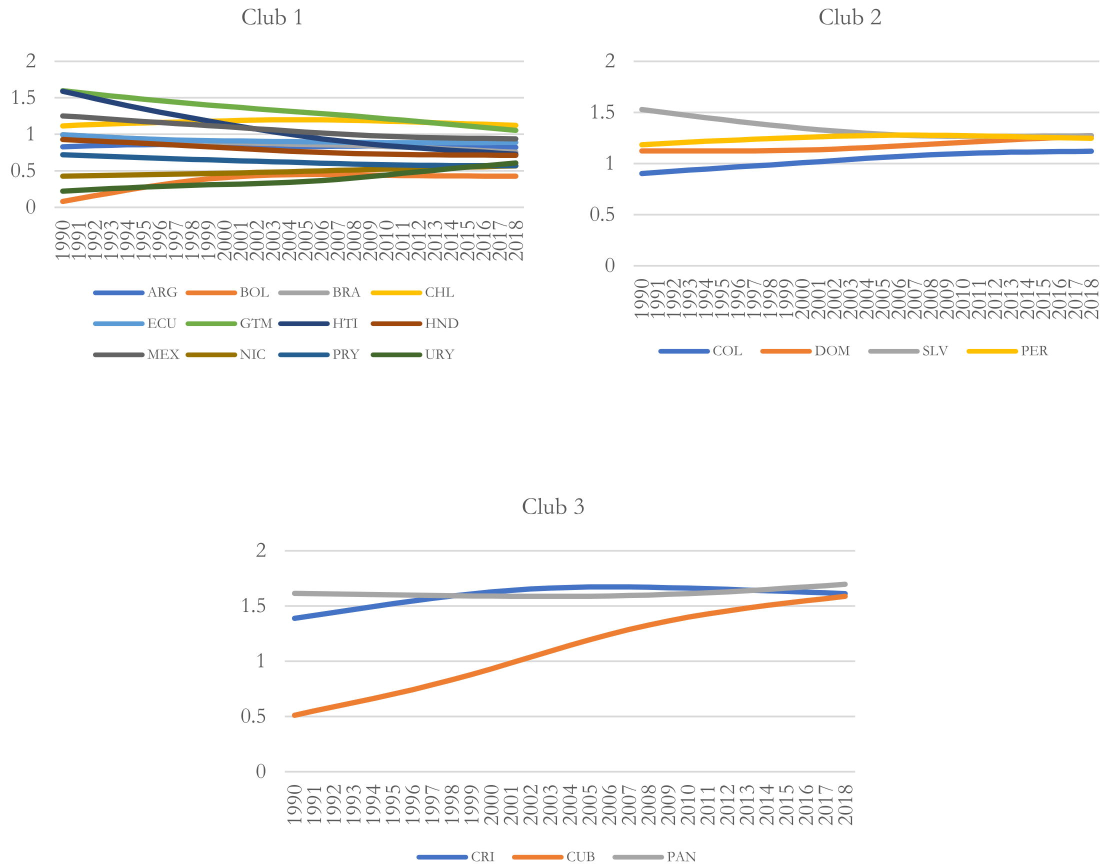

Fig. 5. Transition paths for countries within convergence clubs,1990–2018.

Column 6 of Table 5 shows the ratio between N2O emissions and GDP. After rejecting the null hypothesis of convergence, we find three convergence clubs and one non-converging country. Club 1 consists of Brazil, Mexico, Nicaragua, Paraguay, and Uruguay. The countries in Club 2 are Argentina, Bolivia, Guatemala, Haiti, and Honduras, while Club 3 includes Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, Salvador, and Peru.

Table 6 illustrates the findings of the club convergence methodology for greenhouse gas emissions per-GDP, by polluting sector. In light of the results of club convergence for aggregate greenhouse gas emissions per-GDP, we consider disaggregating total emissions into five broad compositions (buildings, non-combustion, other industrial combustion, transport, and power industry) to test for the existence of club convergence by polluting sector. We consider this to be an original contribution, since few studies have focused on emissions convergence across industrial sectors and looking at the convergence of greenhouse gas emissions by sector could provide better insight in terms of policy design.

Table 6 reveals three convergence clubs with respect to buildings and non-combustion, and two convergence clubs for transport emissions. On the other, we find evidence of one converging club and one diverging club for other industrial combustion and power industry emissions per-GDP.

