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# Are greenhouse gas emissions converging in Latin America?<sup>1</sup>

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## Abstract

This paper investigates greenhouse gas emissions convergence among twenty Latin American countries, for the period 1970 to 2015. 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 state 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 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 economic structure, the unemployment rate, population density, and per-capita income play a crucial role in determining the formation of convergence clubs.

*Keywords:* Greenhouse gas emissions, Convergence analysis, global climate policy, Latin America.

*JEL codes:* Q50, Q01, O54

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# 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 impact of emissions. The issues of fairness and equity in the allocation schemes for emissions are hotly debated, and many developing countries, with lower per-capita emissions, expect developed countries, with higher per-capita emissions, to reduce their outputs. Several authors have pointed out that if emissions were to converge over time, there would be less concern regarding any per-capita emissions 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).

The analysis of the dynamics of greenhouse gas emissions is important for policymakers in order to evaluate environmental impacts, and design efficient proposals to combat climate change. Thus, any group of countries that follows similar steady-state equilibrium can adopt common environmental policies to jointly cope with environmental deterioration.

In this paper, we specifically evaluate whether Latin American countries' greenhouse gas emissions are converging to similar, or different, steady states (Barro and Sala-i-Martin, 1992). Thus, we bridge an important gap, given that the convergence of pollution from greenhouse gases has attracted considerable attention in the developed world, but, to the best of our knowledge, has not previously been analyzed in Latin America. It is important to note that several studies have examined the convergence of carbon dioxide emissions, but no consensus has emerged on the relationship between economic development and pollution (Acar et al., 2018),

Our specific aim is to investigate and test whether convergence in greenhouse gas emissions has occurred among a panel of Latin American countries, using recent datasets and the club-convergence technique. To that end, we use the Phillips-Sul (PS) methodology (Phillips and Sul, 2007, 2009) to provide the first empirical evidence of the regional convergence process in emissions in Latin America. In addition, we consider the disaggregation of the phenomenon by polluting sector and by type of gas. More specifically, we analyze whether Latin America displays a full convergence process among the various countries, or if those countries form convergence clubs.

We analyze the process of regional convergence in emissions for twenty Latin American countries, over the period 1970-2015. Rather than simply describing any observed

convergence clubs, we carry out a deeper analysis of the factors underlying the formation of such clubs. For this purpose, we employ an ordered regression model to analyze the relative importance of different emissions determinants and to test whether the probability of belonging to a given club is determined by regional characteristics, such as population density, economic structure, unemployment rate, or per-capita income.

The convergence approach used in this paper has clear advantages over alternative methods (González et al., 2017). First, we can identify groups of regions converging towards the same growth path through 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*, which greatly limits the results obtained. Second, the 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-Sul (2007).<sup>2</sup> Third, the pace of the convergence parameter can also be estimated, which allows us to empirically discriminate between relative and absolute convergence. The methodology does not depend on particular assumptions concerning trend stationarity or stochastic non-stationarity of the variables. Therefore, we use a suitable framework for analyzing convergence and, in this context, we focus on the process of convergence in terms of greenhouse gas emissions intensity in the Latin American region.

The rest of the paper is organized as follows. To provide context, the next section summarizes and gives an overview of the related literature on national and regional convergence, and we perform a brief analysis of the existing empirical evidence. Section 3 describes the data and contains an analysis of the variables exploited in this study. The methodology adopted is presented in Section 4, and Section 5 contains the main empirical results for the log  $t$  tests and the ordered logit model. We conclude the paper in Section 6 with final comments and a summary of our main findings from the empirical application, drawing some policy implications of this research.

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<sup>2</sup> Convergence clubs can be identified within the panels under study by using a clustering algorithm developed by Phillips and Sul (2007).

## 2. Literature

Convergence is an issue widely discussed 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 literature on economic growth, and refers to a decrease in differences in economic growth across regions or countries over time.<sup>3</sup> Convergence occurs when a negative correlation is observed between the average growth rate and initial income (i. e., a negative relation between the growth rate of the variable of interest and its initial level). However, convergence is an imprecise concept and is not restricted to the economic growth literature alone, since it has been applied to other fields, including energy economics.<sup>4</sup> 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-shape relationship between carbon dioxide emissions and income, also known as the Environmental Kuznets Curve (EKC), but the EKC alone cannot explain whether or not cross-country emissions converge to a steady state. Cross-sectional, time series, and panel studies have all been used to examine convergence using a range of concepts. 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 mean (or relative to another of the sample) are temporary, implying that the logged relative emissions series is 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-Avila (2008), Westerlund and Basher (2008), and Christidou et al. (2013) find support for stochastic convergence of emissions. Barassi et al. (2008) and Barros et al. (2016) find no support for the stochastic convergence of emissions. The procedure testing for stochastic convergence using unit root tests is not flawless and, as Bulte et al. (2007) point out, ADF-type tests that

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<sup>3</sup> 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, and the economic growth of each region will then be maintained at a steady state (Li and Lin, 2013).

<sup>4</sup> The issue of convergence has recently attracted attention in the energy and environmental literature. See Pettersson et al. (2014), Acar et al. (2018) and Payne (2020) for surveys of the literature on emissions convergence and a much more detailed review.

do not allow for structural breaks could lead to a bias against rejecting a false unit root null hypothesis. Several authors have recommended allowing for exogenous or endogenous structural breaks and studies that allow for structural breaks are likely to be more reliable than those that do not.<sup>5</sup>

List (1999), one of the first to apply the concepts of cross-convergence,  $\beta$ -convergence, and stochastic convergence in greenhouse gas emissions, finds convergence in emissions of nitrogen oxides and sulfur dioxide across US regions, from 1929 to 1994. Wang and Zhang (2014), using panel unit root tests, analyze differences in per-capita carbon dioxide emissions from 1996 to 2010 in China, finding evidence of sigma-convergence in all sectors, beta-convergence in the farming, forestry, animal husbandry, fishery and water conservancy, and construction sectors, and stochastic convergence in all sectors.

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) introduced cross-sectional and time series heterogeneity within the parameters of a neoclassical growth model. This convergence approach has certain advantages and has given rise to a substantial literature.

At this point, Panapoulou and Pantelidis (2009) were the first to apply the PS 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 of 1995-2011, and Zang and Broadstock (2016) use the club convergence approach to study energy intensity in China. Their findings indicate the existence of three clubs of regions that differ significantly from one another. Burnett (2016) and Apergis and Payne (2017) provide substantial evidence for CO<sub>2</sub> emissions convergence across all fifty US states. More recently, Haider and Akram (2019) exploit data on per-capita CO<sub>2</sub> emissions for 53 countries over the period 1980-2016, although their results do not support the null hypothesis of absolute convergence and support the evidence of two club convergence of total emissions and

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<sup>5</sup> According to Perron (1989), failure to allow for structural breaks in the variables may lead to wrong conclusions regarding the order of integration of the variable and, as is well-known in the unit root literature, ignoring a structural break in the data may lead the test statistic to be biased toward non-rejection of a false unit root hypothesis. A unit root with structural breaks can reduce the possibility of falsely accepting a unit root in the series tested and, as Montañés et al. (2005) demonstrate, the omission of a break causes significant distortions in unit root tests, potentially leading to mistaken inferences.

emissions from gas and petroleum consumption, while three clubs are found in the case of per-capita carbon dioxide emissions from coal.

### 3. Data

The regional convergence process is analyzed considering the greenhouse gas emissions for 20 Latin American countries in the period 1970-2015.<sup>6</sup> The data that we use to test convergence in this context are taken from the Emissions Database for Global Atmospheric Research (EDGAR), measured in annual tons per-capita and per-GDP, respectively.<sup>7</sup> To normalize the data, the study uses the natural log of per-capita/per unit of GDP greenhouse gas emissions.<sup>8</sup> Additionally, we obtain information and disaggregate the total greenhouse gas emissions intensity, in its components, by fuel source and polluting sector.

These data follow a structure of annual time series for the period 1970-2015, collected for all Latin American countries. The countries we consider are: Argentina (ARG), Brazil (BRA), Bolivia (BOL), 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), Uruguay (URY), and Venezuela (VEN).

Since our objective is to describe the long-run evolution of the time series and isolate dynamics at all other frequencies, we present empirical results from  $\log(t)$  regressions performed on time series, filtered for business cycle fluctuations, using the Hodrick and Prescott (1997) filter, as suggested by Phillips and Sul (2007). The Hodrick-Prescott filter is used to separate the time series into trend and cyclical components (Hodrick and Prescott, 1997) and the smoothing parameter (or the truncation parameter) is chosen following Ravn and Uhlig (2002), who recommend using a value of the smoothing parameter equal to 6.25 for annual data, which is close to the value found in Baxter and King (1999).<sup>9</sup> This filtering technique is well-suited for extracting long-run trends from the data, hence eliminating short-

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<sup>6</sup> In this study, the start and end points were chosen according to the available data. Consequently, we use the time span 1970-2015 for greenhouse gas emissions per-capita and the time span 1990-2015 for greenhouse gas emissions per GDP.

