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GLOBALIZATION AND ENVIRONMENTAL PROBLEMS IN DEVELOPING COUNTRIES

# Convergence of per capita carbon dioxide emissions among developing countries: evidence from stochastic and club convergence tests

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## Abstract

This exploratory study extends the literature on the convergence of per capita carbon dioxide emissions in analyzing stochastic and club convergence within a panel framework for developing countries. The results from Pesaran (Journal of Applied Econometrics, 22(2), 265-312, 2007) and Bai and Carrion-i-Silvestre (Review of Economic Studies, 76(2), 471-501, 2009) panel unit root tests with allowance for cross-sectional dependence confirm stochastic convergence for low-income, lower middle-income, and combined country panels. Further analysis using the nonlinear time-varying factor model of Phillips and Sul (Econometrica, 75(6), 1771-1855, 2007; Journal of Applied Econometrics, 24(7), 1153-1185, 2009) to test for convergence reveals the emergence of multiple convergence clubs within each of the three country panels examined. We observe geographic proximity among many of the countries within the respective convergence clubs.


**Keywords** Carbon dioxide emissions · Developing countries · Cross-sectional dependence · Stochastic convergence · club convergence

**JEL codes** F64 · Q40 · Q50

## Introduction

While renewable energy sources and conservation measures have grown in importance as policymakers attempt to mitigate the global impact of greenhouse gas emissions on climate change and the environment, fossil fuels continue to serve as the primary energy source for a vast majority of countries. With carbon dioxide emissions, a prominent component of greenhouse gas emissions, the debate continues in regard to the appropriate mitigation and emission allocation strategies, as reflected in the Framework Convention on Climate Change in 1992, the Kyoto Protocol in 1997, and the Paris agreement in 2015.[1] Indeed, the generation of carbon dioxide emissions is directly tied to the country's energy mix, level of economic development, economic structure, natural resource endowments, among other factors, and as such, vary greatly across developed and developing countries. This is a relevant point in the discussions related to the emission allocation approaches that focus on the distribution of per capita emissions. Specifically, countries with lower per capita emissions (i.e., developing countries) may very well expect countries with higher per capita emissions (i.e., developed countries) to shoulder more of the burden for the mitigation efforts and the reduction in emissions (Aldy 2006). This issue of fairness and equity associated with emission allocation strategies on a per capita basis becomes less of a concern if there is convergence in per

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[1] See Zhou and Wang (2016) for a review of carbon dioxide emissions allocation approaches.

capita emissions. On the other hand, if per capita emissions fail to converge, then a per capita emissions allocation scheme would trigger the potential for the relocation of emission-intensive industries and resource transfers through international trading of carbon allowances.[2]

The distinction in the convergence behavior between developed and developing is relevant in relation to the environmental Kuznets curve (EKC). The EKC hypothesis postulates that in the early stages of economic development and growth, environmental quality diminishes as income increases. However, at some threshold level of income, the demand for environmental quality increases whereby emissions decrease. Another facet influencing a country's emissions profile is the adoption of clean energy technologies across industries with differing pollution intensities and the substitution toward more environmentally friendly inputs in the production process (Apergis and Payne 2020). Moreover, the green Solow model set forth by Brock and Taylor (2010) demonstrates that technological progress which enhances production efficiencies and abatement is a fundamental consideration in the relationship between the EKC hypothesis and the convergence of emissions.

In this context, the literature on the issue of carbon dioxide emissions convergence has been extensively explored in the literature, as documented in the survey articles by Pettersson et al. (2014), Acar et al. (2018), and Payne (2020).[3] In general, the evidence from large multi-country studies on the convergence of per capita carbon dioxide emissions has been generally mixed (see Nguyen Van 2005; Aldy 2006; Ezcurra 2007a; Westerlund and Basher 2008; Nourry 2009; Panopoulou and Pantelidis 2009; Brock and Taylor 2010; Ordas Criado and Grether 2011; Herrerias 2013; Li and Lin 2013; Acaravci and Erdogan 2016; Ahmed et al. 2017; Brannlund et al. 2017; Churchill et al. 2018; Rios and Gianmoena 2018; Haider and Akram 2019; and Fernandez-Amador et al. 2019). However, studies focused on countries grouped by institutional structure, income classification, and geographic region lend greater support for convergence in per capita carbon dioxide emissions (see Strazicich and List 2003; Barassi et al. 2008, 2011, 2018; Lee et al. 2008; Lee and Chang 2008, 2009; Romero-Avila 2008; Jobert et al. 2010; Herrerias 2012; Yavuz and Yilanci 2013; Solarin 2014; Robalino-Lopez et al. 2016; Presno et al. 2018; Erdogan and Acaravci 2019; and Karakaya et al. 2019).[4,5]

Given that the majority of the studies to date have focused primarily on more developed, industrialized countries, we explore the convergence of per capita carbon dioxide emissions in the case of developing countries due to the differences in their level of economic development and growth prospects relative to industrialized countries as the EKC hypothesis would suggest. Furthermore, this line of inquiry will provide additional insights on the environmental sustainability of the economic development process for developing countries. As such, we test for the convergence of emissions using two approaches: stochastic convergence and club convergence. Following Carlino and Mills (1993) and Bernard and Durlauf (1995, 1996), the stochastic convergence approach evaluates the stationarity of relative per capita carbon dioxide emissions defined for each country i as the natural logarithm of the ratio of per capita carbon dioxide emissions relative to the average of all countries. If relative per capita carbon dioxide emissions follow a stationary process (i.e., stochastic convergence), shocks will be transitory in nature. Unlike the stochastic convergence approach, which relies on unit root/stationarity tests, the club convergence approach of Phillips and Sul (2007, 2009), which is based on a nonlinear time-varying factor model, does not depend on the stationarity properties of variables in question and considers the possibility of multiple convergence clubs. As noted by Panopoulou and Pantelidis (2009), the Phillips-Sul approach is similar to examining conditional σ-convergence and β-convergence within a panel framework.[6] More specifically, the Phillips-Sul approach tests for a decline in the cross-sectional variation of per capita carbon dioxide emissions among countries over time (conditional σ-convergence), as well as tests whether or not heterogeneous time-varying idiosyncratic components converge over time to a constant after controlling for a common growth component among countries (conditional β-convergence).

[2] In addition, the convergence of per capita emissions is also a key assumption inherent in climate change models, and projecting future emissions (Apergis and Payne 2017).

[3] While we focus our attention on per capita carbon dioxide emissions, a number of studies have investigated other types of emissions. In the case of sulfur dioxide and/or nitrogen oxide emissions, see List (1999), Lee and List (2004), Bulte et al. (2007), Ordas Criado et al. (2011), Payne et al. (2014), Hao et al. (2015a, b), Liu et al. (2018), and Solarin and Tiwari (2020); greenhouse gas emissions, see El-Montasser et al. (2015) and de Oliveira and Bourscheidt (2017); ecological footprint, see Biligili and Ulucak (2018), Ulucak and Apergis (2018), Solarin (2019), Ulucak et al. (2020), and Yilanci and Pata (2020); and for protected areas in the measurement of environmental quality, see Bimonte (2009).

[4] In addition to country-wide studies, several studies have examined the convergence of per capita carbon dioxide emissions at the sub-national level, for the USA, see Aldy 2007; Burnett 2016; and Apergis and Payne 2017; and for China, see Huang and Meng 2013;Wang and Zhang 2014; Wu et al. 2016; and Yu et al. 2019.

[5] Ezcurra (2007b), Li et al. (2014), and Tiwari and Mishra (2017) investigate the convergence of the level of carbon dioxide emissions. Camarero et al. (2008) and Camarero et al. (2013b) explore the convergence of environmental performance indicators and eco-efficiency indicators, respectively. Camarero et al. (2013a), Moutinho et al. (2014), Wang et al. (2014), Brannlund et al. (2015), Hao et al. (2015a, b), Zhao et al. (2015), Apergis et al. (2017), Kounetas (2018), Yu et al. (2018), Apergis and Payne (2020), and Apergis et al. (2020) examine the convergence of carbon dioxide emissions intensity.

[6] As pointed out by Quah (1993) along with Evans (1996) and Evans and Karras (1996), cross-sectional β-convergence does not consider the possibility of multiple steady states.

The "Data, methodology, and results" section discusses the data, methodology, and results, while the "Concluding remarks" section provides concluding remarks.

## Data, methodology, and results

### Data

Annual data from 1972 to 2014 for per capita carbon dioxide emissions (in metric tons) is obtained from the World Bank Development Indicators.[7] The data is constructed into three panels: (1) low-income countries (27), lower middle-income countries (38), and the combination of both low- and lower middle-income countries (65) as shown in Appendix A. Table 1 displays the summary statistics of per capita carbon dioxide emissions by income classification. For the case of low-income countries in Table 1, we find that mean per capita carbon dioxide emissions ranges from 0.034 in Burundi and Chad to 2.644 in the Syrian Arab Republic, while the variation (standard deviation) ranges from 0.009 in Burundi to 0.643 in the Syrian Arab Republic. The distribution of per capita carbon dioxide emissions shows positive skewness in 21 of the 27 countries with the kurtosis measure less than three for 17 of the 27 countries. The null hypothesis of normality in the distribution of per capita carbon dioxide emissions is rejected in over half the countries.

In Table 2 for lower middle-income countries, we find much more dramatic ranges in both the mean and variation of per capita carbon dioxide emissions. The mean per capita carbon dioxide emissions ranges from 0.120 in Bangladesh to 4.362 in Mongolia, and the variation (standard deviation) ranges from 0.040 in Comoros to 1.974 in Mongolia. The distribution of per capita carbon dioxide emission also reveals positive skewness in 30 of the 38 countries with the kurtosis measure less than three for 29 of the 38 countries. The null hypothesis of normality in the distribution of per capita carbon dioxide emissions is rejected in nearly half the countries.

### Stochastic convergence

We begin our analysis with examining stochastic convergence within a panel data framework recognizing that first-generation panel unit root tests may yield biased results if positive residual cross-section dependence is present. As a result, second-generation panel unit root tests have evolved to address the need to first determine the degree to which cross-sectional dependence is an issue. As such, we explore whether or not cross-sectional dependence is present in the data using the Pesaran (2004) cross-sectional dependence (CD) statistic. The CD statistic is an average of all pair-wise correlation coefficients of the ordinary least square residuals from the standard augmented Dickey and Fuller (1979) regression. With the null hypothesis of cross-sectional independence, the CD statistic follows asymptotically a two-tailed normal distribution as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\rho}_{ij}\right) \tag{1}$$

where T is the time period and $N$ is the number of countries. $\widehat{\rho}_{ij}$ is the pair-wise correlation coefficient estimates of the residuals. The results in Table 3 show that up to three lags, the null hypothesis of cross-sectional independence is rejected for each of the three country panels.

Given the presence of cross-sectional dependence, we proceed with Pesaran's (2007) augmented ADF-panel unit root test, which incorporates the lagged cross-sectional mean and its first difference in recognition of cross-sectional dependence as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it-1} + \theta_i \overline{y}_{t-1} + \gamma_i \Delta\overline{y}_i + \varepsilon_{it} \tag{2}$$

where $\overline{y}_{t-1}$ denotes the mean of the lagged levels; $\Delta\overline{y}_i$ is the mean of the first-differences; and $\varepsilon_{it}$ is the error term. Pesaran (2007) uses a modified Im et al. (2003) statistic given by the average of the individual cross-sectional-ADF statistics (CADF) from Eq. (2) in defining the cross-sectional augmented IPS (CIPS) to test the null hypothesis of a unit root:

$$\mathrm{CIPS} = \frac{1}{N}\sum_{t=1}^{N} t_i(N,T) \tag{3}$$

where $t_i(N, T)$ represents the $t$ statistic from the ordinary least squares estimate of β in Eq. (2). In addition, we also correct for potential small sample bias via the CIPS* statistic as follows:

$$\mathrm{CIPS}^* = \frac{1}{N}\sum_{t=1}^{N} t_i^*(N,T) \tag{4}$$

where:

$$t_i^*(N,T) = \begin{cases} K_1 & t_i(N,T) \le K_1 \\ t_i(N,T) & K_1 < t_i(N,T) < K_2 \\ K_2 & t_i \ge K_2 \end{cases}$$

The constants $K_1$ and $K_2$ are fixed, where the probability that $t_i(N,T)$ resides in $[K_1, K_2]$ and close to one. Panel A of Table 4 displays the results of the Pesaran (2007) panel unit root tests with respect to relative per capita carbon dioxide emissions for the three country panels. The null hypothesis of a unit root is rejected at the 1% significance level across all three country panels based on the CIPS and CIPS* statistics, thus supporting stochastic convergence with respect to relative per capita carbon dioxide emissions.

[7] The time period is selected in order to include as many countries as possible in the analysis.

**Table 1** Summary statistics. low-income countries (27)

| Country | Mean | Median | Max | Min | SD | Skew | K | JB |
|---|---|---|---|---|---|---|---|---|
| Afghanistan | 0.159 | 0.153 | 0.406 | 0.037 | 0.097 | 0.535 | 2.440 | 2.661 (0.27) |
| Benin | 0.250 | 0.188 | 0.614 | 0.078 | 0.166 | 1.055 | 2.630 | 8.223 (0.01)[a] |
| Burkina Faso | 0.081 | 0.076 | 0.179 | 0.028 | 0.035 | 0.961 | 3.672 | 7.429 (0.02)[b] |
| Burundi | 0.034 | 0.035 | 0.050 | 0.020 | 0.009 | 0.111 | 1.656 | 3.322 (0.19) |
| Central African Rep. | 0.067 | 0.065 | 0.098 | 0.048 | 0.011 | 0.898 | 3.894 | 7.216 (0.02)[b] |
| Chad | 0.034 | 0.039 | 0.053 | 0.011 | 0.013 | − 0.443 | 1.664 | 4.605 (0.10)[c] |
| Congo, Dem. Rep. | 0.081 | 0.067 | 0.151 | 0.017 | 0.050 | 0.120 | 1.287 | 5.360 (0.06)[c] |
| Ethiopia | 0.060 | 0.056 | 0.118 | 0.031 | 0.018 | 1.264 | 4.884 | 17.811 (0.00)[a] |
| Gambia | 0.200 | 0.197 | 0.254 | 0.119 | 0.033 | − 0.475 | 2.873 | 1.649 (0.44) |
| Guinea | 0.196 | 0.194 | 0.267 | 0.157 | 0.024 | 0.826 | 3.986 | 6.630 (0.04)[b] |
| Guinea-Bissau | 0.163 | 0.158 | 0.242 | 0.090 | 0.029 | 0.378 | 3.966 | 2.698 (0.25) |
| Haiti | 0.160 | 0.148 | 0.271 | 0.040 | 0.053 | 0.197 | 2.461 | 0.799 (0.67) |
| Liberia | 0.397 | 0.225 | 1.107 | 0.137 | 0.338 | 1.193 | 2.686 | 10.377 (0.01)[a] |
| Madagascar | 0.113 | 0.107 | 0.224 | 0.069 | 0.031 | 1.564 | 5.827 | 31.842 (0.00)[a] |
| Malawi | 0.085 | 0.080 | 0.114 | 0.062 | 0.015 | 0.498 | 2.147 | 3.080 (0.21) |
| Mali | 0.059 | 0.055 | 0.083 | 0.040 | 0.011 | 0.408 | 1.964 | 3.114 (0.21) |
| Mozambique | 0.144 | 0.099 | 0.369 | 0.065 | 0.090 | 1.115 | 2.858 | 8.949 (0.01)[a] |
| Nepal | 0.089 | 0.072 | 0.298 | 0.021 | 0.067 | 1.224 | 4.133 | 13.027 (0.00)[a] |
| Niger | 0.087 | 0.084 | 0.148 | 0.049 | 0.029 | 0.656 | 2.371 | 3.791 (0.15) |
| Rwanda | 0.071 | 0.069 | 0.122 | 0.017 | 0.023 | − 0.217 | 3.570 | 0.919 (0.63) |
| Sierra Leone | 0.139 | 0.125 | 0.237 | 0.082 | 0.040 | 0.578 | 2.293 | 3.293 (0.19) |
| Somalia | 0.085 | 0.075 | 0.166 | 0.042 | 0.034 | 0.642 | 2.185 | 4.145 (0.12) |
| Syrian Arab Rep. | 2.644 | 2.861 | 3.366 | 1.122 | 0.643 | − 1.000 | 2.872 | 7.189 (0.02)[b] |
| Tanzania | 0.125 | 0.113 | 0.231 | 0.078 | 0.040 | 1.178 | 3.739 | 10.919 (0.00)[a] |
| Togo | 0.248 | 0.226 | 0.523 | 0.129 | 0.085 | 1.308 | 4.567 | 16.669 (0.00)[a] |
| Uganda | 0.072 | 0.060 | 0.142 | 0.036 | 0.032 | 0.816 | 2.236 | 5.822 (0.05)[b] |
| Yemen | 0.742 | 0.820 | 1.091 | 0.234 | 0.227 | − 0.637 | 2.342 | 3.684 (0.16) |

*Max* is the maximum value and *Min* is the minimum value. *SD* represents the standard deviation. *Skew* is skewness and *K* kurtosis. *JB* is the Jarque-Bera test for normality. *p* values are in round brackets with the significance levels a(1%), b(5%), and c(10%)

To address the possibility of spurious results due to the absence of structural breaks, we also report tests for panel unit roots under multiple structural breaks using the Bai and Carrion-i-Silvestre (2009) approach. The Bai and Carrion-i-Silvestre (2009) panel unit root test takes into consideration both multiple structural breaks and cross-section dependence through the common factors model proposed by Bai and Ng (2004). Their method allows for structural breaks in the level, slope, and both the level and slope, thus providing a certain degree of heterogeneity in the number of breaks across countries. This approach relies on the following two models:

$$D_{it} = \mu_i + \sum_{j=1}^{l_i} \theta_{ij} DU_{ijt} \tag{5}$$

and

$$D_{it} = \mu_i + \beta_{it} + \sum_{j-1}^{l_i} \theta_{ij} DU_{ijt} + \sum_{k=1}^{m_i} \gamma_{ik} DT_{ikt} \tag{6}$$

where the component $D_{it}$ represents the deterministic component. The structural breaks associated with the mean and the trend of a series, respectively, are denoted by $l_i$ and $m_i$, in which the number of breaks, $l_i$ and $m_i$, may differ. The dummy variables are defined as $DU_{ijt}$ = 1 for $t > T^i_{aj}$ and 0 otherwise, and $DT_{ikt} = \left(t - T^i_{bk}\right)$ for $t > T^i_{bk}$, and 0 otherwise. $T^i_{aj}$ and $T^i_{bk}$ represent the $j$th and $k$th dates of the structural breaks in the level and trend, respectively, for the $i$th individual with $j = 1, \ldots, l_i$ and $k = 1, \ldots, m_i$. The test is based on simplified test statistics, which are invariant to both mean and trend breaks:

$$Z^* = \sqrt{N\left\{\frac{\left[MSB^*(\lambda) - \xi^*\right]}{\zeta^{*2}}\right\}} \to N(0,1) \tag{7}$$

where $MSB^*(\lambda) = \frac{1}{N}\sum_{i=1}^{N} MSB^*_i(\lambda_i)$, $\xi^* = \frac{1}{N}\sum_{i=1}^{N}\xi^*_i$, and $\zeta^{*2} = \sum_{i=1}^{N}\zeta^{*2}_i$. $MSB^*(\lambda)$ is the pool modified Sargan and

**Table 2** Summary statistics. lower middle-income countries (38)

| Country | Mean | Median | Max | Min | SD | Skew | K | JB |
|---|---|---|---|---|---|---|---|---|
| Angola | 0.717 | 0.611 | 1.330 | 0.288 | 0.305 | 0.829 | 2.282 | 5.843 (0.05)[b] |
| Bangladesh | 0.120 | 0.164 | 0.474 | 0.053 | 0.120 | 0.832 | 2.619 | 5.219 (0.07)[c] |
| Bhutan | 0.415 | 0.400 | 1.392 | 0.010 | 0.367 | 0.827 | 3.158 | 4.952 (0.08)[c] |
| Bolivia | 1.085 | 1.005 | 1.906 | 0.599 | 0.354 | 0.535 | 2.329 | 2.857 (0.23) |
| Cabo Verde | 0.515 | 0.362 | 1.235 | 0.114 | 0.338 | 0.702 | 1.988 | 5.360 (0.07)[b] |
| Cambodia | 0.143 | 0.141 | 0.438 | 0.004 | 0.119 | 0.783 | 2.723 | 4.527 (0.10)[c] |
| Cameroon | 0.295 | 0.229 | 0.697 | 0.091 | 0.163 | 1.388 | 3.903 | 15.263 (0.00)[a] |
| Comoros | 0.163 | 0.155 | 0.258 | 0.074 | 0.040 | 0.506 | 2.948 | 1.837 (0.39) |
| Congo, Rep. | 0.493 | 0.505 | 1.089 | 0.174 | 0.217 | 0.426 | 2.600 | 1.590 (0.45) |
| Cote d'Ivoire | 0.503 | 0.484 | 0.826 | 0.282 | 0.141 | 0.516 | 2.341 | 2.686 (0.26) |
| Djibouti | 0.672 | 0.611 | 1.080 | 0.451 | 0.183 | 0.630 | 2.130 | 4.198 (0.12) |
| Egypt | 1.604 | 1.474 | 2.569 | 0.645 | 0.573 | 0.187 | 1.942 | 2.255 (0.32) |
| El Salvador | 0.740 | 0.691 | 1.143 | 0.330 | 0.280 | 0.042 | 1.285 | 5.282 (0.07)[c] |
| Eswatini | 0.790 | 0.787 | 1.248 | 0.149 | 0.284 | − 0.161 | 2.093 | 1.660 (0.44) |
| Ghana | 0.317 | 0.301 | 0.549 | 0.208 | 0.078 | 1.155 | 4.115 | 11.786 (0.00)[a] |
| Honduras | 0.704 | 0.597 | 1.124 | 0.419 | 0.223 | 0.548 | 1.756 | 4.927 (0.08)[a] |
| India | 0.833 | 0.780 | 1.728 | 0.375 | 0.380 | 0.671 | 2.509 | 3.661 (0.16) |
| Indonesia | 1.115 | 1.079 | 2.564 | 0.358 | 0.549 | 0.723 | 2.967 | 3.751 (0.15) |
| Kenya | 0.280 | 0.281 | 0.383 | 0.190 | 0.054 | 0.184 | 2.039 | 1.897 (0.39) |
| Kiribati | 0.449 | 0.418 | 0.739 | 0.280 | 0.123 | 0.560 | 2.195 | 3.407 (0.18) |
| Lao | 0.129 | 0.096 | 0.294 | 0.045 | 0.081 | 0.578 | 1.855 | 4.746 (0.09)[c] |
| Mauritania | 0.562 | 0.470 | 1.748 | 0.204 | 0.313 | 2.838 | 10.514 | 158.889 (0.00)[a] |
| Mongolia | 4.362 | 3.804 | 13.447 | 2.419 | 1.974 | 2.785 | 12.292 | 210.282 (0.00)[a] |
| Morocco | 1.108 | 1.079 | 1.887 | 0.482 | 0.388 | 0.434 | 2.053 | 2.958 (0.23) |
| Myanmar | 0.182 | 0.167 | 0.414 | 0.100 | 0.058 | 1.562 | 7.082 | 47.347 (0.00)[a] |
| Nicaragua | 0.681 | 0.693 | 0.951 | 0.362 | 0.125 | − 0.242 | 2.544 | 0.792 (0.67) |
| Nigeria | 0.650 | 0.684 | 1.010 | 0.326 | 0.192 | − 0.180 | 2.034 | 1.906 (0.39) |
| Pakistan | 0.635 | 0.666 | 0.947 | 0.308 | 0.203 | − 0.169 | 1.712 | 3.178 (0.20) |
| Papua New Guinea | 0.547 | 0.515 | 0.899 | 0.397 | 0.120 | 1.066 | 3.428 | 8.475 (0.01)[a] |
| Philippines | 0.799 | 0.828 | 1.051 | 0.517 | 0.124 | − 0.456 | 2.770 | 1.586 (0.45) |
| Sao Tome and Principe | 0.417 | 0.410 | 0.603 | 0.141 | 0.107 | − 0.446 | 2.987 | 1.423 (0.49) |
| Senegal | 0.458 | 0.436 | 0.642 | 0.322 | 0.085 | 0.585 | 2.394 | 3.106 (0.21) |
| Solomon Islands | 0.411 | 0.375 | 0.569 | 0.290 | 0.081 | 0.759 | 2.291 | 5.035 (0.08)[c] |
| Tunisia | 1.791 | 1.777 | 2.606 | 0.893 | 0.483 | − 0.139 | 2.211 | 1.254 (0.53) |
| Vanuatu | 0.470 | 0.451 | 0.931 | 0.222 | 0.113 | 1.429 | 8.156 | 62.258 (0.00)[a] |
| Vietnam | 0.693 | 0.447 | 1.820 | 0.263 | 0.487 | 1.039 | 2.611 | 8.000 (0.02)[b] |
| Zambia | 0.384 | 0.291 | 0.994 | 0.154 | 0.235 | 1.125 | 3.108 | 9.093 (0.01)[a] |
| Zimbabwe | 1.193 | 1.267 | 1.671 | 0.447 | 0.326 | − 0.513 | 2.251 | 2.888 (0.24) |

*Max* is the maximum value and *Min* is the minimum value. *SD* represents the standard deviation. *Skew* is skewness and *K* kurtosis. *JB* is the Jarque-Bera test for normality. *p* values are in round brackets with the significance levels a(1%), b(5%), and c(10%).

Bhargava (1983) test for individual time series. $\xi_i^*$ and $\zeta_i^{*2}$ denote the mean and the variance of the individual modified $MSB_i^*(\lambda_i)$ statistics, respectively, where $\lambda_i = T_i^b/T$ is the break fraction parameter. The results of the Bai and Carrion-i-Silvestre (2009) test rejects the null hypothesis of a unit root in relative per capita carbon dioxide emissions, confirming stochastic convergence.

## Club convergence

Finally, we follow Panopoulou and Pantelidis (2009), Apergis et al. (2017), and Apergis and Payne (2020), among others, in the use of the time-varying nonlinear factor model approach by Phillips and Sul (2007, 2009). The Phillips-Sul approach tests whether there is convergence with respect to the

**Table 3** Tests of cross-sectional dependence

| | | | |
|---|---|---|---|
| Panel A: low-income countries | | | |
| | 1 lag | 2 lags | 3 lags |
| Relative per capita carbon dioxide emissions | 10.673 (0.00)[a] | 10.120 (0.00)[a] | 9.728 (0.00)[a] |
| Panel B: lower middle-income countries | | | |
| | 1 lag | 2 lags | 3 lags |
| Relative per capita carbon dioxide emissions | 8.137 (0.00)[a] | 7.925 (0.00)[a] | 6.348 (0.00)[a] |
| Panel C: low- and lower middle-income countries | | | |
| | 1 lag | 2 lags | 3 lags |
| Relative per capita carbon dioxide emissions | 11.964 (0.00)[a] | 10.916 (0.00)[a] | 10.026 (0.00)[a] |

Under the null hypothesis of cross-sectional independence, the CD statistic is distributed as a two-tailed standard normal distribution. Results reported based on the test of Pesaran (2004) with $p$ values in round brackets.

[a] $p \leq 0.01$

heterogeneous time-varying idiosyncratic components after controlling for a common growth component among the countries that share the same convergence pattern. This approach has the comparative advantage that it does not rely on any assumptions regarding the stationarity of the variables as in tests of stochastic convergence. Specifically, the Phillips-Sul approach utilizes a time-varying common factor defined as:

$$PCCO2_{it} = \delta_{it}\mu_t \tag{8}$$

where $PCCO2_{it}$ represents per capita carbon dioxide emissions in country i at time t, which is comprised of a common component, $\mu_t$, and an idiosyncratic component, $\delta_{it}$, both of which are time-varying. Note that the idiosyncratic component is a measure of the distance between $PCCO2_{it}$ and the common component, $\mu_t$.

**Table 4** Panel unit root tests of stochastic convergence

| | | |
|---|---|---|
| Panel A: panel unit root tests without breaks | | |
| Low-income countries | | |
| | Pesaran CIPS | Pesaran CIPS* |
| Relative per capita carbon dioxide emissions | − 6.48 (0.00)[a] | − 6.19 (0.00)[a] |
| Lower-middle income countries | | |
| | Pesaran CIPS | Pesaran CIPS* |
| Relative per capita carbon dioxide emissions | − 6.14 (0.00)[a] | − 5.83 (0.00)[a] |
| Low- and lower middle-income countries | | |
| | Pesaran CIPS | Pesaran CIPS* |
| Relative per capita carbon dioxide emissions | − 6.95 (0.00)[a] | − 6.61 (0.00)[a] |
| Panel B: panel unit root test with breaks | | |
| Low-income countries | | |
| | Bai and Carrion-i-Silvestre Z* | |
| Relative per capita carbon dioxide emissions | − 1.54 (0.00)[a] | |
| Lower middle-income countries | | |
| | Bai and Carrion-i-Silvestre Z* | |
| Relative per capita carbon dioxide emissions | − 1.86 (0.00)[a] | |
| Low- and lower middle-income countries | | |
| | Bai and Carrion-i-Silvestre Z* | |
| Relative per capita carbon dioxide emissions | − 1.97 (0.00)[a] | |

$p$ values are in round brackets. For the Bai and Carrion-i-Silvestre Z* test, the number of common factors is estimated using the panel Bayesian information criterion proposed by Bai and Ng (2002), and the test is estimated with a maximum number of breaks at 3

[a] $p \leq 0.01$

Phillips and Sul (2007, 2009) use the relative transition parameter, $h_{it}$, as follows:

$$h_{it} = \frac{PCCO2_{it}}{\frac{1}{N}\sum_{i=1}^{N} PCCO2_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum_{i=1}^{N} \delta_{it}} \tag{9}$$

Equation (9) measures the loading coefficient, $\delta_{it}$, relative to the panel average, thus the transition path for per capita carbon dioxide emissions in country i relative to the panel average. In the case that the factor loadings, $\delta_{it}$, converge to a constant, $\delta$, then the cross-sectional mean of the relative transition path for country i, $h_{it}$, converges to unity, and the cross-section variation, $H_t$, of the relative transition path converges to zero as $t \to \infty$:

$$H_t = \frac{1}{N}\sum_{i=1}^{N} (h_{it}-1)^2 \to 0 \tag{10}$$

The semi-parametric form of $\delta_{it}$ is given as:

$$\delta_{it} = \delta_i + \frac{\sigma_i \xi_{it}}{L(t)t^{\alpha}} \tag{11}$$

where $\delta_i$ is fixed; $\xi_{it}$~iid (0,1) varies across countries i = 1, 2, …, $N$; $\sigma_i$ is an idiosyncratic scale parameter; L(t) is a slow varying function where L(t)→∞ and t→∞; and $\alpha$ represents the speed of convergence. Equation (11) ensures that $\delta_{it}$ converges to $\delta_i$ for $\alpha \geq 0$. Hence, the null hypothesis of convergence is the following: $H_0 : \delta_i = \delta$ and $\alpha \geq 0$, against the alternative hypothesis, $H_A : \delta_i \neq \delta$ for some i and/or $\alpha < 0$.

Following Phillips and Sul (2007, 2009), we set L(t) = logt in the decay model, so the empirical log t regression can be used to test for convergence and the deployment of the clustering algorithm to identify convergence clubs as follows:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log L(t) = \widehat{a} + \widehat{b}\log t + \varepsilon_t \tag{12}$$

for t = rT, rT + 1, …, T where $r > 0$ set on the interval (0.2, 0.3).[8] For $\widehat{b} = 2\alpha$, the null hypothesis is considered a one-sided test of $\widehat{b} \geq 0$ against $\widehat{b} < 0$. To address estimates in Eq. (12) that may be weakly time-dependent, heteroskedasticity and autocorrelation-consistent standard errors are employed in the least squares estimates of $\widehat{b}$.

The Phillips and Sul (2007, 2009) procedure uses a club convergence approach to identify convergence clubs as follows: (1) order the N countries in the panel using the final values of per capita carbon dioxide emissions for the respective countries; (2) starting from the highest-order country in terms of per capita carbon dioxide emissions, sequentially estimate Eq. (12) on the k highest member countries to identify a core group of countries using the cut-off point criterion: $k^* = ArgMax_k\left\{t_{\widehat{b}_k}\right\}$, subject to $Min_k\left\{t_{\widehat{b}_k}\right\} > 1.65$, for k = 2, 3, …$N$; (3) add one country at a time from the remaining countries to the core group, and re-estimate Eq. (12) using the sign criterion ($\widehat{b} \geq 0$ ) to determine whether to add a country to the core group; and (4) repeat the above steps iteratively for the remaining countries until clubs can no longer be formed. Given this iterative approach, each club formed is associated with its own convergence path. Countries that do not exhibit a convergence pattern are considered non-convergent.

We begin with examining tests of club convergence in the case of the panel of 27 low-income countries as shown in panel A of Table 5. The null hypothesis of overall panel convergence is rejected at the 1% significance level given the $t$ statistic of − 30.606. Given the absence of overall panel convergence, we proceed with the algorithm of Phillips and Sul (2007, 2009) to determine whether convergence clubs are formed. As documented in panel A of Table 5, three convergence clubs emerge with only Haiti exhibiting non-convergent behavior. Club 1 consists of four countries: Afghanistan, Nepal, Syrian Arab Republic, and Yemen; Club 2 encompasses 18 African countries: Benin, Burkina Faso, Burundi, Central African Republic, Chad, Democratic Republic of Congo, Ethiopia, Madagascar, Malawi, Mali, Mozambique, Niger, Rwanda, Sierra Leone, Somalia, Tanzania, Togo, and Uganda; and Club 3 contains four West African countries: Gambia, Guinea, Guinea-Bissau, and Liberia. An examination of the speed of convergence, $\alpha$, shows that club 2 (0.4790) has the fastest speed of convergence, followed by club 1 (0.3310) and club 3 (0.2480).[9] However, as noted by Phillips and Sul (2009), the convergence algorithm may lead to over-estimation of the true number of clubs. To address this potential issue, we evaluate merging adjacent numbered clubs into larger clubs by performing club merging tests via regression (12). The club merging tests in panel B of Table 5 reject the null hypothesis of merging clubs. Interestingly enough, the convergence clubs reveal the geographic proximity of the respective club members, similar to previous convergence studies tied to geographic regions.

Next, we undertake the same tests of club convergence, but in this case for the panel of 38 lower middle-income countries. In panel A of Table 6, the null hypothesis of overall panel convergence is again rejected at the 1% significance level with a $t$ statistic of − 30.837. Following the algorithm of Phillips and Sul (2007, 2009), we determine the number of convergence clubs. From panel A of Table 6, we identify five convergence clubs with seven countries (Cabo Verde, Comoros, Mongolia, Papua New Guinea, Sao Tome and Principe, Solomon Islands, and Vanuatu) considered non-convergent. Club 1 consists of 15 African countries (Angola, Cameroon, Republic of Congo, Cote d'Ivoire, Djibouti, Eswatini, Ghana,

[8] Set $r = 0.3$.

[9] $\alpha$ defined as $\widehat{b}/2$.

**Table 5** Tests of club convergence: low-income countries

| | | | |
|---|---|---|---|
| Panel A: club convergence tests | | | |
| Low-income countries, overall: Afghanistan, Benin, Burkina Faso, Burundi, Central African Republic, Chad, Democratic Republic of Congo, Ethiopia, Gambia, Guinea, Guinea-Bissau, Haiti, Liberia, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Rwanda, Sierra Leone, Somalia, Syrian Arab Republic, Tanzania, Togo, Uganda, Yemen | | | |
| | $\widehat{b}$ coefficient | *t* statistic | |
| Per capita carbon dioxide emissions | − 0.912 | − 30.606[a] | |
| Club 1: Afghanistan, Nepal, Syrian Arab Republic, Yemen | | | |
| | $\widehat{b}$ coefficient | *t* statistic | $\alpha$ |
| Per capita carbon dioxide emissions | 0.662 | 1.013 | 0.3310 |
| Club 2: Benin, Burkina Faso, Burundi, Central African Republic, Chad, Democratic Republic of Congo, Ethiopia, Madagascar, Malawi, Mali, Mozambique, Niger, Rwanda, Sierra Leone, Somalia, Tanzania, Togo, Uganda | | | |
| | $\widehat{b}$ coefficient | *t* statistic | $\alpha$ |
| Per capita carbon dioxide emissions | 0.958 | 1.216 | 0.4790 |
| Club 3: Gambia, Guinea, Guinea-Bissau, Liberia | | | |
| | $\widehat{b}$ coefficient | *t* statistic | $\alpha$ |
| Per capita carbon dioxide emissions | 0.496 | 1.029 | 0.2480 |
| Non-converging countries: Haiti | | | |
| Panel B: club merging tests | | | |
| Clubs | | $\widehat{\gamma}$ | $t_{\widehat{\gamma}}$ |
| Club 1 + Club 2 | | − 0.109 | − 6.44[a] |
| Club 2 + Club 3 | | − 0.126 | − 7.95[a] |

Club convergence tests: Test for the one-sided null hypothesis, $\widehat{b} \geq 0$ against $\widehat{b} < 0$, using the critical value $t_{0.05} = -1.65156$. Club merging tests: Test for the one-sided null hypothesis, $\widehat{\gamma} \geq 0$ against $\widehat{\gamma} < 0$, using the critical value $t_{0.05} = -1.65156$

[a] $p \leq 0.01$

Kenya, Kiribati, Mauritania, Nigeria, Senegal, Zambia, and Zimbabwe). Club 2 includes only three North African countries (Egypt, Morocco, and Tunisia); Club 3 comprises five Asian countries (Bangladesh, Bhutan, Cambodia, Laos, Myanmar, and Vietnam); Club 4 consists of four Central and Latin American countries (Bolivia, El Salvador, Honduras, and Nicaragua); and Club 5 contains four Asian countries (India, Indonesia, Pakistan, and the Philippines). A review of the speed of convergence associated with each convergence club reveals that club 5 (0.6685) exhibits the fastest speed of convergence, followed by club 4 (0.5140), club 2 (0.4195), club 1 (0.3490), and club 3 (0.2555). As in the case of the convergence clubs for low-income countries reported in Table 5, the club merging tests, shown in panel B of Table 6, do not support the merger of the respective convergence clubs. Likewise, convergence clubs among lower middle-income countries again reflect a high degree of geographic proximity.

Finally, we combine low-income and lower middle-income countries to form a developing country panel of 65 countries. Panel A of Table 7 shows that the null hypothesis of overall panel convergence is once again rejected at the 1% significance level with a $t$ statistic of − 31.219. We find six convergence clubs with 11 countries (Cabo Verde, Comoros, Haiti, Malawi, Mongolia, Papua New Guinea, Sao Tome and Principe, Solomon Islands, Syrian Arab Republic, Vanuatu, and Yemen) non-convergent. Club 1 includes 32 African countries (Angola, Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Republic of Congo, Cote d'Ivoire, Democratic Republic of Congo, Djibouti, Eswatini, Gambia, Ghana, Kenya, Kiribati, Liberia,

**Table 6** Tests of club convergence: lower middle-income countries

| | | | |
|---|---|---|---|
| Panel A: club convergence tests | | | |
| Lower middle-income countries, overall: Angola, Bangladesh, Bhutan, Bolivia, Cabo Verde, Cambodia, Cameroon, Comoros, Republic of Congo, Cote d'Ivoire, Djibouti, Egypt, El Salvador, Eswatini, Ghana, Honduras, India, Indonesia, Kenya, Kiribati, Laos, Mauritania, Mongolia, Morocco, Myanmar, Nicaragua, Nigeria, Pakistan, Papua New Guinea, Philippines, Sao Tome and Principe, Senegal, Solomon Islands, Tunisia, Vanuatu, Vietnam, Zambia, Zimbabwe | | | |
| | $\widehat{b}$ coefficient | $t$ statistic | |
| Per capita carbon dioxide emissions | − 0.756 | − 30.837[a] | |
| Club 1: Angola, Cameroon, Republic of Congo, Cote d'Ivoire, Djibouti, Eswatini, Ghana, Kenya, Kiribati, Mauritania, Nigeria, Senegal, Zambia, Zimbabwe | | | |
| | $\widehat{b}$ coefficient | $t$ statistic | $a$ |
| Per capita carbon dioxide emissions | 0.698 | 1.317 | 0.3490 |
| Club 2: Egypt, Morocco, Tunisia | | | |
| | $\widehat{b}$ coefficient | $t$ statistic | $a$ |
| Per capita carbon dioxide emissions | 0.839 | 1.109 | 0.4195 |
| Club 3: Bangladesh, Bhutan, Cambodia, Laos, Myanmar, Vietnam | | | |
| | $\widehat{b}$ coefficient | $t$ statistic | $a$ |
| Per capita carbon dioxide emissions | 0.511 | 1.093 | 0.2555 |
| Club 4: Bolivia, El Salvador, Honduras, Nicaragua | | | |
| | $\widehat{b}$ coefficient | $t$ statistic | $a$ |
| Per capita carbon dioxide emissions | 1.028 | 1.196 | 0.5140 |
| Club 5: India, Indonesia, Pakistan, Philippines | | | |
| | $\widehat{b}$ coefficient | $t$ statistic | $a$ |
| Per capita carbon dioxide emissions | 1.337 | 1.462 | 0.6685 |
| Non-converging countries: Cabo Verde, Comoros, Mongolia, Papua New Guinea, Sao Tome and Principe, Solomon Islands, Vanuatu | | | |
| Panel B: club merging tests | | | |
| Clubs | | $\widehat{\gamma}$ | $t_{\widehat{\gamma}}$ |
| Club 1 + Club 2 | | − 0.088 | − 5.91[a] |
| Club 2 + Club 3 | | − 0.109 | − 6.74[a] |
| Club 3 + Club 4 | | − 0.093 | − 6.22[a] |
| Club 4 + Club 5 | | − 0.115 | − 7.12[a] |

Club convergence tests: Test for the one-sided null hypothesis, $\widehat{b}\geq 0$ against $\widehat{b} < 0$, using the critical value $t_{0.05} = -1.65156$. Club merging tests: Test for the one-sided null hypothesis, $\widehat{\gamma}\geq 0$ against $\widehat{\gamma} < 0$, using the critical value $t_{0.05} = -1.65156$

[a] $p \leq 0.01$

Madagascar, Mali, Mauritania, Mozambique, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, Tanzania, Togo, Uganda, Zambia, and Zimbabwe); Club 2 comprises three North African countries (Egypt, Morocco, and Tunisia); Club 3 consists of six Asian countries (Bangladesh, Bhutan, Cambodia, Laos, Myanmar, and Vietnam); Club 4 encompasses four Central and Latin America countries (Bolivia, El Salvador, Honduras, and Nicaragua); Club 5 includes six Asian countries (Afghanistan, India, Indonesia, Nepal, Pakistan, and the Philippines), and three African countries in club 6 (Ethiopia, Guinea, and Guinea-Bissau). As is the case with Tables 5 and 6, the speed of convergence varies greatly across the convergence clubs with the fastest convergence in club 5 (0.5145), followed by club 4 (0.3915), club 2 (0.3310), club 1 (0.2705), club 3 (0.2195), and club 6 (0.2040). Similar to panel B of Tables 5 and 6, the club merging tests reported in

**Table 7** Tests of club convergence: low- and lower middle-income countries

| | | | |
|---|---|---|---|
| Panel A: club convergence tests | | | |
| Low-income and lower middle-income countries, overall: Afghanistan, Angola, Bangladesh, Benin, Bhutan, Bolivia, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Central African Republic, Chad, Comoros, Democratic Republic of Congo, Republic of Congo, Cote d'Ivoire, Djibouti, Egypt, El Salvador, Eswatini, Ethiopia, Gambia, Ghana, Guinea, Guinea-Bissau, Haiti, Honduras, India, Indonesia, Kenya, Kiribati, Laos, Liberia, Madagascar, Malawi, Mali, Mauritania, Mongolia, Morocco, Mozambique, Myanmar, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Papua New Guinea, Philippines, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Solomon Islands, Somalia, Syrian Arab Republic, Tanzania, Togo, Tunisia, Uganda, Vanuatu, Vietnam, Yemen, Zambia, Zimbabwe | | | |
| | $\widehat{b}$ coefficient | *t* statistic | |
| Per capita carbon dioxide emissions | − 0.944 | − 31.219[a] | |
| Club 1: Angola, Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Republic of Congo, Cote d'Ivoire, Democratic Republic of Congo, Djibouti, Eswatini, Gambia, Ghana, Kenya, Kiribati, Liberia, Madagascar, Mali, Mauritania, Mozambique, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, Tanzania, Togo, Uganda, Zambia, Zimbabwe | | | |
| | $\widehat{b}$ coefficient | *t* statistic | $\alpha$ |
| Per capita carbon dioxide emissions | 0.541 | 1.168 | 0.2705 |
| Club 2: Egypt, Morocco, Tunisia | | | |
| | $\widehat{b}$ coefficient | *t* statistic | $\alpha$ |
| Per capita carbon dioxide emissions | 0.662 | 0.784 | 0.3310 |
| Club 3: Bangladesh, Bhutan, Cambodia, Laos, Myanmar, Vietnam | | | |
| | $\widehat{b}$ coefficient | *t* statistic | $\alpha$ |
| Per capita carbon dioxide emissions | 0.439 | 0.922 | 0.2195 |
| Club 4: Bolivia, El Salvador, Honduras, Nicaragua | | | |
| | $\widehat{b}$ coefficient | *t* statistic | $\alpha$ |
| Per capita carbon dioxide emissions | 0.783 | 0.863 | 0.3915 |
| Club 5: Afghanistan, India, Indonesia, Nepal, Pakistan, Philippines | | | |
| | $\widehat{b}$ coefficient | *t* statistic | $\alpha$ |
| Per capita carbon dioxide emissions | 1.029 | 1.223 | 0.5145 |
| Club 6: Ethiopia, Guinea, Guinea-Bissau | | | |
| | $\widehat{b}$ coefficient | *t* statistic | $\alpha$ |
| Per capita carbon dioxide emissions | 0.408 | 0.816 | 0.2040 |
| Non-converging group: Cabo Verde, Comoros, Haiti, Malawi, Mongolia, Papua New Guinea, Sao Tome and Principe, Solomon Islands, Syrian Arab Republic, Vanuatu, Yemen | | | |
| Panel B: club merging tests | | | |
| Clubs | | $\widehat{\gamma}$ | $t_{\widehat{\gamma}}$ |
| Club 1 + Club 2 | | − 0.096 | − 6.13[a] |
| Club 2 + Club 3 | | − 0.126 | − 7.10[a] |
| Club 3 + Club 4 | | − 0.108 | − 6.84[a] |
| Club 4 + Club 5 | | − 0.120 | − 7.05[a] |
| Club 5 + Club 6 | | − 0.095 | − 6.24[a] |

Club convergence tests: Test for the one-sided null hypothesis, $\widehat{b} \geq 0$ against $\widehat{b} < 0$, using the critical value $t_{0.05} = -1.65156$. Club merging tests: Test for the one-sided null hypothesis, $\widehat{\gamma} \geq 0$ against $\widehat{\gamma} < 0$, using the critical value $t_{0.05} = -1.65156$

[a] $p \leq 0.01$

panel B of Table 7 reject the null hypothesis of merging clubs. While panel unit root tests find stochastic convergence in relative per capita carbon dioxide emissions for each of the three country panels, the club convergence tests reveal multiple convergence clubs in each country panel that show unique transition paths for countries within each convergence club to a steady state.

## Concluding remarks

With the ongoing debate on the appropriate mitigation and emission allocation strategies pertaining to per capita carbon dioxide emissions, this exploratory study provided additional evidence with respect to the convergence of per capita carbon dioxide emissions in the case of developing countries. Specifically, Pesaran (2007) and Bai and Carrion-i-Silvestre (2009) panel unit root tests with allowance for cross-sectional dependence lend support for stochastic convergence in per capita carbon dioxide emissions for the respective country panels. The nonlinear time-varying factor model of Phillips and Sul (2007, 2009) revealed multiple convergence clubs within the country panels with the speed of convergence varying across convergence clubs. Within the low-income country panel, the analysis identified three convergence clubs, five convergence clubs for the lower middle-income country panel, and six convergence clubs for the country panel that combined both low- and lower middle-income countries. A common theme for many of the convergence clubs was the geographical proximity of countries within the club. With respect to the non-convergent countries, a common characteristic was that many were island countries and to some extent geographically isolated.

As noted by Rios and Gianmoena (2018), rather than the two-track emission allocation framework in which developing countries did not have mitigation requirements, as in the case of industrialized countries under the Framework Convention on Climate Change and the Kyoto Protocol, the Paris 2015 agreement provided for carbon dioxide emissions mitigation to be tied to country-specific circumstances. This is particularly relevant as our results from the Phillips-Sul club convergence procedure illustrate that countries in geographic proximity, as defined within the convergence clubs, exhibit unique transition paths toward their respective steady states. The geographic proximity between countries within their respective convergence clubs may reflect similar natural resource endowments, weather conditions, and economic structure, all of which influence their energy consumption mix. Moreover, the geographical proximity may also indicate the potential for strategic interactions between governments with respect to environmental policy actions whose economies are spatially linked relative to other countries (Fredriksson et al. 2004). In addition, the quality of a country's institutions and governance structure plays a critical role in the effective implementation of the appropriate economic instruments (price-based and rights-based measures) to mitigate emissions as their level of economic development evolves over time. The ability of developing countries to adopt emerging mitigation and low carbon technologies, alongside movement toward renewable energy sources and improvement in energy efficiency, should be given serious consideration in order to control carbon dioxide emissions in these countries.

## Appendix A

| | |
|---|---|
| Low-income countries (27) | |
| Afghanistan | Malawi |
| Benin | Mali |
| Burkina Faso | Mozambique |
| Burundi | Nepal |
| Central African Republic | Niger |
| Chad | Rwanda |
| Democratic Republic of Congo | Sierra Leone |
| Ethiopia | Somalia |
| Gambia | Syrian Arab Republic |
| Guinea | Tanzania |
| Guinea-Bissau | Togo |
| Haiti | Uganda |
| Liberia | Yemen |
| Madagascar | |
| Lower middle-income countries (38): | |
| Angola | Kiribati |
| Bangladesh | Laos |
| Bhutan | Mauritania |
| Bolivia | Mongolia |
| Cabo Verde | Morocco |
| Cambodia | Myanmar |
| Cameroon | Nicaragua |
| Comoros | Nigeria |
| Republic of Congo | Pakistan |
| Cote d'Ivoire | Papua New Guinea |
| Djibouti | Philippines |
| Egypt | Sao Tome and Principe |
| El Salvador | Senegal |
| Eswatini | Solomon Islands |
| Ghana | Tunisia |
| Honduras | Vanuatu |
| India | Vietnam |
| Indonesia | Zambia |
| Kenya | Zimbabwe |

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