Regarding building emissions per-GDP, the results suggest three convergence clubs, consisting of Club 1 (4 countries), Club 2 (5 countries), and Club 3 (9 countries). In terms of non-combustion emissions per-GDP, the results also reveal three convergence clubs: Club 1 (7 countries), Club 2 (7 countries), and Club 3 (4 countries). We find evidence of two convergence clubs for transport emissions per-GDP: Club 1 (12 countries), and Club 2 (4 countries). Finally, Table 6 shows the presence of a convergence club in other industrial combustion and power industry emissions per unit of GDP, composed in both cases of 17 countries. In other words, convergence analysis results change depending on the indicator of emissions intensity used.

5.3. Factors conditioning the formation of convergence clubs: Results from an ordered logit model

The Phillips and Sul (2007, 2009) approach clusters regions according to their transition paths, revealed through factorizing the variable of interest. At this point, we have shown that greenhouse gas emissions per-GDP are not converging to a single steady state, but there exist subgroups of countries within which greenhouse gas emissions intensity

Table 5
Convergence analysis by type of gas.

CO_2 per-capita		CO_2 per-GDP		CH_4 per-capita		CH_4 per-GDP		N_2O per-capita		N_2O per-GDP	
Overall test		Overall test		Overall test		Overall test		Overall test		Overall test	
$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat
4.2505	87.7272	−0.5458	−17.7813*	−1.0223	−29.6350*	−0.8490	−103.7886*	−0.9216	−25.6370*	−1.0207	−1,993.8805*
		Club 1 [5] ARG, BOL, ECU, HND, MEX		**Club 1 [7]** ARG, BRA, ECU, HTI, MEX, NIC, PRY		**Club 1 [8]** BOL, BRA, GTM, HTI, HND, NIC, PRY, URY		**Club 1 [6]** ARG, BRA, MEX, NIC, PRY, URY		**Club 1 [5]** BRA, MEX, NIC, PRY, URY	
		$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat
		0.1189	0.3375	−0.1298	−1.2973	0.0607	1.2750	−1.1426	−1.5896	0.1904	7.4023
		Club 2 [14] BRA, CHL, COL, CRI, CUB, DOM, SLV, GTM, HTI, NIC, PAN, PRY, PER, URY		**Club 2 [2]** CHL, CUB		**Club 2 [6]** COL, DOM, ECU, SLV, MEX, PER		**Club 2 [13]** BOL, CHL, COL, CRI, CUB, DOM, ECU, SLV, GTM, HTI, HND, PAN, PER		**Club 2 [5]** ARG, BOL, GTM, HTI, HND	
		$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat
		0.2280	4.1165	−1.3018	−1.5488	0.1999	3.1642	−0.0165	−1.0191	−0.0435	−0.6765
				Club 3 [7] CRI, DOM, SLV, GTM, HND, PAN, PER		**Club 3 [4]** CHL, CRI, CUB, PAN				**Club 3 [8]** CHL, COL, CRI, CUB, DOM, ECU, SLV, PER	
				$\hat{b}$ coef.	t-stat	$\hat{b}$ coef.	t-stat			$\hat{b}$ coef.	t-stat
				3.9432	3.6034	0.8946	4.0794			0.0335	2.1934
				Non-converging [3] BOL, COL, URY		**Non-converging [1]** ARG				**Non-converging [1]** PAN	

Notes: * denotes statistical significance at the 5% level and indicates rejection of the null hypothesis of convergence at the 5% level (if the t-statistic <-1.65). The term b coef. stands for a parameter that is twice the rate of convergence of each club towards the panel average. The t-stat is the convergence test statistic and is a simple one-sided t-test with a critical value of -1.65. Entries in square brackets represent the number of countries in a group.

tends to be converging. However, this alone does not prove the club convergence hypothesis (Azariadis and Drazen, 1990; Azariadis, 1996; Galor, 1996) and the algorithm cannot identify the possible factors that could drive the convergence clubs creation, which is particularly important for policy questions. Consequently, we follow Bartkowska and Riedl (2012), who propose a two-step procedure: the first is clustering and the second is the application of an ordinal model to identify variables that may drive club formation.