<sup>7</sup> More information about this database can be found in: <https://edgar.jrc.ec.europa.eu/>.

<sup>8</sup> In time series analysis, this transformation is often considered to stabilize the variance of a series.

<sup>9</sup> The smoothing parameter penalizes the acceleration in the trend relative to the business cycle component. Note that the PS methodology is used only on the trend of the variables, thus the Hodrick-Prescott filter is applied to the natural log of the greenhouse gas emissions intensity.

run erratic behavior. We adopt this procedure because convergence is a long-run concept and only the trend component is used when applying the log  $t$  test.

Given that the measure of greenhouse gas emissions intensity needed to analyze convergence is a matter of debate, we will define greenhouse gas emissions intensity as the ratio of emissions (in tons) per unit of GDP value and per capita. In most studies, per-capita emissions are used (Huang and Meng, 2013; Persson et al., 2007; Zhuang, 2008). Nevertheless, the applicability of per GDP in greenhouse gas emissions has also been examined extensively (Fan et al., 2007), since it reflects the productive efficiency of a country (the lower the greenhouse gas emissions per unit of GDP, the more environmentally efficient the country). Consequently, our study defines intensity as the ratio of greenhouse gas emissions to population and GDP, respectively.<sup>10</sup> We use the STATA software for the empirical analysis.<sup>11</sup>

Table 1 displays the summary statistics associated with each measure of greenhouse gas emissions. We observe that the mean value of greenhouse gas emissions per-capita (per GDP) is around 4.347 (0.424). The maximum and minimum values of greenhouse gas emissions intensity are approximately 12.460 and 0.784 (1.030 and 0.147), respectively. The disaggregated analysis by type of gas shows that the mean value of greenhouse gas emissions intensity is higher from CH<sub>4</sub> and non-combustion. Furthermore, these series are also more volatile.

[Insert Table 1 about here]

Table 2 displays the summary statistics associated with per-capita greenhouse gas emissions for each of the 20 Latin American countries. The average ranges from 1.047 (Haiti) to 10.758 (Uruguay), whereas the average per GDP ranges from 0.214 (Costa Rica) to 0.782 (Uruguay). The standard deviation or volatility in per-capita greenhouse gas emissions ranges from 0.136 (Haiti) to 1.151 (Chile) and the standard deviation in per GDP greenhouse gas emissions ranges from 0.011 (Guatemala) to 0.124 (Haiti). Ecuador, Salvador, Honduras, and Mexico (Brazil, Colombia, Cuba, Dominican Republic, Salvador, Haiti, Mexico, Panama, Paraguay, and Uruguay) all exhibit negative skewness in per-capita greenhouse gas emissions (greenhouse gas emissions per GDP). Finally, kurtosis is above 3 in Ecuador, Paraguay, and

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<sup>10</sup> 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 emission intensities. Emission intensity normalizes emissions across countries to offer a more compatible apples-to-apples comparison (Zhao et al., 2015).

<sup>11</sup> To perform the log  $t$  test we use the routine *logtreg* developed for Stata users (Du, 2017).



Venezuela in per-capita greenhouse gas emissions, and the kurtosis of greenhouse gas emissions per GDP is higher than 3 in Bolivia, Mexico, and Venezuela.

[Insert Table 2 about here]

To provide a visual context of the time series behavior, Figure 1 shows the evolution of the greenhouse gas emissions intensity (per-capita and per GDP, respectively) between 1970 and 2015. We can claim that greenhouse gas emissions per-capita has historically been higher in Uruguay, Argentina, and Venezuela. A similar pattern emerges with respect to greenhouse gas emissions over GDP, with Uruguay, Bolivia, Haiti, and Nicaragua having the highest levels per GDP.

[Insert Figure 1 about here]

Alternatively, drawing from the work of Barro and Sala-i-Martin, Figure 2 depicts the standard deviation of per-capita and per unit of GDP greenhouse emissions, 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 its square root. This is an initial approach to testing convergence and if the standard deviation decreases over time, it can be interpreted as evidence of sigma-convergence. The cross-sectional standard deviation is calculated according to the following expression:

$$S = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (Y_{it} - \bar{Y}_t)^2} \quad (1)$$

where  $Y_{it}$  denotes the greenhouse gas emissions intensity of country “i” at time “t” and  $\bar{Y}_t$  is its mean for each year “t”. As a consequence, we have a series that computes the standard deviation of greenhouse gas emissions intensity for all countries in each year. Results are displayed in Figure 2.

[Insert Figure 2 about here]

In both cases, the dispersion at the end of the period is much lower than that observed at the beginning, which can be interpreted as evidence in favour of  $\sigma$ -convergence. From 1970 to 2015 (1990 to 2015) the cross-sectional standard deviation of per-capita greenhouse gas emissions (per GDP) decreases, indicating smaller variability and supporting sigma convergence. Furthermore, the coefficient of variation in Fig. 3 also shows a decreasing trend

in per-capita emissions, indicating convergence.<sup>12</sup> Nevertheless, no decreasing trend is found in greenhouse gas emissions per GDP, indicating no evidence of sigma-convergence.

[Insert Figure 3 about here]

## 4. Methodology

Since we are interested in analysing whether the convergence process of our set of countries is homogeneous and whether the countries form convergence subgroups, we will use an econometric analysis based on a convergence test developed by Phillips and Sul (2007, 2009), and in a subsequent analysis, we will explain why this convergence does or does not exist. All econometric analyses are conducted using log of per-capita/per GDP greenhouse gas emissions and, as is standard in the economic literature, we refer to convergence as a process in which several countries or regions tend towards equalisation of some indicator, such as per-capita income, development, health, or greenhouse gas emissions, as in our case.

Phillips and Sul (2007) propose a new econometric approach for testing the convergence hypothesis and the identification of convergence clubs, using a nonlinear time-varying factor model and providing the 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.

Phillips and Sul (2007) constructed an algorithm to identify clusters of convergence subgroups, a data-driven methodology that avoids a priori sample separation and can be used as a general panel to cluster individuals into groups with similar transition paths.

The methodology tests the null hypothesis of convergence using a simple regression that includes a ratio of cross-sectional variance  $H_1/H_t$ , 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  $H_1/H_t$ , this ratio then measures the distance of the panel from the common limit. Using the heteroskedasticity and autocorrelation consistent with HAC standard error methods, the null hypothesis of convergence is rejected if the computed one-sided  $t$ -test, robust to heteroskedasticity and autocorrelation, is  $< -1.65$  at the 5% significance level. This

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<sup>12</sup> We define the Coefficient of Variation (CV) as  $CV = \frac{\sigma}{\mu}$ , where  $\sigma$  is the cross-country standard deviation of greenhouse gas emissions intensity and  $\mu$  is the cross-country average of the same variable.

ensures that the  $t$ -ratio converges towards a standard  $N(0,1)$  distribution and, therefore, we will reject the null hypothesis of convergence whenever this  $t$ -statistic takes values lower than  $-1.65$ .<sup>13</sup>

We consider  $X_{it}$  the variable of interest, greenhouse gas emissions intensity (emissions per-capita and per GDP, respectively), with  $i = 1, 2, \dots, 20$  (the 20 Latin American countries considered in this study) and  $t$  denoting the time-span. We can break this variable down into a product of two components, as  $X_{it} = \delta_{it}\mu_t$ , where  $\mu_t$  is the common component (i.e. a common trend in greenhouse gas emissions intensity) and  $\delta_{it}$  is the idiosyncratic component measuring the distance between some component factor  $\delta_{it}$  and the systematic part of  $X_{it}$ , capturing time as well as individual specific effects, and hence the deviation of country  $i$  from the common path defined by  $\mu_t$ .<sup>14</sup> If  $\delta_{it}$  converges towards to  $\delta$ , there is evidence in favour of the hypothesis of convergence. Since we cannot estimate  $\delta_{it}$  directly, due to over-parameterization because the number of parameters exceeds the number of observations, the common component is eliminated through rescaling by the panel average and defining the relative transition component as:

$$h_{it} = \frac{X_{it}}{N^{-1} \sum_{i=1}^N X_{it}} = \frac{\delta_{it}}{N^{-1} \sum_{i=1}^N \delta_{it}} \quad (2)$$

Eq. (2) measures the transition path for greenhouse gas emissions intensity relative to the panel average. The cross-sectional variation ratio  $H_1/H_t$  is constructed as in Eq. (3) below:

$$H_t = \frac{1}{N} \sum_{i=1}^N (h_{it} - 1)^2 \quad (3)$$

Notably,  $H_t$  (i.e., the cross-sectional variation) tends to zero when long-term convergence exists and  $T$ , the sample size, moves toward infinity. Consequently,  $h_{it}$  should converge towards unity in the presence of convergence. However, when convergence does not hold, the distance remains positive as  $T \rightarrow \infty$ . Then, the null hypothesis of convergence (and non-convergence) can be statistically tested using the log  $t$  regression:

$$\log(H_1/H_t) - 2 \log L(t) = c + b \log t + u_t, \quad t = T_0, \dots, T \quad (4)$$

This null hypothesis defines relative/conditional convergence and is analogous with the conditional sigma convergence for the case of panel data (Phillips and Sul, 2007). This null

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<sup>13</sup> The one-sided  $t$ -test is called the log  $t$  test due to the presence of the log  $t$  regressor in the equation.