Having identified the convergence clubs, we explain the formation of clubs across Latin America, and determine whether there are statistically significant differences in the factors underlying the formation of clubs. For this purpose, we employ an ordered regression model, first introduced by McKelvey and Zavoina (1975). The variable to be explained is the club to which a country belongs, which can take on values from 1 to 3, the number of clubs that the club convergence algorithm has identified for greenhouse gas emissions per-GDP. The empirical model takes the following general form:

$$y_i^* = \alpha + X_{it}'\beta + \varepsilon_{it} \; (i = 1, 2, \ldots, 19; t = 1990, 1991, \ldots, 2018) \tag{7}$$

where the subscripts i denote the Latin American country and t denotes the time period. The dependent variable y_i^*, 'Club membership', is a latent variable that takes on ordinal values from 1 to 3, since the ordered logit model assigns each country to one convergence club. α is the constant erm, X_{it} is the set of explanatory variables, β is a vector of coefficients, and ε_{it} is the error term. According to the above results, the highest, medium, and lowest greenhouse gas emissions intensity clubs are assigned the values of 1, 2, and 3, respectively. Consequently, the higher the value of the dependent variable, the higher the environmental performance.

Many factors affect GHG emissions intensity but, drawing on the literature and based on data availability for the nineteen Latin American countries, we consider the following explanatory variables, X_{it}: GDP per-capita (constant 2015 US$) to measure the scale of economic activity, the population density to account for the degree of economic agglomeration and demographic differences, trade openness to capture trade policy and industry connectivity, natural resources rents to account for the non-renewables energy sources dependence, and the level of corruption to measure the institutional quality. All variables come from the World Bank's World Development Indicators database, except the corruption level which is collected from the V-Dem Dataset.

A summary of descriptive statistics for the variables is presented in Table 7. Due to the high dispersion of the GDP per-capita, we include this variable in the logarithm form in our model. Population density is defined as the midyear population divided by land area in square kilometers. Trade openness is constructed as the sum of imports and exports of goods and services as a percentage of GDP, whereas natural resources rents are the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents as a percentage of GDP. The measure of corruption, a continuous

Table 6
Convergence analysis by sector.

Buildings emissions per-GDP		Non-combustion emissions per-GDP		Other industrial combustion emissions per-GDP		Transport emissions per-GDP		Power industry emissions per-GDP	
Overall test		Overall test		Overall test		Overall test		Overall test	
$\hat{b}$ coefficient	t-stat	$\hat{b}$ coefficient	t-stat	$\hat{b}$ coefficient	t-stat	$\hat{b}$ coefficient	t-stat	$\hat{b}$ coefficient	t-stat
−1.7498	−26.9380*	−0.8428	−252.4618*	−0.5780	−78.6668*	−2.1613	−57.0568*	−0.8527	−8.8065*
Club 1 [4] ARG, ECU, HTI, NIC		**Club 1 [7]** BOL, BRA, HTI, HND, NIC, PRY, URY		**Club 1 [17]** ARG, BOL, BRA, CHL, COL, CUB, DOM, ECU, SLV, GTM, HTI, HND, MEX, NIC, PAN, PER, URY		**Club 1 [12]** BOL, BRA, CHL, CRI, ECU, SLV, GTM, HTI, HND, MEX, NIC, PER		**Club 1 [17]** ARG, BOL, BRA, CHL, COL, CUB, DOM, ECU, SLV, GTM, HTI, HND, MEX, NIC, PAN, PER, URY	
$\hat{b}$ coefficient	t-stat	$\hat{b}$ coefficient	t-stat	$\hat{b}$ coefficient	t-stat	$\hat{b}$ coefficient	t-stat	$\hat{b}$ coefficient	t-stat
0.0746	0.8210	0.2544	15.6869	0.2369	18.8634	−0.1243	−0.9556	0.0380	0.6146
Club 2 [5] CHL, COL, GTM, HND, URY		**Club 2 [7]** ARG, COL, DOM, ECU, SLV, GTM, MEX		**Non-converging [2]** CRI, PRY		**Club 2 [4]** ARG, COL, DOM, URY		**Non-converging [1]** CRI	
$\hat{b}$ coefficient	t-stat	$\hat{b}$ coefficient	t-stat			$\hat{b}$ coefficient	t-stat		
−0.0168	−0.1090	0.1333	3.1145			0.6176	1.4897		
Club 3 [9] BRA, CRI, CUB, DOM, SLV, MEX, PAN, PRY, PER		**Club 3 [4]** CHL, CRI, CUB, PAN				**Non-converging [3]** CUB, PAN, URY			
$\hat{b}$ coefficient	t-stat	$\hat{b}$ coefficient	t-stat						
0.1906	4.7509	1.0748	5.7210						
Non-converging [1] BOL		**Non-converging [1]** PER							