<sup>14</sup> Note that  $\delta_{it}$  is a random component, which absorbs the error term as a result.

hypothesis of convergence is rejected whenever parameter  $b$  in Eq. (4) is statistically lower than 0. Following Phillips and Sul (2007, 2009) we set  $L(t) = \log t$ .

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. If the convergence cannot be verified for the full sample, it should be investigated for the case of sub-groups or clubs. Phillips and Sul (2007) develop a data-based algorithm that identifies clubs based on the value of the dependent variable. First, this algorithm sorts the countries in descending order, according to their final values in the panel, and identifies whether countries can form a club based on the corresponding  $\log t$  test. Second, it forms all possible core clubs  $C_k$  by selecting the first  $k$  highest countries, with  $k = 2, 3 \dots N$ . The  $\log t$  test is repeated within each subgroup of size  $k$  to test if they can be merged in a same club. More precisely, this is accomplished by adding regions one by one to the group of the two highest emissions intensity regions at the beginning and running the  $\log t$  test until the  $\log t$  test for this group is larger than -1.65 and the null hypothesis of convergence cannot be rejected. Next, the  $\log t$  test is repeated for this group and all the units (one by one) remaining in the sample, to check whether they converge. If no clubs can be found and the last group does not have a convergence pattern, then we will conclude that the members are diverging.

## 5. Results

We have separately applied the PS procedure to greenhouse gas emissions intensity (emissions per-capita, and per unit of GDP, respectively) and analyzed its decomposition by sector and gas type.

An ordered logistic regression has been estimated to predict how the economic characteristics affect the likelihood that any given country will be a member of any convergence club.<sup>15</sup> Many studies have examined convergence in emissions, but relatively little is known about the factors driving the formation of clubs.

### 1.1. Convergence of total emissions intensity

We first test the full panel convergence in greenhouse gas emissions intensity, with Table 3 presenting the results. When the total sample is considered, the  $t$  value for  $\log t$  test of the null hypothesis of overall emissions convergence is -0.5896 and -19.4160 for the greenhouse

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<sup>15</sup> We have repeated this estimation using an ordered probit estimator. Nonetheless, we only present the results using the ordered logit method since its explanatory power is greater. These results are available upon request.

gases emissions per-capita and per GDP, respectively, indicating that the null hypothesis of full convergence in greenhouse gas emissions per-capita is not rejected at the 5% level, but is clearly rejected when we measure that intensity as the ratio of greenhouse gas emissions over GDP, since the tabulated value (-19.4160) is much smaller than the critical value (-1.65) suggested by Phillips and Sul (2007).<sup>16</sup> We cannot reject the null hypothesis of full convergence for the emissions per-capita, indicating the presence of a single convergent club. 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 emissions per unit of GDP. This result is also supported by Figures 2 and 3, showing that the cross-sectional dispersion does not tend towards 0 in the case of emissions per GDP, and offering additional evidence of the absence of sigma-convergence.

Phillips and Sul (2007) argue that rejection of the null hypothesis of full convergence does not necessarily mean that there are no convergence clubs and we can apply the cluster algorithm in order to identify some convergence clubs. In fact, the PS 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 emissions per GDP but, in order to identify some convergence clubs and their member countries, and the existence of any divergent behavior of any countries in the sample, we apply the cluster algorithm (Panel B of Table 3). The results of the club-clustering algorithm illustrate the presence of three distinct clubs and one non-converging country. Club 1 consists of Bolivia, Haiti, Nicaragua, Paraguay, and Uruguay, with the coefficient  $b$  on  $\log t$  equal to 0.0814 and  $t$ -stat equal to 0.5302 ( $> -1.65$ ), which fails to reject the null hypothesis of convergence. Club 2 encompasses Brazil, Ecuador, Honduras, Mexico, and Venezuela, with  $b=0.2194$  and  $t$ -stat= $1.3286$  ( $> -1.65$ ), which again fails to reject the null hypothesis of convergence. Club 2 experiences the fastest convergence speed. Club 3 contains Argentina, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Guatemala, Peru, and Salvador, with  $b=0.0293$  and  $t$ -stat= $0.3919$  ( $> -1.65$ ), again failing to reject the null hypothesis of convergence, and the one with the slowest speed of convergence.<sup>17</sup> Figure 4 represents the geographical distribution of the convergence clubs in a map of the Latin American continent.

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<sup>16</sup> We should note that the available data is clearly smaller for this definition of greenhouse gas emissions intensity, since it covers the period from 1990 to 2015.

<sup>17</sup> The coefficient  $b$  provides a scaled estimator of the speed of convergence parameter  $\alpha$ , 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. See Appendix B, Phillips and Sul (2007).

[Insert Table 3 and Figure 4 about here]

However, as Phillips and Sul (2009) noted, the cluster algorithm may lead to over-estimation of the true number of clubs. Phillips and Sul (2009) propose to rerun 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 to measure whether there is evidence in support of merging clubs into larger clubs, or between clubs.<sup>18</sup>

Having determined 3 convergent clubs, the club-merging statistics shown in Panel C of Table 3 also reveal the presence of 3 convergence subgroups, and the results do not support the merger of any clubs. Consequently, when we measure emissions intensity as greenhouse gas emissions per-capita, we find the existence of a single pattern of behavior of greenhouse 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 0.01465 (0.0293/2) to 0.1097 (0.2194/2). 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, Clubs 2 and 3, or Club 3 and PAN (i.e., the divergent country), so Panel B of Table 3 shows the final club classification and per GDP greenhouse gas emissions across 20 countries in Latin America, converged to three clubs whose  $t$  statistics are significantly greater than -1.65. Panama forms a divergent group and does not converge to any of the above clubs since it is converging to a particular transition path. The  $b$  values for Clubs 1, 2, and 3 are neither negative nor greater than 2, in absolute terms, indicating that the members of these clubs neither diverge nor converge to the same level, but converge conditionally and diverge with respect to their own emissions levels. The convergence speeds  $\alpha$  substantially differ across clubs. Countries in Club 1 converge at a rate of 4.07 per cent, whereas the convergence speed in Clubs 2 and 3 is 10.97 and 1.46 per cent, respectively. The fact that the  $b$  coefficient in Club 3 is lower than the coefficient in the rest of the clubs, but not significantly different from zero ( $t > -1.65$ ), suggests that this is the weakest convergence club. Therefore, a common policy will not yield similar outcomes in the case of greenhouse gas emissions per GDP, unlike greenhouse emissions per-capita, because these ratios and these groups are not converging to a single transition path.

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<sup>18</sup> As can be seen from Table 3, 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.

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 Figure 5. Clubs 1 and 2 exhibit the highest values of the ratio at the end of the sample. The average of Club 1 exceeds the average of Club 2 by 0.22 points at the beginning of the sample period, though this gap is reduced to 0.19 points in 2015, so the final distance between the emissions intensities of these two clubs has been reduced. Consequently, the average greenhouse gas emissions per GDP of the countries in Club 1 are always greater than those of Club 2. 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 -1.85 per cent), than for Clubs 1 and 2 (-0.545 per cent and -0.536 per cent, respectively). As can be seen from Table 4, for the three convergence clubs, the mean values of per GDP emissions vary; Club 1 has the highest mean value of 0.651, Club 2 has the medium mean value of 0.436, and Club 3 has the lowest mean value of 0.314. Therefore, Clubs 1, 2, and 3 are defined as the highest emissions intensity club, the medium intensity club, and the lowest club, respectively.

[Insert Figure 5 and Table 4 about here]

## 1.2. 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 algorithm for carbon dioxide gas emissions (CO<sub>2</sub>), the major component of greenhouse gases, and for methane (CH<sub>4</sub>) and nitrous oxide (N<sub>2</sub>O) emissions. The results are presented in Table 5. We cannot reject the null hypothesis of absolute convergence when we use per-capita CO<sub>2</sub> emissions. Nevertheless, we find two convergence clubs when we measure greenhouse gas emissions intensity as the ratios between CH<sub>4</sub> emissions or N<sub>2</sub>O emissions and population, respectively. The first subgroup consists of Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guatemala, Haiti, Nicaragua, Paraguay and Venezuela (Argentina, Brazil, Mexico, Paraguay and Uruguay) for CH<sub>4</sub> emissions per-capita (N<sub>2</sub>O emissions per-capita). The second convergence club is composed of Costa Rica, Cuba, Dominican Republic, Honduras, Mexico, Panama, Peru and Salvador (Bolivia, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, Guatemala, Honduras, Haiti, Nicaragua, Panama, Peru, Salvador and Venezuela).

The results for the 20 countries in CO<sub>2</sub> 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 three convergence clubs. The first consists of

Bolivia, Ecuador, and Venezuela. Club 2 is the largest, and includes Argentina, Brazil, Chile, Dominican Republic, Salvador, Guatemala, Haiti, Honduras, Mexico, Nicaragua, and Peru. Club 3 includes Colombia, Costa Rica, Cuba, Panama, Paraguay, and Uruguay.

In the case of CH<sub>4</sub> 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, four clubs are identified, along with three non-converging countries. The first club corresponds to Haiti, Paraguay, and Uruguay. Brazil and Honduras form Club 2, and Club 3 - the largest - contains Argentina, Chile, Colombia, Dominican Republic, Ecuador, Guatemala, Mexico, Peru, Salvador, and Venezuela. Club 4 includes Costa Rica, Cuba, and Panama.

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

[Insert Table 5 about here]

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

Table 6 reveals four convergence clubs with respect to buildings emissions, two convergence clubs for other industrial combustion, and three convergence subgroups in non-combustion and transport emissions. We find evidence of full convergence for power industry emissions since, given that the *t*-statistic turn out to be positive, the null hypothesis of overall convergence cannot be rejected.

Regarding building emissions per GDP, the results suggest four convergence clubs, consisting of Club 1 (2 countries), Club 2 (3 countries), Club 3 (4 countries), and Club 4 (9



countries). In terms of per GDP non-combustion emissions, the results reveal three convergence clubs: Club 1 (5 countries), Club 2 (10 countries), and Club 3 (4 countries). We find evidence of two convergence clubs in other industrial combustion emissions per GDP: Club 1 (17 countries), and Club 2 (2 countries). Table 6 shows the presence of three convergence clubs in transport emissions per unit of GDP: Club 1 (6 countries), Club 2 (9 countries), and Club 3 (3 countries). In other words, convergence analysis results change depending on the indicator of GHG intensity used.

[Insert Table 6 about here]

### 1.3. 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 log of greenhouse gas emissions intensity. However, this alone does not prove the club convergence hypothesis (Azariadis and Drazen, 1990; Azariadis, 1996; Galor, 1996), so we follow Bartkowska and Riedl (2012), who propose a two-step procedure: the first is clustering and the second is application of an ordered logit model to identify variables that may drive club formation. The ordered logit regression model is designed for dependent variables that are ordinal but not interval level.

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 as 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 PS algorithm has estimated for the greenhouse gas emissions per GDP. The empirical model takes the following general form:

$$y_i^* = X_i' \beta + \varepsilon_i \quad (i = 1, 2, \dots, 19) \quad (5)$$

where the dependent variable  $y_i^*$  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;  $X_i$  is the set of explanatory variables and  $i = 1, 2, \dots, 19$  indicates the Latin American country (there is one country that does not converge to any emissions intensity club).<sup>19</sup>  $\beta$  is a vector of regression coefficients. The dependent variable, ‘Club membership’, varies from 1 to 3 with an average

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<sup>19</sup> We have eliminated Panama (PAN) in the estimation since it is the divergent club. Therefore, we have three categories for our dependent variable (Clubs 1, 2, and 3).

value of 2.21 and a median of 2. According to the above results, the highest greenhouse gas emissions intensity club, the medium club, and the lowest club are assigned the values of 1, 2, and 3, respectively. Consequently, the higher the value, the better the performance.

Many factors affect GHG emissions intensity but, in this study, we only consider the following explanatory variables ( $X_i$ ): GDP per capita (constant 2015 \$US) to measure the economic situation, the unemployment rate, industry share of GDP (to capture the composite effect), manufacturing industries share of GDP, services share of GDP, and total population density (to account for demographic factors). All the variables come from the World Bank's World Development Indicators database.

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. The shares of manufacturing, industry, and services are defined as the sums of the value-added of the manufacturing, industry, and services sectors as a percentage of GDP, respectively. We present the descriptive statistics of these key determinants by convergence clubs in Table 8. Countries in Club 1 have a higher unemployment rate, while countries in Club 2 have higher GDP per capita, industry, and manufacturing share. Countries in Club 3 have higher services share and population density. Club 2 may be classified as a high-income group, Club 1 as a low-income group, and Club 3 as a middle-income group.

[Insert Table 7 and 8 about here]

Table 9 shows the results of our ordered logit estimations with  $y_i^*$  as the dependent variable, based on a maximum likelihood (ML) estimation method.<sup>20</sup>

According to Table 9, GDP per capita, industry, manufacturing, services share of GDP, population density, and the unemployment rate are significant club membership predictors. The positive signs of GDP per capita, industry, manufacturing and services, and population density indicate that larger values help to explain the formation of the club classification. However, the unemployment rate bears a negative sign and, consequently, smaller values consolidate the grouping results.

The estimated coefficient of log GDP per capita is 1.202, which is significantly positively correlated at the 1% level. The estimated value for industry share is 0.045, which is significantly positively correlated at the 10% level. The estimated value for manufacturing

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<sup>20</sup> The variables were selected according to a general-to-specific procedure in which we first estimate the model including more variables and then drop the insignificant ones. These additional results are available upon request.

share is 0.158, which is significantly positively correlated at the 1% level. The estimated coefficient for population density is 0.006 and is positively correlated at the 1% level. The services share displays a 0.120 coefficient significant at the 1% level, and unemployment is negatively correlated with club membership, with a -0.062 coefficient statistically significant at the 10% level.

Hence, the ordered logit model shows that the differences in GDP per capita, share of industrial, manufacturing, or services sectors, population density, and unemployment rate play a significant role in determining convergence club membership, with a positive relationship found for all, except for the unemployment rate, which has an opposite effect.

In Table 9, 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 regional specific characteristics affect the likelihood that a given country will be a member of a convergence club, and to facilitate the interpretation of our initial results. These effects refer to the average marginal effects for each club outcome. The marginal effects show 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 Table 9, increases in industry, manufacturing, and services share make memberships of Club 3 (Club 1-2) more (less) likely in varying degrees. By contrast, the higher the unemployment rate, the greater the probability of belonging to Clubs 1 and 2. GDP per capita and the population density increase the probability of belonging to Clubs 2 and 3.

A one-unit increase in GDP per capita increases the probability of belonging to Clubs 2 and 3. A 1% increase in the industry, manufacturing, and services share is associated with a higher probability of belonging to Club 3, and a lower probability of belonging to Clubs 1 and 2. A 1% increase in the population density increases the likelihood of being in Clubs 2 and 3 by 0.02% and 0.10%, respectively. The sign of the average marginal effect of the unemployment rate implies that a 1% increase in the unemployment rate decreases the likelihood of being in Club 3 by 1.1%, the lowest greenhouse gases emissions intensity club. However, a 1% increase in the unemployment rate increases the likelihood of belonging to Club 1 and 2 by 0.89% and 0.25%, respectively.

Results show that the share of industry value-added in GDP is positively associated with emissions efficiency, in line with the evidence that the energy structure of each polluting sector does not necessarily imply that the industrial sector is the least energy efficient sector,

in such a way that sectoral energy efficiency will depend on the composition and structure of each sector (Yu et al., 2015).