Notes: * denotes statistical significance at the 5% level and indicates rejection of the null hypothesis of convergence at the 5% level (if the t-statistic <-1.65). The term b coefficient stands for a parameter that is twice the rate of convergence of each club towards the panel average. The t-stat is the convergence test statistic and is a simple one-sided t-test with a critical value of −1.65. Entries in square brackets represent the number of countries in a group.

Table 7
Summary statistics of the ordered logit variables.

Variable	Obs.	Mean	Std. Dev.	Minimum	Maximum
Club membership	551	1.526	0.752	1	3
GDP per capita	551	5754.934	3544.999	1173.794	16,037.930
Population density	551	80.255	90.562	6.337	403.599
Trade openness	551	60.564	29.820	13.753	166.698
Natural resources rents	551	3.140	3.408	0.023	18.859
Level of corruption	551	0.554	0.259	0.031	0.938

index from 0 to 1 where higher values mean higher levels of corruption, captures to what extent political actors use political office for private or political gain.

Table 8 shows the results of the determinant analysis of the Ordered Logit Model, based on a maximum likelihood (ML) estimation method. (Collinearity analysis reveals no problems of multicollinearity, since the highest variance inflation factor (VIF) estimated was 1.89).

According to Table 8, GDP per capita, population density, trade openness, natural resources rents, and the level of corruption are all significant club membership predictors. All these variables display coefficients statistically significant at the 1% level.

The estimated coefficient of log GDP per capita is 0.569, which is significantly positively correlated at the 1% level. Regarding the effect of population density, we obtain a coefficient equal to 0.005, statistically significant at the 1% level. The estimated value for trade openness is 0.018, which is significantly positively correlated at the 1% level. All these positive coefficients show that the countries with higher GDP per-capita, population density, and openness are more likely to converge to Club 3, the lower emissions intensity club. On the other hand, the estimated coefficients for natural resources rents and level of corruption are −0.339 and −2.702, respectively, and are statistically significant at the 1% level. These last estimates imply that countries with greater natural resources rents and level of corruption tend to converge to Club 1, the least environmentally efficient club.

Table 8
Ordered Logit Model results.

Variables	Coefficients	Marginal effects		
		Club 1	Club 2	Club 3
Log of GDP per capita	0.569***	−0.097***	0.035***	0.062***
	(0.168)	(0.027)	(0.011)	(0.017)
Population density	0.005***	−0.001***	0.000***	0.001***
	(0.001)	(0.000)	(0.000)	(0.000)
Trade openness	0.018***	−0.003***	0.001***	0.002***
	(0.003)	(0.000)	(0.000)	(0.000)
Natural resources rents	−0.339***	0.057***	−0.021***	−0.037***
	(0.064)	(0.009)	(0.003)	(0.007)
Level of corruption	−2.702***	0.458***	−0.165***	−0.293***
	(0.552)	(0.086)	(0.025)	(0.065)
Observations	551			
Log Pseudo-Likelihood	−409.478			
χ^2	119.770***			
Pseudo R^2	0.183			

Note: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Table 8, we also present the associated marginal effects on the probabilities of belonging to each club of the Ordered Logit Model, in order to determine how these covariates affect the likelihood that a given country will be a member of a convergence club, and to facilitate the interpretation of our results. These effects refer to the average marginal effects and represent the instantaneous change in the probability of belonging to a particular club, given a small change in an explanatory variable (Long and Freese, 2014). According to the average marginal effects calculated, increases in GDP per capita, population density, and trade openness make memberships of Clubs 2 or 3 (Club 1) more (less) likely. By contrast, the higher the natural resources rents and the corruption level, the greater (lower) the probability of belonging to Club 1 (Clubs 2 or 3). When we focus on the magnitude of the marginal effects, the coefficients estimated for the impact of the corruption level are relatively large, suggesting that this variable is the most important factor in explaining club membership.