[Insert Table 9 about here]

## 6. Conclusions

We have explored the convergence process of greenhouse gas emissions intensity across Latin American countries by identifying groups of countries converging to the same steady state without an ex ante classification. This study considers 20 Latin American countries, over the period 1970 to 2015, and not only provides evidence of convergence in greenhouse gas emissions intensity across Latin American countries, but also examines convergence by sector and gas source. This division allows us to establish more precise results. First, we examine the sigma-convergence and compute the cross-sectional deviation and the coefficient of variation (CV). Second, the shortcomings of the sigma convergence approach motivate us to utilize the recent 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, against the traditional approach of unit root tests or beta and sigma convergence.

Results show clear evidence against the null hypothesis of absolute convergence and suggest the presence of four clubs in greenhouse gas emissions per GDP. Results also indicate multiple convergence clubs by polluting sector (building, non-combustion, other industrial combustion, power industry, and transport) and type of gas (CO<sub>2</sub>, CH<sub>4</sub>, and N<sub>2</sub>O). Furthermore, economic and demographic variables, such as GDP per capita, share of polluting sectors value-added in GDP, unemployment rate, and population density, are important predictors of the convergence club creation and can explain regional disparities and the heterogeneous behavior of the Latin American countries in emissions intensity.

All these findings may contribute to future policies of environmental protection, since the convergence of air pollutants is a major concern for policy makers, and all countries pursue the goal of allocating emissions equally in the future. Understanding the distribution of greenhouse gases through time and space can help policy makers in designing policies to combat climate change and allocate emissions obligations, since developments in energy efficiency appear to be the main driving force for convergence in energy intensities and, by extension, in emissions intensity. Having knowledge of the convergence or divergence pattern in emissions is fundamental for suitable policy design, and we trust that our analysis

of the driving forces of country-level convergence in emissions intensity will also help Latin American policymakers determine where to invest their resources to mitigate greenhouse emissions more efficiently. Based on the results presented here, we conclude that differences in economic structure, GDP per capita, unemployment rate, and population density have played an important role in Latin America's greenhouse gas emissions intensity. However, it is also important to remember that developed countries are, historically, the main drivers of the human-produced greenhouse emissions and most Latin American countries are still in the stage of accelerating industrialization and urbanization.

One key question is whether differences in emissions across regions tend to increase or decrease over time (Burnett, 2016) and, for this reason, this study may provide valuable insights for policymakers to implement efficient national policies and to achieve proposed environmental goals. The very existence of clubs in greenhouse gas emissions invalidates a common environmental policy among Latin American countries, since they are converging to their respective steady states and each group of countries has its own characteristic behaviour. Country-specific emissions policies need to be designed and our results indicate that a common Latin American emissions policy is sub-optimal and, on the contrary, the task ahead must be to reduce emissions via a common policy for each club. In addition, the disparities reflected in our results suggest that convergence analysis results change depending on the indicator of emissions intensity used.

One limitation of this study is that our results do not offer evidence of causality, a question that is left to future research. Other possible and promising extensions are expanding the determinants of greenhouse gases emissions, and extending the country sample to include developed and more developing countries. These questions are left for the future as very promising research lines.

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Table 1. Summary statistics for the GHG series

	Observations	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
<b><i>Panel A. GHG emissions intensity</i></b>							
GHG emissions per capita	920	4.347	2.611	0.784	12.460	1.041	3.379
GHG emissions per GDP	520	0.424	0.169	0.147	1.030	0.826	3.389
<b><i>Panel B. Gas emissions intensity</i></b>							
CO2 emissions per capita	1000	1.841	1.353	0.055	6.660	1.169	3.761
CO2 emissions per GDP	600	0.171	0.061	0.034	0.406	0.816	4.071
CH4 emissions per capita	924	1.953	1.488	0.378	7.900	1.983	7.058
CH4 emissions per GDP	520	0.191	0.133	0.036	0.678	1.285	4.000
N2O emissions per capita	920	0.570	0.437	0.131	2.350	2.161	7.868
N2O emissions per GDP	520	0.059	0.040	0.010	0.192	1.222	3.691
<b><i>Panel C. Sector GHG emissions intensity</i></b>							
GHG emissions per GDP from building	520	0.024	0.011	0.006	0.064	0.777	3.191
GHG emissions per GDP from non-combustion	520	0.261	0.167	0.052	0.861	1.220	3.917
GHG emissions per GDP from other industrial combustion	520	0.041	0.029	0.002	0.170	2.203	9.099
GHG emissions per GDP from power industry	520	0.037	0.025	0.000	0.123	0.676	3.067
GHG emissions per GDP from transport	520	0.060	0.017	0.005	0.109	-0.660	4.496

Table 2. Summary statistics, by country

<i>Panel A. GHG emissions per capita</i>						
Latin American countries	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
ARG	8.953	0.549	7.880	10.150	0.374	2.587
BOL	3.990	0.475	3.120	4.960	0.547	2.545
BRA	4.780	0.622	3.610	6.080	0.306	2.473
CHL	5.588	1.151	3.660	8.090	0.146	2.374
COL	3.820	0.292	3.380	4.350	0.083	1.767
CRI	2.926	0.285	2.450	3.550	0.402	2.469
CUB	4.938	0.720	3.950	6.260	0.390	1.738
DOM	2.775	0.434	2.070	3.680	0.274	1.620
ECU	3.834	0.523	2.380	4.590	-0.919	3.571
SLV	1.600	0.255	1.160	2.060	-0.094	1.858
GTM	1.559	0.224	1.250	2.150	0.559	2.532
HTI	1.047	0.136	0.784	1.290	0.020	1.768
HND	1.998	0.161	1.690	2.290	-0.186	1.923
MEX	5.889	0.526	4.810	6.980	-0.253	2.316
NIC	2.729	0.426	2.110	3.660	0.807	2.594
PAN	3.585	0.448	2.820	4.290	0.076	1.754
PRY	4.973	0.499	4.110	6.140	0.613	3.060
PER	2.422	0.401	1.890	3.290	0.511	1.963
URY	10.758	0.803	9.230	10.460	0.199	2.175
VEN	8.775	0.689	7.690	11.080	1.096	4.360
<i>Panel B. GHG emissions per GDP</i>						
Latin American countries	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
ARG	0.450	0.062	0.361	0.610	0.511	2.988
BOL	0.705	0.114	0.597	1.030	1.655	4.757
BRA	0.415	0.022	0.378	0.444	-0.534	1.672
CHL	0.343	0.051	0.265	0.460	0.339	2.144
COL	0.365	0.071	0.250	0.475	-0.069	1.709
CRI	0.214	0.051	0.147	0.311	0.619	2.044
CUB	0.315	0.083	0.200	0.422	-0.065	1.305
DOM	0.322	0.053	0.223	0.391	-0.439	1.760
ECU	0.436	0.057	0.359	0.537	0.446	1.821
SLV	0.263	0.021	0.217	0.284	-0.935	2.660
GTM	0.256	0.011	0.236	0.281	0.136	2.451
HTI	0.596	0.124	0.395	0.754	-0.022	1.459
HND	0.447	0.023	0.412	0.500	0.469	2.837
MEX	0.364	0.013	0.329	0.388	-0.716	4.049
NIC	0.616	0.058	0.523	0.730	0.146	2.272
PAN	0.216	0.037	0.148	0.264	-0.365	1.802
PRY	0.554	0.021	0.507	0.587	-0.446	2.306
PER	0.299	0.043	0.239	0.372	0.140	1.681
URY	0.782	0.114	0.566	0.933	-0.632	2.233
VEN	0.518	0.045	0.439	0.638	0.589	3.287

Figure 1. Evolution of GHG emissions

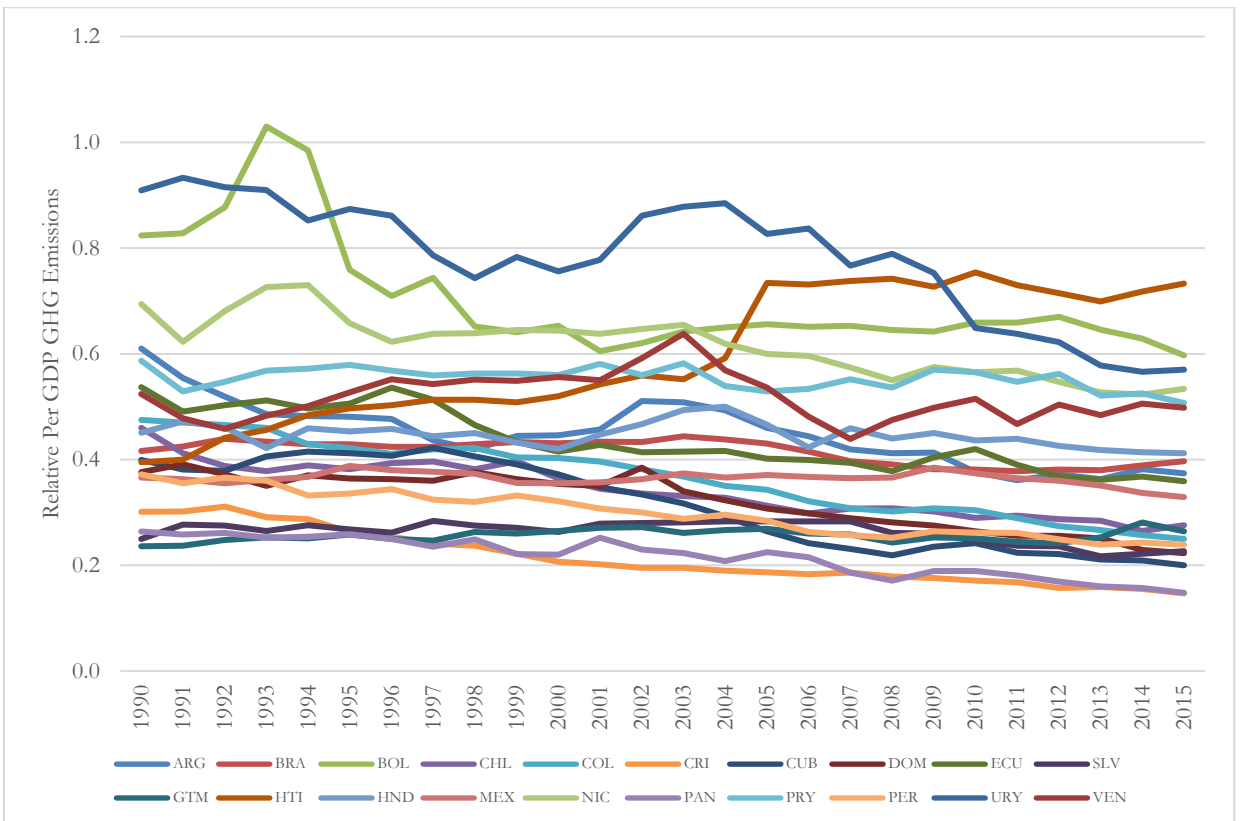
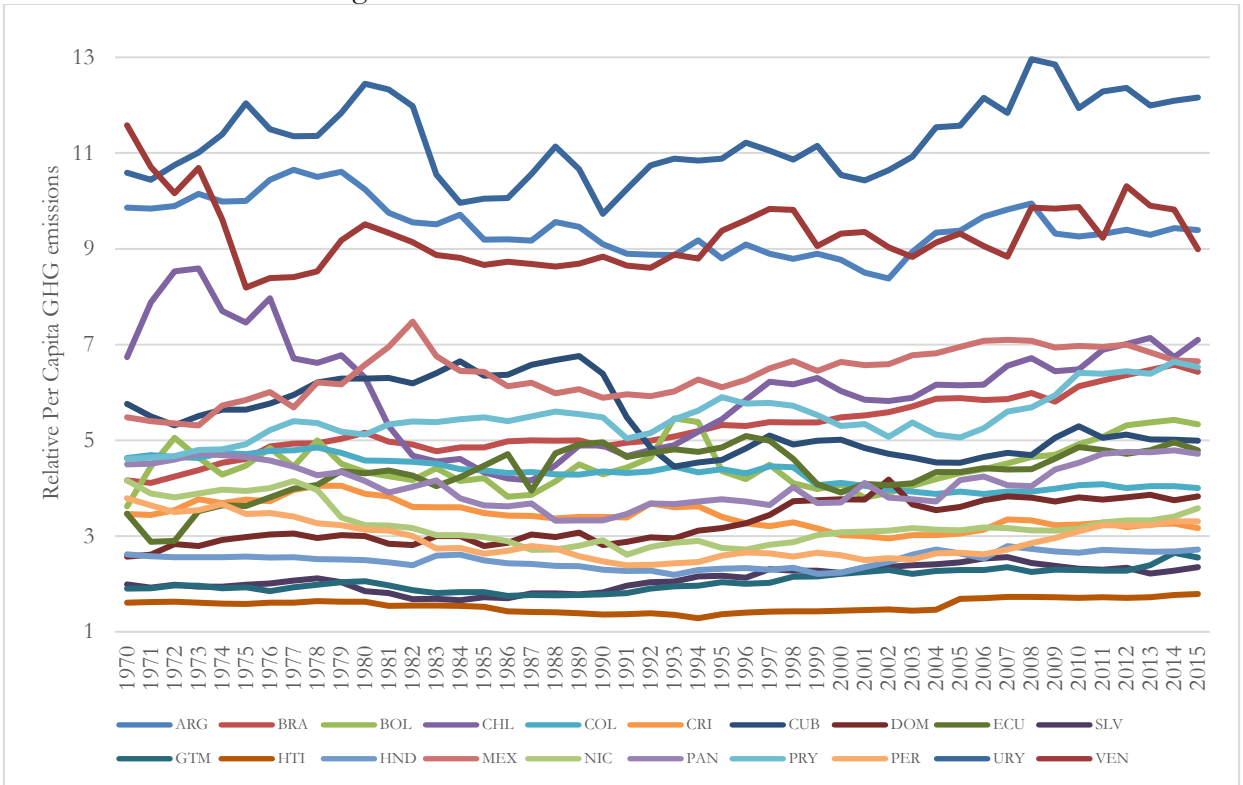


Figure 2. Cross-sectional standard deviation GHG emissions intensity

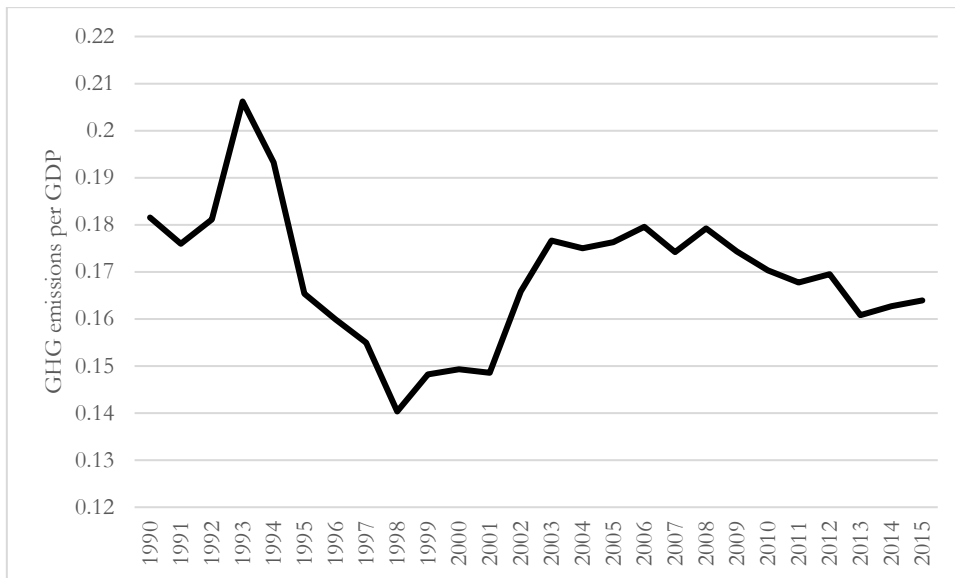
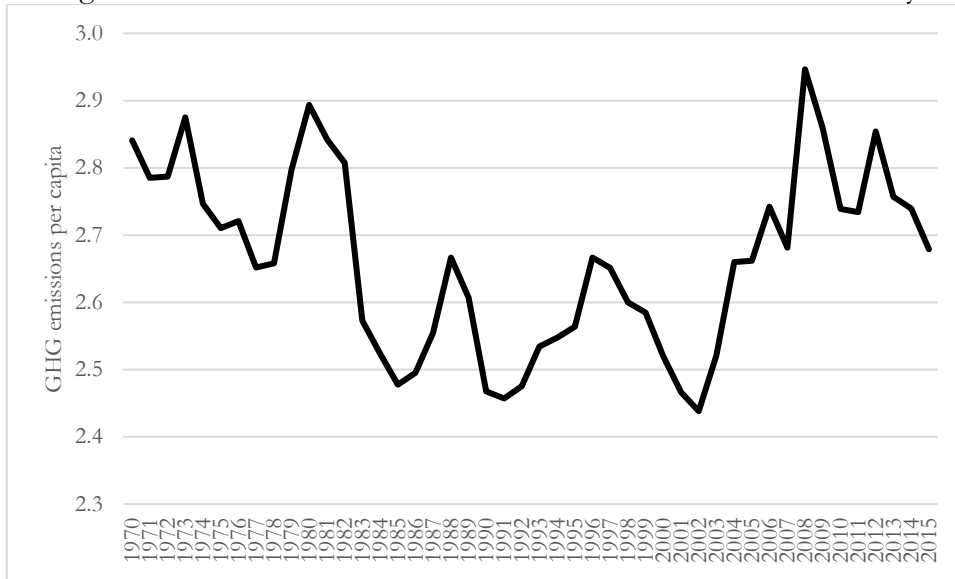