6. Conclusions and policy implications

This paper examines the convergence process of greenhouse gas emissions intensity across Latin American countries, identifying groups of countries converging to the same steady state without an ad-hoc grouping classification. We consider a sample of 19 Latin American countries, over the period 1970 to 2018, and not only examine convergence in greenhouse gas emissions intensity across Latin American countries, but also by gas source and polluting sector. Our paper bridges a significant gap in the literature by exploring, for the first time, club convergence in greenhouse gas emissions on the entire Latin American continent, using a highly detailed dataset.

To examine the convergence process of greenhouse gas emissions in Latin America we follow two approaches: first, we examine the sigma-convergence concept and compute the coefficient of variation. We find that the coefficient of variation of greenhouse gas emissions per-capita declined from 1970 to 2018, whereas that of greenhouse gas emissions per-GDP has not been reduced over 1990–2018. Second, we use the club convergence methodology developed by Phillips and Sul (2007, 2009), a technique that allows us to test the null hypothesis of convergence for a pool of data. Finally, we explore the club convergence results in greater detail and identify what forces may explain the formation of clubs, estimating an Ordered Logit Model.

The findings can be summarized as follows. First, results support overall convergence across all Latin American countries for greenhouse gas emissions per-capita, whereas results suggest the presence of three convergence clubs for greenhouse gas emissions per-GDP. Consequently, although Latin America as a whole is not converging to a common steady-state in greenhouse gas emissions per-GDP, we find that various subgroups of countries are converging to various steady-states. Results also indicate multiple convergence clubs by type of gas (CO2, CH4, and N2O) and polluting sector (building, non-combustion, other industrial combustion, power industry, and transport). Furthermore, our results offer important insights into the determinants of club convergence and economic, socio-demographic and institutional variables, such as GDP per-capita, population density, trade openness, natural resources rents, and corruption level are important predictors of the heterogeneities observed. Specifically, the results of the Ordered Logit Model suggest that countries with a higher income per capita, population density, and trade openness converge to the lowest greenhouse gas emissions intensity club, whereas those countries with greater dependence on natural resources and level of corruption tend to converge to the club with the highest greenhouse gas emissions intensity. In fact, the magnitude of the average marginal effects points to the importance of the corruption level in explaining the formation of clubs.

Based on the major findings of this paper, we suggest that a common environmental policy among all Latin American countries is sub-optimal, whereas club-specific emissions policies, based on the clubs detected, should be designed to reduce the rates of greenhouse gas emissions. Consequently, existing policies in Latin America need to be modified towards club-specific measures.

Our results suggest that most Latin American countries are still in the worst environmental performance club (i.e., Club 1), and, consequently, some common regulations can be very useful for these countries. From the economic perspective, price-based measures (e.g., a carbon tax to reduce CO2 emissions) or environmental laws (e.g., a subsidy or fiscal benefits at the firm level to promote cleaner production methods), should be applied, taking into account the diversity detected, in order to facilitate the achievement of environmental goals in each region. Thus, countries within each club should strive to find policy spaces for cooperation to manage agreements on taxes or environmental laws.

The estimations of the logit regressions suggest that trade openness increases the probability of belonging to the lowest greenhouse gas emissions intensity club, and openness strategies should be encouraged and continued in the region through the signing of trade agreements with both South and North economies. As is well-known, since the 1990s Latin American countries have increased their participation in external markets, and we strongly recommend maintaining this tendency from an environmental perspective, especially among the Southern Common Market (MERCOSUR) economies, all of which are included in the Club 1. Thus, this integration should go even deeper, with a more comprehensive range of agreements that specifically pursue the reduction of greenhouse gas emissions.

Latin American countries should also increase the diversification in the use of renewable energy sources (such as wind, solar, biomass). Appropriate education policies in schools, as well as public campaigns to show the consequences of current behaviors, should change the consumption patterns of the inhabitants towards sustainable sources. Finally, the findings of our ordinal model reveal that countries with lower corruption levels have lower levels of greenhouse gas emissions intensity and it would be beneficial to enhance the institutional quality in these other countries to reduce the environmental pressure, implementing an effective approach against corruption.

One limitation of this study is that our results do not offer evidence of causality, a question that is left for future research as a complement to the current analysis. Other possible and promising extensions are to look at the source and distribution of emissions within a country. Finally, constrained by data availability, we test club convergence in greenhouse gas emissions until 2018 and adding more recent data would help to better understand trends in greenhouse gas emissions intensity and evaluate the impact of the COVID-19 pandemic.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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