Figure 3. Coefficient of variation GHG emissions intensity

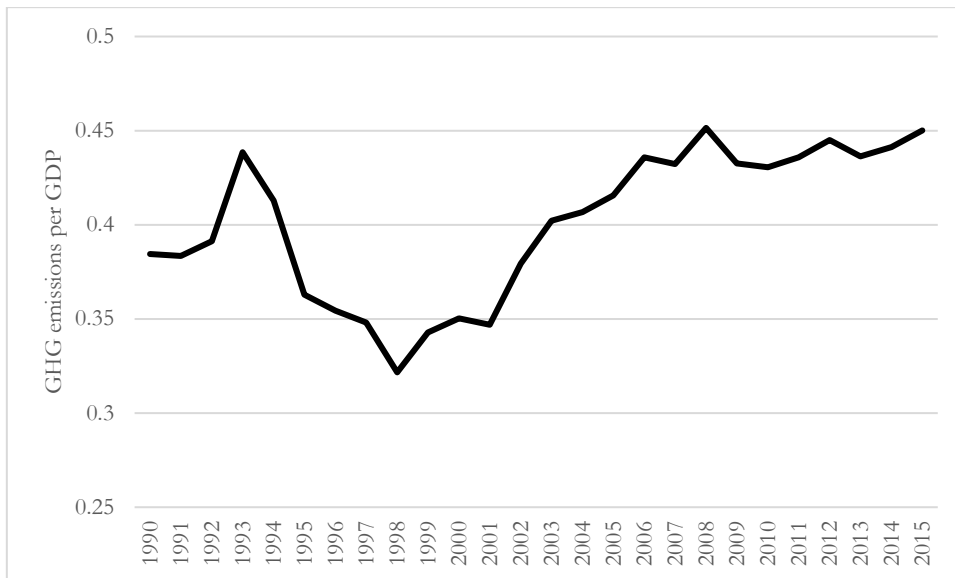
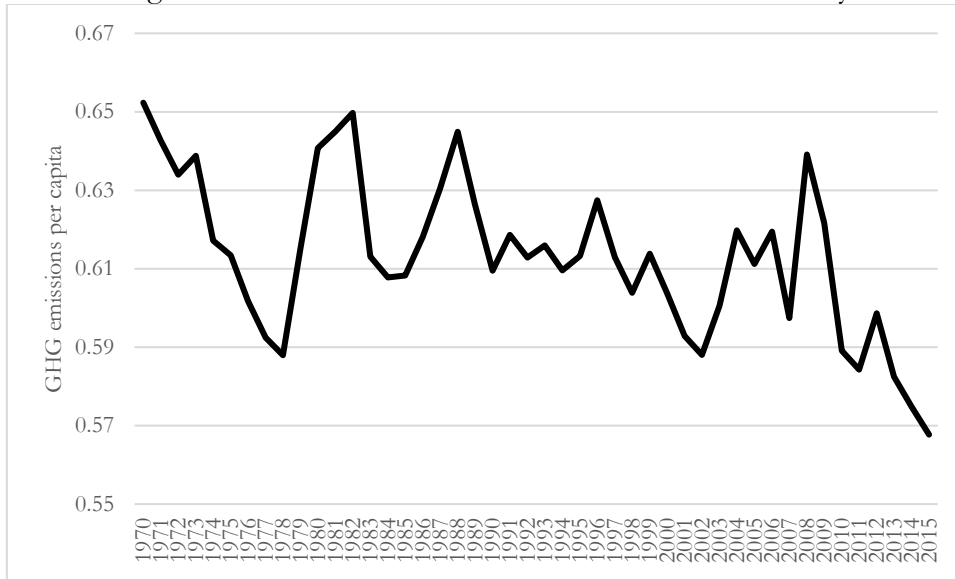


Table 3. Convergence analysis in GHG emissions intensity

<i>Panel A. Overall convergence</i>			
GHG emissions per capita		GHG emissions over GDP	
$\hat{b}$ coefficient	$t$ -stat	$\hat{b}$ coefficient	$t$ -stat
-0.0401	-0.5896	-0.8319	-19.4160*
<i>Panel B. Convergence clubs</i>			
Club 1 [5]			
BOL, HTI, NIC, PRY, URY			
$\hat{b}$ coefficient		$t$ -stat	
0.0814		0.5302	
Club 2 [5]			
BRA, ECU, HND, MEX, VEN			
$\hat{b}$ coefficient		$t$ -stat	
0.2194		1.3286	
Club 3 [9]			
ARG, CHL, COL, CRI, CUB, DOM, GTM, PER, SLV			
$\hat{b}$ coefficient		$t$ -stat	
0.0293		0.3919	
Non-converging [1]			
PAN			
<i>Panel C. Club merging convergence analysis</i>			
	$\hat{b}$ coefficient	$t$ -stat	
Merging Clubs 1 + 2	-0.5457	-6.7722*	
Merging Clubs 2 + 3	-0.6526	-13.8369*	
Merging Club 3 + Non-converging	-0.1239	-2.1868*	

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 which 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. The numbers in brackets stand for the number of countries in a group.



Figure 4. Map of Latin America: Convergence clubs for GHG emissions per GDP

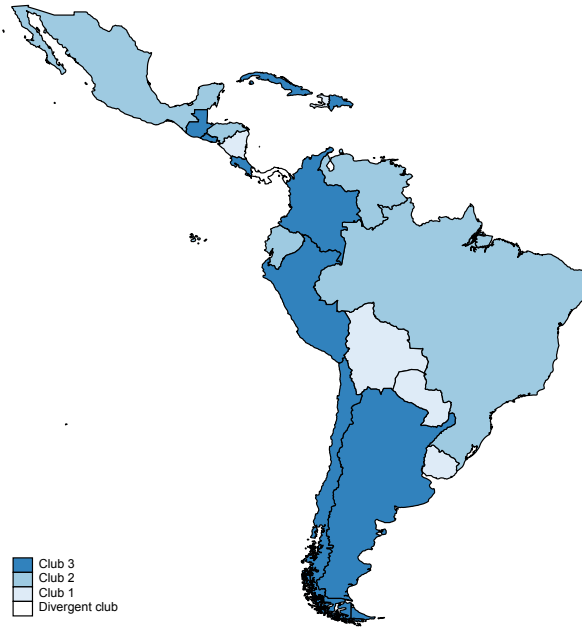


Figure 5. Average values Clubs 1 – 4

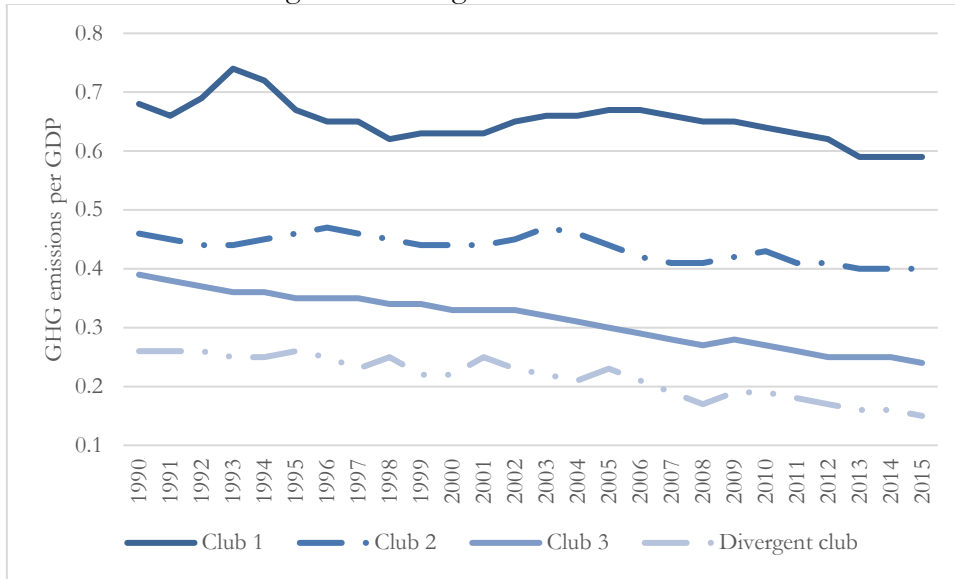


Table 4. Descriptive statistics of the convergence clubs

<b>Club</b>	<b>Sample Size</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Minimum</b>	<b>Maximum</b>
Club 1	5	0.651	0.125	0.395	1.030
Club 2	5	0.436	0.061	0.329	0.638
Club 3	9	0.314	0.084	0.147	0.610

Table 5. Convergence analysis by type of gas

CO2 per capita		CO2 per GDP		CH4 per capita		CH4 per GDP		N2O per capita		N2O per GDP	
Overall test		Overall test		Overall test		Overall test		Overall test		Overall test	
$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat
3.6206	46.7658	-0.8280	-30.7629*	-0.9630	-21.1219*	-0.9415	-31.6068*	-0.8026	-23.653*	-0.9292	-34.4354*
<b>Club 1 [3]</b>		<b>Club 1 [11]</b> ARG, BOL, BRA, CHL, COL, ECU, GTM, HTI, NIC, PRY, VEN		<b>Club 1 [3]</b> HTI, PRY, URY		<b>Club 1 [5]</b> ARG, BRA, MEX, PRY, URY		<b>Club 1 [8]</b> BOL, BRA, HND, HTI, MEX, NIC, PRY, URY			
$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat
0.0157	0.0764	0.4455	9.2462	0.3127	1.2926	2.2933	1.5465	0.0033	0.0416		
<b>Club 2 [11]</b> ARG, BRA, CHL, DOM, SLV, GTM, HTI, HND, MEX, NIC, PER		<b>Club 2 [8]</b> CRI, CUB, DOM, HND, MEX, PAN, PER, SLV		<b>Club 2 [2]</b> BRA, HND		<b>Club 2 [15]</b> BOL, CHL, COL, CRI, CUB, DOM, ECU, GTM, HND, HTI, NIC, PAN, PER, SLV, VEN		<b>Club 2 [2]</b> ARG, GTM			
$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat
0.2141	6.979	0.7785	0.6291	2.2712	3.5219	-0.0172	-0.4307	0.1004	0.2155		
<b>Club 3 [6]</b> COL, CRI, CUB, PAN, PRY, URY		<b>Non-converging [1]</b> URY		<b>Club 3 [10]</b> ARG, CHL, COL, DOM, ECU, GTM, MEX, PER, SLV, VEN		<b>Club 3 [9]</b> CHL, COL, CRI, CUB, DOM, ECU, PER, SLV, VEN					
$\hat{b}$ coef.	<i>t</i> -stat			$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat	$\hat{b}$ coef.	<i>t</i> -stat
1.1902	21.751			-0.0558	-0.8514			0.3719	5.608		
				<b>Club 4 [3]</b> CRI, CUB, PAN		<b>Non-converging [1]</b> PAN					
				$\hat{b}$ coef.	<i>t</i> -stat						
				0.5721	3.3532						
				<b>Non-converging [2]</b> BOL, NIC							

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 which 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. The numbers in brackets stand for the number of countries in a group.

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	<i>t</i> -stat	$\hat{b}$ coefficient	<i>t</i> -stat	$\hat{b}$ coefficient	<i>t</i> -stat	$\hat{b}$ coefficient	<i>t</i> -stat	$\hat{b}$ coefficient	<i>t</i> -stat
-1.8568	-53.8368*	-0.8347	-21.9009*	-0.7082	-23.1413*	-2.0743	-45.7836*	0.1724	0.8377
<b>Club 1 [2]</b>		<b>Club 1 [5]</b>		<b>Club 1 [17]</b>		<b>Club 1 [6]</b>			
BOL, HTI		BOL, HTI, NIC, PRY, URY		ARG, BOL, BRA, CHL, COL, CUB, DOM, ECU, GTM, HTI, HND, MEX, NIC, PAN, PER, URY, VEN		BOL, ECU, HTI, HND, MEX, VEN			
$\hat{b}$ coefficient	<i>t</i> -stat	$\hat{b}$ coefficient	<i>t</i> -stat	$\hat{b}$ coefficient	<i>t</i> -stat	$\hat{b}$ coefficient	<i>t</i> -stat		
1.0909	0.8014	0.4836	1.9980	-0.0027	-0.0388	0.9128	2.6327		
<b>Club 2 [3]</b>		<b>Club 2 [10]</b>		<b>Club 2 [2]</b>		<b>Club 2 [9]</b>			
ARG, ECU, NIC		ARG, BRA, COL, DOM, ECU, SLV, GTM, MEX, PER, VEN		CRI, SLV		BRA, CHL, CRI, SLV, GTM, NIC, PRY, PER, URY			
$\hat{b}$ coefficient	<i>t</i> -stat	$\hat{b}$ coefficient	<i>t</i> -stat	$\hat{b}$ coefficient	<i>t</i> -stat	$\hat{b}$ coefficient	<i>t</i> -stat		
0.1887	4	-0.1325	-1.6426	2.5786	5.6231	0.2367	4.4422		
<b>Club 3 [4]</b>		<b>Club 3 [4]</b>		<b>Non-converging [1]</b>		<b>Club 3 [3]</b>			
COL, GTM, HND, MEX		CHL, CRI, CUB, PAN		PRY		ARG, COL, DOM			
$\hat{b}$ coefficient	<i>t</i> -stat	$\hat{b}$ coefficient	<i>t</i> -stat			$\hat{b}$ coefficient	<i>t</i> -stat		
0.2568	1.2319	0.5431	2.8266			0.4782	0.9655		
<b>Club 4 [9]</b>		<b>Non-converging [1]</b>				<b>Non-converging [2]</b>			
BRA, CHL, CUB, DOM, SLV, PAN, PER, URY, VEN		HND				CUB, PAN			
$\hat{b}$ coefficient	<i>t</i> -stat								
0.1270	3.2984								
<b>Non-converging [2]</b>									
CRI, PRY									

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 which 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. The numbers in brackets stand for the number of countries in a group.

Table 7. Descriptive statistics of the ordered logit variables

<b>Variable</b>	<b>Obs</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Minimum</b>	<b>Maximum</b>
Club membership	494	2.211	0.833	1	3
GDP per capita	520	5,773.956	3,450.580	1,134.138	1,5613.750
Share of industry in GDP	514	28.571	6.529	16.294	57.747
Share of manufacturing industries in GDP	513	15.795	3.483	6.232	28.311
Population density	520	76.160	87.245	6.337	388.082
Share of rural population	520	32.316	15.299	4.955	71.490
Share of service industries in GDP	508	54.467	7.902	32.395	73.448
Unemployment rate	500	6.699	3.548	1.580	20.520

Table 8. Descriptive statistics, by convergence club

	GDP per capita	Share of industry in GDP	Share of manufacturing industries in GDP	Share of service industries in GDP	Unemployment rate	Population density
Club 1	4,046.230 (3,770.084)	27.514 (5.382)	14.879 (3.126)	50.191 (7.145)	7.531 (3.791)	81.065 (122.340)
Club 2	6,595.086 (3,022.624)	32.523 (8.427)	16.679 (3.408)	52.064 (7.436)	6.114 (2.992)	43.489 (17.381)
Club 3	6,004.057 (3,182.046)	27.789 (4.756)	16.426 (3.027)	56.472 (6.002)	6.919 (3.647)	95.276 (86.011)

Notes: The entries are the mean values of the variables and the numbers in parentheses denote their standard deviations.

Table 9. Ordered Logit regression results

<i>Explanatory variables</i>	<b>Dependent variable:</b> Club membership	<b>Marginal effects</b>		
		Club 1	Club 2	Club 3
Log of GDP per capita	1.202*** (5.514)	-0.172*** (-5.856)	0.048*** (-4.709)	0.220*** (6.176)
Share of industry in GDP	0.045* (1.929)	-0.006* (-1.963)	-0.002* (-1.823)	0.008* (1.953)
Share of manufacturing industries in GDP	0.158*** (5.163)	-0.023*** (-5.926)	-0.006*** (-3.916)	0.029*** (5.765)
Population density	0.006*** (4.140)	-0.001*** (-3.935)	0.000*** (-4.161)	0.001*** (4.201)
Share of service industries in GDP	0.120*** (4.551)	-0.017** (-5.185)	-0.005*** (-3.415)	0.022** (4.915)
Unemployment rate	-0.062* (-1.788)	0.009** (1.747)	0.002*** (2.035)	-0.011*** (-1.819)
Observations	466			
Pseudo R <sup>2</sup>	0.173			

Note: The values in parentheses are the robust z-statistics of the corresponding coefficient. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .