Decoding Emission Puzzle: How Methane and Nitrous Oxide Drive GHG Convergence Clubs

Keshav Sethi
O.P. Jindal Global University, Sonipat, Haryana, India. Email: ksethi@jgu.edu.in
Debajit Jha
O.P. Jindal Global University, Sonipat, Haryana, India.
Email:jhadebajit@gmail.com

Abstract

The recent literature on emission convergence reveals the presence of convergence clubs of GHG emissions across countries. Interestingly, although GHG emissions show evidence of club convergence, CO_2 emissions (which constitute more than 75% of GHG emissions) demonstrate convergence across countries. Then, what causes the convergence clubs of GHG emissions? The study seeks to solve this emission puzzle of convergence in CO_2 and club convergence in GHG by highlighting the role of other primary greenhouse gases i.e., methane and nitrous oxide, in determining the GHG convergence clubs. To test this hypothesis, we first identify the presence of absolute convergence in per capita CO_2 emissions while three convergence clubs of per capita emissions for GHG, methane, and nitrous oxide across 168 countries from 1990 to 2019 using a time-varying dynamic factor model. Then, using bivariate probit regression, we show that per capita methane and nitrous oxide emissions convergence clubs are significant determinants of per capita GHG emissions convergence clubs. The results suggest that countries in the high-emission club of methane or nitrous oxide are also likely to be members of the high GHG emissions club, despite these gases contributing less to total GHG emissions than CO_2. Our findings underscore the need to shift policy attention from CO_2 emissions to methane and nitrous oxide emissions for substantial climate benefits.

Keywords: SDG, Emissions convergence, Convergence clubs, Greenhouse gas, Methane, Nitrous oxide, Carbon dioxide

1. Introduction

There is general consensus among policymakers and researchers across countries that anthropogenic greenhouse gas (GHG) emissions are the potential cause of twenty-first-century climate changes.[1] The Sixth Assessment Report (AR6) of the United Nations Intergovernmental Panel on Climate Change (IPCC) consistently highlights how human activities contribute to climate change, particularly the burning of fossil fuels, which has been identified as one of the most important primary causes of the climate crisis.[2] Global GHG emissions persistently increased with unequal historical and present contributions arising from unsustainable energy use, land use change, lifestyles, and consumption, and production patterns across countries. As a result, mitigating the catastrophic effects of GHG emissions becomes important to protect the deteriorating health of the population and to tackle the climate crisis.

The policy effort to mitigate the problems arising from GHG emissions requires an analysis of whether these emissions are converging or diverging or forming convergence clubs across countries. It is important because the policy intervention may vary extensively depending on whether one gets evidence of cross-country emission convergence, divergence, or club convergence. For example, if there is evidence of emission convergence across countries, this suggests that we don't need any policy intervention. The only thing policy can do here is to fasten the process of convergence by identifying the factors determining convergence across countries. Similarly, if there is evidence of divergence, then we need to equalize the factors

[1] Rising temperatures, changing weather patterns, sea level rise, ocean acidification, agricultural disruptions, and threats to biodiversity and ecosystems are all results of the natural greenhouse effect caused by human activities. See Jain (1993) and Mitchell (1989).

[2] IPCC AR6 finds that global GHG emissions peak before 2025 with more than 50% chance that earth's temperature rise will reach or surpass 1.5 degrees between 2021 and 2040 under a high-emission pathway. Human activities, principally through GHG emissions, have unequivocally caused global warming, with global surface temperature reaching 1.1°C above 1850-1900 in 2011-2020.

responsible for divergence across countries. However, the policy intervention is a little complicated, if one finds the evidence of convergence clubs. This is because the policies that are suitable for countries in the high-emission convergence club may not be suitable for the countries situated in the low-emission convergence club due to differences in the composition and characteristics of their emissions (Belloc and Molina, 2023b).

While there is a large literature on emission convergence, most of the studies in the literature have focused on carbon dioxide (CO_2) emissions, a primary driver of GHG emissions with 76% contribution, most probably due to the fact that emission-related policies are formed based on the identified trajectories of CO_2 emissions. The studies on the convergence of aggregate GHG emissions and other primary greenhouse gases like methane (CH_4) and nitrous oxide (N_2O) have attracted relatively lesser attention despite global recognition of the fact that these gases contribute respectively 16% and 6% of human-induced GHGs (IPCC, 2014) and are often having more harmful impacts.[3] Out of the total twenty-four recent papers (covering the post-1990 period) on emission convergence we reviewed, twelve were on CO_2 emissions while only seven were on GHG emissions, five were on CH_4 emissions and three were on N_2O emissions.[4] Moreover, in the post-1990 period, a significant body of literature has focused on the convergence of GHG emissions across various gases, with a distinct divergence in findings related to CO_2 emissions and aggregate GHG emissions. While the cross-country studies on CO_2 emissions identified evidence of either conditional or absolute convergence (e.g., Borowiec and Papiez, 2024; Marrero et al., 2021; Fernández-Amador et al., 2019), the studies on aggregate GHG emissions (e.g., Belloc and Molina, 2023a; 2023b; Presno et al., 2021; El-Montassera et al., 2015; Payne et al., 2022) and other primary sources of GHG emissions like CH_4 and N_2O (e.g., Fernández-Amador et al., 2022; Camarero et al.,

[3] Methane is short-lived in the atmosphere, having 28 to 36 times the global warming potential that of carbon dioxide over 100 years, while nitrous oxide is long-lived, having an atmospheric-warming potential 265 to 298 times greater than that of carbon dioxide over a century.
[4] The details of the literature have been presented in Table A.1 in the appendix.

2014; de Oliveira and Bourscheidt, 2017) have predominantly found the evidence of club convergence.[5] [6] This disparity reflects a puzzle that requires further investigation to understand the underlying dynamics driving these differing convergence patterns. We call this "emission puzzle". In this paper, we tried to empirically resolve this puzzle by identifying the impact of other primary greenhouse gases (i.e., CH_4 and N_2O) convergence clubs in determining aggregate GHG convergence clubs in the cross-country emission data by employing a technique that controls for endogeneity bias.

Resolving this puzzle is important because the evidence of CO_2 convergence suggests that we will be able to implement common environmental policies more effectively across these countries (Presno et al., 2021).[7] However, the evidence of GHG club convergence suggests that the common set of policies suggested by the evidence of CO_2 convergence may not be sufficient for aggregate GHG to converge. We need differential policies for different sets of countries situated at different GHG convergence clubs.

In order to resolve the emission puzzle discussed above, we divide the paper into two parts. In the first part, we tried to identify whether the emission puzzle holds in GHG emissions and its primary components (CO_2, CH_4, and N_2O) using time-varying factor model developed by Phillips and Sul (2007b, 2009) (hereafter PS) for 168 countries for the period 1990 to 2019. There are several advantages of using the PS method. First, this is the only method that can clearly distinguish between the four different types of convergence dynamics - absolute convergence, conditional convergence, divergence, and club convergence. Second, this

[5] See Payne (2020), Lee et al. (2021), and Pettersson et al. (2013) for detailed surveys of the literature on emissions convergence.
[6] Out of 7 papers on cross-country GHG convergence in the post-1990 period that we reviewed, 6 papers show evidence of club convergence and 1 paper has shown evidence of conditional convergence. Similarly, out of the 12 papers on CO_2 convergence in the post-1990 period, 10 papers have shown evidence of convergence, and 2 papers have shown evidence of either divergence or club convergence.
[7] If emissions were to converge over time, then there would be less concern regarding any per capita allocation scheme across a converging group of countries to deliver its desired outcomes, thereby protecting environmental conditions. However, if per capita emissions diverge then this allocation approach may drive the relocation of emissions-intensive industries and resource transfers through international trading of carbon allowances (Lee et al., 2021).

method takes into consideration the cross-section heterogeneities present in the underlying data. Third, unlike stochastic convergence methods either using time series or panel data, there is no requirement for the data to be stationary. Fourth, this is an OLS-based method and hence, easy to carry out and interpret. Finally, the method is robust to structural break present in the data (Antonakakis et al., 2017). In the second part, we tried to identify the role played by convergence clubs of other primary greenhouse gases (CH_4 and N_2O) in determining GHG convergence clubs using the bivariate probit model.

This paper makes five key contributions. First, this paper analyses the convergence dynamics of per capita GHG emissions and its primary components (CO_2, CH_4, and N_2O) across 168 countries from 1990 to 2019 using the PS technique. To the best of our knowledge, this is the first study that analyses the convergence dynamics of GHG emissions and its primary contributors together for such a large sample of countries.[8] Second, instead of the traditional HP filter in convergence clubs estimation, we apply the machine learning-based boosted HP filter by Phillips and Shi (2021), offering more reliable convergence estimates.[9] Third, our findings help resolve the emission puzzle, guiding global emission policies. Fourth, using bivariate-probit regressions, we show that per capita CH_4 and N_2O emissions convergence clubs are significant determinants of per capita GHG emissions convergence clubs. To the best of our knowledge, no prior study ever tried to empirically examine this relationship instead of relying on scientific evidence. Finally, we identify key determinants of club membership for GHG, CH_4, and N_2O, which are critical for environmental policymaking. These contributions are highly relevant to ongoing climate discussions.

[8] Belloc and Molina (2023b) identified convergence of different greenhouse gases across 114 countries. Other studies in the literature have taken a relatively small number of countries.
[9] This filtering technique involves a reapplication of the standard HP filter until leftover trend residuals from the cyclical component are completely removed. Hence, the estimated convergence clubs in the present study are more reliable compared to the earlier studies. See Tomal (2024) for potential shortcomings of the HP filter.

Our results suggest the existence of three convergence clubs of per capita emissions for aggregate GHG, CH_4, N_2O, and absolute convergence for per capita CO_2 emissions. This highlights the existence of emission puzzle in our sample of countries. Moreover, using bivariate-probit regressions, we show that per capita CH_4 and N_2O emissions convergence clubs significantly determine per capita GHG emissions convergence clubs. More specifically, the results show that if one more country joins the high per capita CH_4 emissions club, then the probability of belonging to the high per capita GHG emissions club is increased by 51%. Similarly, if one more country joins the high per capita N_2O emissions club, then the probability of belonging to the high per capita GHG emissions club is increased by 34%. We also found that energy consumption, population, and KOF trade globalisation index are significant predictors of club membership.

The rest of the study is organised as follows. In section 2, we discuss whether the emission puzzle described above actually holds in our sample of 168 countries for the period 1990 to 2019. Section 3 tries to resolve the emission puzzle by identifying the impact of other primary greenhouse gases like CH_4 and N_2O in determining the GHG emissions convergence clubs along with additional exogenous determinants. Finally, Section 5 concludes with policy prescriptions.

2. Identification of Emission Puzzle

In this section, we are going to identify the convergence clubs of per capita GHG, carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) emissions to identify whether the emission puzzle discussed above actually present in the cross-country data for 168 countries for the period 1990 to 2019 using the PS technique. First, we present the details of the data that has been used in the study and then discuss the methodology.

2.1 Data

We gathered data on per capita production-based, CO_2, CH_4, N_2O, and GHG emissions from the Our World in Data*,* which provides annual country-level emissions over the period 1990-2019. For identifying the exogenous determinants in the next section, we have used different variables such as population size, GDP, trade, natural resource rents, etc. from the World Development Indicators, the V-Dem Dataset, and the KOF Swiss Economic Institute databases. Specifically, for the analysis of determinants of club membership, we have used log of GDP per capita, log of primary energy consumption, log of population, trade globalization index, total natural resources rents, and political corruption index.[10] These variables are selected based on their popularity in the existing literature. Table 1 presents the summary statistics for all variables used in the study.

[INSERT TABLE 1 HERE]

2.2 Phillip and Sul Methodology

In this paper, we used a methodology developed by Phillips-Sul (2007, 2009) to identify convergence clubs. This is the only method that allows us to distinguish between four cases of convergence dynamics, i.e., (i) absolute convergence (ii) conditional convergence (iii) divergence and (iv) club convergence. It is a regression-based convergence test, also known as log t test, that accommodates heterogeneity in the cross-sectional behaviour of units in the panel. This is done by modelling the panel as follows:

$$X_{it} = \alpha_i \mu_t + \epsilon_{it} \tag{1}$$

This equation decomposes X_{it} into short-run idiosyncratic (or unit-specific) effects, α_i, and a common factor, μ_t. The idiosyncratic elements in the panel, which include the error term ϵ_{it}, allow for short-run heterogeneity in the panel. Equation (1) can be rewritten as a time-varying dynamic factor model:

[10] Information on all the variables used in the study is given in Appendix Table 7.A.

$$X_{it} = \left(\alpha_i + \frac{\epsilon_t}{\mu_t}\right)\mu_t = b_{it}\mu_t \qquad (2)$$

Equation (2) rearranges the idiosyncratic elements (α_i and ϵ_{it}) affecting the long-run movement of units X_i together. These elements together are represented by b_{it}, which signifies the distance of an individual unit from the common trend component μ_t. Therefore, a variety of transition paths can be taken by units in the panel, with b_{it} reflecting the economy-specific characteristics that determine this variety.

In equation (2), the number of observations in the panel are less than the number of unknowns, making it impossible to estimate b_{it}. Therefore, testing for convergence in the framework presented by equation (2) requires imposing some structure on b_{it} and μ_t. To solve this issue, convergence is defined through a relative transition coefficient h_{it}, where:

$$h_{it} = \frac{X_{it}}{1/N\,(\sum_{i=1}^{n} X_n)} = \frac{b_{it}}{1/N\,(\sum_{i=1}^{n} b_{it})} \qquad (3)$$

Like b_{it}, h_{it} also traces out the transition path of each unit *i* in the panel. This is done relative to the cross-section average of the panel at each point in time, eliminating μ_t, and defining transition solely in terms of the idiosyncratic element b_{it}. For convergence, we require that $h_{it} \rightarrow 1$ for each unit i as $t \rightarrow \infty$. Thus, this framework allows room for heterogeneity in the transition paths of individual economies in the short run, while still allowing for ultimate convergence in the long run as $h_{it} \rightarrow 1$. This is a key advantage of the log t test over the traditional regression-based framework used for testing absolute convergence since cross-sectional homogeneity is imposed in the latter (Phillips and Sul, 2009).

Next, the cross-sectional variance of h_{it} is defined by:

$$H_{it} = \frac{1}{N} \sum_{i=1}^{n} (h_{it} - 1)^2 \quad (4)$$

Wherein the property that H_t 0 over time translates into the null hypothesis of convergence among units in the panel. Further structure is imposed on b_{it}, in order to formalize a null hypothesis of convergence. It is assumed that b_{it} follows a decay model which has the following semi-parametric form:

$$b_{it} = b_i + \frac{\sigma_i \zeta_{it}}{L(t)t^{\beta}} \quad (5)$$

In equation (5), b_i represents a fixed value that b_{it} may reach in the long run, σ_i is an idiosyncratic scale parameter and ζ_{it} represents a random variable that is *iid (0,1)* across the cross-section i, but maybe a weakly dependent time series. *L(t)* is a slowly varying function, like *log(t)*, for which *L(t)* → ∞ as *t* → ∞. β is the decay rate, which governs the rate at which the variation in the cross-section decays to zero over time.

In terms of equation (5), the null hypothesis can be written as:

$$H_0: b_i = b \ for\ all\ i\ and\ \beta \geq 0$$

This null hypothesis implies that all idiosyncratic transition elements b_i converge towards a common value *b* over time. The alternative hypothesis is defined as follows:

$$H_A = Either\ i)\ b_i = b\ for\ all\ i\ and\ \beta < 0\ (Divergence) \qquad Or \quad ii)\ b_i \neq b\ for\ some\ i\ and\ \beta \geq$$

Note that case ii) embeds the possibility of club-convergence in the test. Thus, in case the null hypothesis of convergence is rejected, the alternative is not necessarily divergence but could also be club-convergence, wherein the transition paths b_i for some units in the panel converge towards their respective long-run values b. In this manner, multiple equilibria on the road towards convergence are accommodated.

Lastly, to test for convergence, a regression model is proposed by Phillips and Sul (2007) that tests whether H_t, the cross-sectional variance of the relative transition coefficient h_{it} tends to zero in the long run. Using equations (3), (4) and (5), Phillips and Sul (2007) prove that this condition can be reduced to the following regression:

$$log(H_1/H_t) - 2logL(t) = p + b\,log\,t + u_t, \quad for\,t = [rT], [rT] + 1, ..., T \quad (6)$$

Equation (6) above is the log t-test, where $\hat{b} = 2\beta$, with β being the decay rate in equation (5). H_1 is the variance of the relative transition coefficient at time t = 1, and H_t is its variance at any given point in time. Since convergence of the relative transition coefficients would require H_t to go down over time as a proportion of H_1, $log(\frac{H_1}{H_t})$ represents a measure of this convergence. *L(t)* is assumed to be a slowly varying function of time, with Phillips and Sul (2007) suggesting that $L(t) = log(t)$. Equation (6) is estimated over a truncated sample, defined by a parameter r and the size of the total sample T. The truncated sample thus goes from rT (or its closest integer value) to T. The parameter r can take any value between zero and one. Based on Monte Carlo simulations, Phillips and Sul (2007) suggest a value of $r \in [0.2,\ 0.3]$ for log-t tests, which balances the limit distribution and power properties of the test. For small or moderate samples ($T \leq 50$), Phillips and Sul (2007) recommend keeping $r = 0.3$. Using an autocorrelation and heteroscedasticity consistent one-sided t-test, equation (6) is estimated on the truncated sample, and the null hypothesis of convergence, i.e. $\beta \geq 0$ is tested.

If the t-statistic has a value higher than -1.65, the null hypothesis of convergence cannot be rejected at the 5% significance level. Here, both divergence and club convergence are ruled out, but it could be a case of either absolute or conditional convergence. In this case, Phillips and Sul (2009) point out that not only the sign of the estimated coefficient $\hat{b}$, but also its magnitude becomes important, as it measures the speed of convergence (since $\hat{b} = 2\beta$). Values of $\hat{b}$ equal to or larger than 2 imply absolute convergence, while values in the range $2 \geq \hat{b} \geq 0$ imply conditional convergence. Thus, in the case where convergence cannot be rejected, the Phillips-Sul methodology enables us to distinguish between two sub-cases of convergence, i.e., absolute and conditional convergence. This aspect of the Phillips-Sul methodology has been used in a number of recent studies (e.g., Marrero et al, 2021; Ajit and Ghosh, 2024).

If the t-statistic has a value less than -1.65, the null hypothesis of convergence is rejected at the 5% significance level. As mentioned above, the log t-test allows for the possibility of club convergence in case the null hypothesis of convergence is rejected. Assuming the null hypothesis is, in fact, rejected, the next step involves identifying sub-groups, clusters or clubs in the panel for which the null hypothesis of convergence does hold.

Phillips and Sul (2007) developed an algorithm for identifying such clusters. The steps the algorithm follows are:

1) **Sorting:** In the last period for which data is available, units in the cross-section are sorted in descending order by the variable of interest (say, per capita emissions). The units thus ordered are indexed *1, ..., N.*
2) **Core-group formation:** Next, a core group of units is identified. For this, the k highest units in the panel are selected, with $2 \leq k < N$. k is chosen such that the t-statistic from equation (6) is maximized among all the subgroups that do not reject the null of convergence. These k units constitute the core group.
3) **Sieving:** Once the core group has been formed, additional units are 'sieved' into it as long as their inclusion does not lead to the rejection of the null of convergence. The

core group, with some additional members sieved in, together form the first convergence club.

4) **Recursion:** With the leftover units, the same steps above are repeated in order to identify further clubs until no unit is left or there are some units that do not converge to any club. Units in the latter case exhibit divergence.

In case multiple convergence clubs are identified from the above steps, tests are conducted in order to determine whether some clubs can be merged to form larger clubs. To do this, first, the two highest clubs and their respective units are taken together. A log-t test is conducted and if the null of convergence is not rejected, the two clubs are merged and now constitute a single club. Members from the third-highest club are then included in this new, merged club and the log-t test is conducted again. If the null of convergence is not rejected, the third club too gets subsumed within this larger club. If the null is rejected, the same process is repeated with clubs $3, 4, \ldots, n$ in order to identify possible mergers. After the first merger, the process continues until all possible mergers are concluded. Finally, if the null hypothesis of convergence is rejected, and the algorithm described above is unable to identify any convergence clubs, then we conclude that the units manifest divergence in their growth dynamics. The merging algorithm that we have employed is essentially an updated version of PS's original proposal, as suggested by Schnurbus et al. (2017) where one can also repeat the above procedure on the newly obtained club classifications until no clubs can be merged, which leads to the classifications with the smallest number of convergence clubs.[11]

The result of the PS can vary depending on the filter that has been used to separate out trend component from the aggregate data. PS suggests to use the HP filter. Tomal (2024) pointed

[11] Schnurbus et al. (2017) argued that the merging of initial convergence clubs can be iterated as follows: with the two highest convergence clubs (e.g., 1 and 2) run a log t-test; if the value of the t-stats is greater than -1.65 merge them to form the new club 1, then run the log t-test for the new club 1 and the initial club 3 jointly; if t-stats value less than -1.65, run the log t test for initial clubs 2 and 3, etc.

out two limitations of the standard HP filter. The first limitation is related to end-point bias associated with denoting the excessive influence of the last observation in a time series, causing the oversizing of the log t regression in small samples for which the speed of convergence is small. The second problem is associated with the correct choice of tuning parameter λ. In particular, if λ is too large, the HP-fitted trend creates a residual trend, which pollutes the cyclical component. In contrast, if λ is too small, the fitted trend is too flexible and imitates short-term fluctuations. Fortunately, Phillips and Shi (2021) have developed a machine learning based version of the standard HP filter known as the boosted HP filter. This involves a reapplication of the standard HP filter until leftover trend residuals from the cyclical component are completely removed. Hence, the club convergence results derived from using boosted HP filter is more reliable. In the present paper, we have used boosted HP filter.

2.3 Empirical Evidence of Emission Puzzle

In this section, we present the results obtained from the PS method to identify the presence of emission puzzle described above. The results are presented in Tables 2 and 3, as well as in Figure 1.

We have reported the results of the log t regression test i.e., coefficient of log t and t-statistic values for all four gases in Table 2. These results are divided into two parts: Panel A presents the results of the null hypothesis of absolute convergence against the alternative of divergence or club convergence in the sample. We present the results of convergence clubs in Panel (B). In Panel A, the value of the coefficient of log t and t-statistics for all four gases are presented respectively in columns 2 to 5. Expect for per capita CO_2 emission the t-statistic for the other gases (i.e., GHG, CH_4, and N_2O) falls below -1.65. This suggests that while in the case of per capita CO_2 emission, the null hypothesis of absolute convergence has been accepted, the null hypothesis of absolute convergence is rejected for the other three gases at 5% significance level. Similarly, the coefficient of log t for all three gases except CO_2 is less than zero, indicating either divergence or a possibility of convergence club formation. In the case of per capita CO_2 emissions, the value of the coefficient of log t is 0.67, indicating growth rate convergence or conditional convergence.

Next, we proceed to explore the possibility of the formation of convergence clubs for the three gases (GHG, CH_4, and N_2O), where the null hypothesis of absolute convergence has been rejected, using the clustering algorithm proposed by PS. These results are presented in Panel B. The Panel B is divided into two parts. In the upper panel, we present the initial number of clubs and the respective club size. In the lower panel, we present the coefficient of log t and t-statistics for each of these initial clubs. The results in the upper part of Panel B suggest that there are respectively nine, three, and thirteen initial convergence clubs for per capita GHG, per capita CH_4, and per capita N_2O emissions.

[INSERT TABLE 2 HERE]

Subsequently, we examined the possibility of iterative merging of the initial clubs using the algorithm developed by Schnurbus et al. (2017). The final convergence clubs for all gases are reported respectively in panels A, B, C, and D of Table 3.[12] For per capita GHG emissions in Panel A, three convergence clubs are identified with 77, 71, and 20 countries respectively. These clubs are characterized by a coefficient of log t ranging from 0 to 2 indicating growth rate convergence or conditional convergence. Similarly, for per capita CH_4 emissions in Panel C, the initial three convergence clubs persist with 4, 13, and 151 countries respectively. In this case, while the coefficient of log t for clubs 1 and 2 falls between 0 and 2, indicating growth rate convergence or conditional convergence, the coefficient for club 3 comes to be

[12] The list of countries in final convergence clubs for all greenhouse gases is given in Appendix Tables 3.A, 4.A, and 5.A.

5.04 exhibiting level convergence. For per capita N_2O emissions presented in Panel D, the initial thirteen convergence clubs are merged into three final clubs with 96, 31, and 41 countries respectively. The coefficient of log t comes to be close to zero (-0.02, 0.20, and -0.04 respectively) indicating growth rate or conditional convergence. Our results are consistent with the existing literature, which suggests club convergence in CH_4, (e.g., Fernández-Amador et al., 2022; de Oliveira and Bourscheidt, 2017), N_2O (e.g., Infante et al., 2024; Camarero et al., 2014), and GHG (e.g., Presno et al., 2021; Payne et al., 2022; Ursavas and Apaydin, 2023) emissions and absolute convergence in CO_2 emissions (e.g., Borowiec and Papiez, 2024; Fernández-Amador et al., 2019; Belloc and Molina, 2023a; 2023b).

[INSERT TABLE 3 HERE]

Figures 1.1 to 1.4 represent the relative transition paths of the final convergence clubs.[13] [14] These clubs are categorized into high and low-emission clubs based on their relative transition path. Clubs with transition path above the average are classified as high-emission clubs, while those with transition path below the average are classified as low-emission clubs. The figure shows that high-emission club(s) diverge from low-emission club(s) and prevent the corresponding countries from converging to the lower steady state.

The empirical evidence presents a striking contrast between the convergence of per capita CO_2 emissions and the club convergence of per capita GHG emissions, including CH_4 and N_2O emissions.[15] This puzzle demands further research to understand why CO_2 emissions exhibit broader convergence, while GHG emissions often form distinct convergence clubs. A

[13] Transition paths are calculated by taking the mean per capita emissions of each club member and expressing it as a ratio to the average per capita emissions trend of all countries.
[14] Average transition paths for all the countries (gas-wise) are also presented in Appendix Figures 1.A, 2.A, 3.A, and 4.A.
[15] We got the same emission puzzle when adjusting the log t-test in line with the suggestions made by Kwak (2022) or when using different trend extraction methods (filters) and different trimming fractions (r). Results are available upon request.

better understanding of these dynamics could inform more targeted international climate policies that address not only CO_2 emissions but also other important greenhouse gases.

[INSERT FIGURE 1 HERE]

3. Resolving the Emission Puzzle

In this section, we try to identify the relationship between greenhouse gas (GHG) emissions convergence clubs and convergence clubs of methane (CH_4) and nitrous oxide (N_2O) emissions. This can be done by running a probit model where the dependent variable (per capita GHG emissions clubs) is binary (above average = 1 & below average = 0), and the main independent variables (per capita CH_4 and N_2O emissions clubs) are also binary (above average = 1 & below average = 0) along with other exogenous determinants.[16] However, there is a possibility of endogeneity bias in our explanatory variables, meaning that the factors (or unobservables) influencing per capita CH_4 and N_2O emissions clubs may also affect our outcome variable i.e., per capita GHG emissions clubs. In order to remove endogeneity, we need an appropriate estimation method.

3.1 Estimation Strategy

Since there is a possibility of endogeneity bias, we have to use an appropriate estimation procedure to take care of this problem. It may be noted that both the per capita GHG emissions clubs (outcome variable) and per capita methane and nitrous oxide emission clubs (explanatory variables) are binary variables and hence, they are discrete. The instrumental variables method (IV) or the IV-Probit method, the standard workhorses for correcting the endogeneity bias, becomes invalid for discrete explanatory variables. For binary endogenous explanatory variables, the appropriate estimation technique is the bivariate probit model (Greene, 2008). This is because, unlike the two-step least square regression (2SLS) where the

[16] If the average transition path of a club is above the value of 1 then it is categorized as a high-emission club and 0 otherwise, as tending toward the value of 1 represents absolute convergence.

instrumental variable approach solves the endogeneity problem, the bivariate probit framework models the joint distribution of the two variables and estimates the structural model using the maximum likelihood estimator. According to Greene (2012), in this case, "the endogenous nature of one of the variables on the right-hand side of the second equation can be ignored in formulating the log-likelihood" as the model is identified and can be consistently and efficiently estimated using the full information maximum likelihood estimator.

The bivariate probit model is estimated using a structural latent variable model with two equations that capture the effect of an endogenous binary regressor on a binary outcome variable. The model may be represented as:

$$z = \alpha` x_1 + \varepsilon_1 \qquad (7)$$

$$y = \beta` x_2 + \gamma z + \varepsilon_2 \qquad (8)$$

In our analysis, $z = 1$ if a country belongs to the high per capita methane or nitrous oxide emissions clubs, and $z = 0$ if it does not. Similarly, $y = 1$ if a particular country belongs to the high per capita GHG emission club, otherwise $y = 0$. In equations (7) and (8), x_1 and x_2 are the column vectors of exogenous variables, α, and β are vectors of unknown parameters, γ is an unknown scaler, and ε_1 and ε_2 are the error terms. The joint distribution of y and z is fully determined once the joint distribution of ε_1 and ε_2 is known. In the bivariate probit model, it is assumed that the ε_1 and ε_2 have a joint bivariate standard normal distribution with a coefficient of correlation $\rho \neq 0$. If $\rho \neq 0$, z is considered to be endogenous, and joint estimation is required. If $\rho = 0$, equations (7) and (8) can be estimated independently.

For bi-probit regressions, we have chosen appropriate exogenous variables for the column vectors x_1 and x_2 from the existing literature. The GHG emissions and its primary contributors are influenced by various economic, environmental, and institutional factors that differ across countries (e.g., Alkhathlan and Javid, M., 2013; Agovino et al., 2019; Cao et al, 2022; Bektas and Ursavas, 2023; Cai et al., 2022; Marrero, 2010). One key driver of emissions is population size, as larger populations increase demand for energy, transportation, and goods and services, leading to higher emissions. Similarly, GDP is strongly linked to GHG emissions due to higher industrial output and energy consumption. However, this relationship may decouple over time as wealthier nations invest in cleaner technologies. Energy consumption also influences emissions, especially in countries relying on fossil fuels, though investment in renewables can mitigate this effect. Trade and globalization contribute to emissions through increased industrial activity and transportation but can also facilitate green technology transfer, depending on whether environmentally friendly practices are adopted. Natural resource rents from carbon-intensive industries further elevate emissions, while corruption weakens environmental regulations, exacerbating emissions. Effective governance is thus essential for reducing GHG emissions.

3.3 Results of bi-probit regression

We have presented the results of bivariate probit regressions in Table 4.[17] [18] There are two regression models. The first one determines the impact of per capita CH_4 emissions clubs on per capita GHG emissions clubs (model 1 in Table 4), while the second one determines the impact of per capita N_2O emissions clubs on per capita GHG emissions clubs (model 2 in Table 4). In both the models, the results of the first stage regression (equation 7) have been presented in panel A. Panel B presents the result of the second stage of the bi-probit model

[17] It should be noted that due to the limited availability of data for the covariates in the bivariate probit analysis, the sample size is reduced to 117 as opposed to 168 countries used in the club convergence analysis. This raises the question as to whether the results will remain stable when the PS technique is conducted with the smaller sample countries. To check this, we re-do the club convergence analysis with a smaller sample of 117 countries and found that our emission puzzle results remain consistent.

[18] The full regression models (with all control variables) have been presented here. We have also run stepwise regressions (alternate specifications) given in Appendix Tables 6.A.1 and 6.A.2. We found that no matter which set of control variables we include in the primary GHG component clubs and GHG clubs equations, our findings that high emission club of per capita CH_4 or N_2O emissions is a positive and significant determinant of high per capita GHG emissions club remains robust to alternate specifications.

(equation 8). Therefore, in Panel A, the estimated coefficients capture the likelihood of a country in high per capita CH_4 emissions club (model 1) or high per capita N_2O emissions club (model 2) and a set of explanatory variables. Similarly, Panel B presents the estimated coefficients that capture the likelihood of a country in high per capita GHG emissions club and a set of explanatory variables including the primary GHG component clubs as the key variable of interest.

The coefficient of primary GHG component clubs (per capita CH_4 emissions) in model 1 shows that if one more joins the high per capita CH_4 emissions club the likelihood of belonging to the high GHG per capita emissions club is increased by 2.77. Similarly, the coefficient of primary GHG component clubs (per capita N_2O emissions) in model 2 shows that if one more country joins the high N_2O per capita emissions then the likelihood of belonging to the high per capita GHG emissions club is increased by 1.26. The results reported in Panel B imply that per capita GHG emissions convergence clubs are caused by per capita CH_4 convergence clubs (in model 1) and per capita N_2O convergence clubs (in model 2) (as both are positive and significant determinants). We have also found that primary energy consumption and population contribute positively and significantly to the likelihood of a country being in the high per capita GHG emissions club. In contrast, the trade globalization index negatively and significantly impacts the likelihood of a country being in the high per capita GHG emissions club.

[INSERT TABLE 4 HERE]

The marginal effects are also presented for both models. In the case of model 1, the marginal effects show that if one more country joins the high per capita CH_4 emissions club then the probability of belonging to the high per capita GHG emissions club is increased by 51%.

Similarly, if one more country joins the high per capita N_2O emissions club then the probability of belonging to the high per capita GHG emissions club is increased by 34%.

Moreover, the Likelihood ratio test of rho = 0 in Panel C represents the correlation of the errors of the two probit models estimated in equations 7 and 8. The test rejects the null hypothesis of zero correlation for both models, indicating that unobserved factors influencing a country's likelihood of belonging to high per capita CH_4 or N_2O emissions club also impact its likelihood of being part of a high per capita GHG emissions club. Furthermore, the overall model fit is evaluated using the Wald test in Panel D, which confirms the significance of both models.

4. Robustness tests

We also performed some robustness checks of our main results. The results of the robustness checks are presented in Table 5.

4.1. Robustness Test 1

There is a possibility that a truncated sample can alter the results. In order to test this possibility, we carried out two bi-probit regressions on two separate truncated samples. In the first case, we have taken a sample of countries that are in the low per capita methane (CH_4) emissions club and carried out the same bi-probit regression. Countries in this truncated sample are moving towards a lower steady state of per capita CH_4 emissions. Despite this trend, the sample reveals, that there is considerable variation in per capita greenhouse gas (GHG) emissions across countries, with some in the high-emission club and others in the low-emission club. Similarly, within this sample, there are high and low emission clubs of per capita nitrous oxide (N_2O) emissions. This result is presented in Table 5 under model 1 where the endogenous dependent variable i.e., high per capita N_2O emissions club, determines the high per capita GHG emissions club. Next, we have taken another truncated sample of countries where countries are in the low per capita N_2O emissions club and carried out the same bi-probit regression. Countries in this truncated sample are moving towards a lower steady state of per capita N_2O emissions. Within this sample, we observed a similar trend, with countries falling into high and low-emission clubs of per capita GHG and CH_4 emissions. This result is presented in Table 5 under model 2 where the endogenous dependent variable i.e., high per capita CH_4 emissions club, determines the high per capita GHG emissions club. In both these regressions, we have again observed that energy consumption, population, and trade globalization index are significant determinants of high per capita GHG emissions club. This suggests that some countries have successfully reduced CH_4 emissions but are not able to address N_2O and GHG emissions as effectively and vice versa.

4.2 Robustness Test 2

We tried to test whether a change in constructing the right-hand side variable has any impact on our results. We have constructed a new variable i.e., overall per capita emissions which takes value 1 if a country is considered to be in either high per capita CH_4 emissions club or high per capita N_2O emissions club or both, and 0 otherwise. Again, we run the same bi-probit regression. The results have been presented under model 3 in Table 5. The results remained unchanged. Thus, our results are robust to the change in the construction of the dependent binary variables.

[INSERT TABLE 5 HERE]

5. Conclusion and Policy Recommendation

The study tried to empirically examine the role of methane and nitrous oxide emissions convergence clubs in determining GHG emissions convergence clubs. For this purpose, we applied the Phillips and Sul (2007b; 2009) technique to identify the number of convergence clubs for all greenhouse gases (in per capita terms) across 168 countries from 1990 to 2019.

We found three convergence clubs for all greenhouse gases except for carbon dioxide which showed absolute convergence. These findings are consistent with the existing literature on emission convergence. We termed this set of results as "emission puzzle". Furthermore, using bivariate probit regression, we resolved this puzzle by demonstrating that countries in the high-emission club of methane or nitrous oxide are also likely to be members of the high GHG emissions club. Therefore, while efforts to reduce carbon dioxide emissions remain crucial, prioritizing methane and nitrous oxide emissions offers substantial climate benefits. Moreover, we found that primary energy consumption and population significantly increase the likelihood of a country joining the high GHG emissions club. Conversely, trade globalization reduces the likelihood of being in the high GHG emission club.

Targeted measures to reduce methane emissions include improving agricultural practices, reducing methane leakage from fossil fuel and infrastructure, and implementing methane capture and utilization technologies in waste management. Similarly, mitigating nitrous oxide emissions includes optimizing fertilizer application practices, enhancing soil management techniques, and promoting sustainable agricultural practices that reduce nitrogen input and enhance nitrogen use efficiency. By prioritizing targeted measures to reduce these potent greenhouse gases, we can make significant strides toward achieving global climate goals, safeguarding the environment, and fostering a more sustainable and resilient future for generations to come.

In conclusion, our study underscores the urgent need to shift policy attention towards methane and nitrous oxide emissions. The evidence presented highlights the significant impact of these gases besides carbon dioxide in determining GHG differences across countries. While carbon dioxide remains the primary driver of climate change due to its long-lasting presence in the atmosphere, methane, and nitrous oxide are potent greenhouse gases with significantly higher global warming potentials.

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Tables and figures

Table 1 Summary statistics

Variables	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Panel (A) Main Variables						
Per capita GHG emissions	6.10	6.39	0.32	33.04	2.08	5.06
Per capita CO_2 emissions	4.14	5.89	0.03	38.95	2.84	11.39
Per capita CH_4 emissions	1.58	1.67	0.10	8.40	2.43	5.81
Per capita N_2O emissions	0.67	0.81	0.13	4.64	2.96	9.26
Panel (B) Determinants						
Log of population	2.10	0.68	0.43	4.11	0.21	0.23
Log of primary energy consumption per capita	3.87	0.72	2.28	5.19	-0.25	-0.90
Log of GDP per capita	3.92	0.53	2.92	5.00	-0.01	-1.01
Political corruption index	0.48	0.29	0.002	0.95	-0.33	-1.27
KOF trade globalization index	49.91	22.79	11.57	92.34	0.46	-0.85
Total natural resource rents	6.93	8.92	0.00	43.32	2.05	4.48
Number of observations	**3510**					
Number of countries	**117**					

Source: Authors' computation based on data.

Table 2 Log t regression for absolute and club convergence

Emissions	Per capita GHG	Per capita CO_2	Per capita CH_4	Per capita N_2O
Panel (A) Absolute convergence				
Sample size	168	168	168	168
b-coefficient (t-statistic)	-0.42 (-18.79)	0.67 (16.74)	-2.92 (-13.21)	-0.35 (-7.59)
Panel (B) Initial convergence clubs				
Number of clubs (club sizes)	9 (15, 18, 10, 34, 37, 15, 9, 10, 20)	1 (168)	3 (4, 13, 151)	13 (4, 6, 4, 8, 2, 6, 41, 5, 2, 2, 17, 31, 40)
b-coefficient (t-statistic)				
Club-1	0.44 (6.55)	0.67 (16.74)	0.09 (0.60)	-2.11 (-1.35)
Club-2	0.32 (4.07)	-	0.32 (2.25)	0.49 (6.47)
Club-3	0.20 (2.32)	-	5.04 (2.10)	0.10 (1.53)
Club-4	0.20 (2.20)	-	-	1.13 (12.03)
Club-5	0.48 (5.58)	-	-	-3.19 (-0.63)
Club-6	0.73 (8.21)	-	-	-0.01 (-0.32)
Club-7	0.29 (2.51)	-	-	0.25 (4.70)
Club-8	0.45 (4.34)	-	-	6.77 (4.84)
Club-9	1.10 (6.96)	-	-	2.02 (1.09)
Club-10	-	-	-	4.10 (2.84)
Club-11	-	-	-	0.66 (1.97)
Club-12	-	-	-	0.20 (6.97)
Club-13	-	-	-	-0.03 (-0.52)

Source: Authors' computation based on data.

Note: The number of countries is 168. The number of time periods is 30. The first 10 periods are discarded before regression. t-statistic greater than -1.65 indicates convergence. b-coefficient between 0 to 2 implies convergence in growth rates, $b < 0$ implies divergence, and $b > 2$ implies convergence in levels.

Table 3 Final convergence clubs classification

Clubs	**Club-1**	**Club-2**	**Club-3**
Panel (A) Per capita GHG emissions			
Club size	77	71	20
b-coefficient (t-statistic)	0.02 (0.38)	0.11 (1.91)	1.10 (6.96)
Emission category	High emission	Low emission	Low emission
Panel (B) Per capita CO_2 emissions			
Club size	168	-	-
b-coefficient (t-statistic)	0.67 (16.74)	-	-
Emission category	-	-	-
Panel (C) Per capita CH_4 emissions			
Club size	4	13	151
b-coefficient (t-statistic)	0.09 (0.60)	0.32 (2.25)	5.04 (2.09)
Emission category	High emission	High emission	Low emission
Panel (D) Per capita N_2O emissions			
Club size	97	31	40
b-coefficient (t-statistic)	-0.02 (-0.32)	0.20 (6.97)	-0.03 (-0.52)
Emission category	Low emission	High emission	High emission

Source: Authors' computation based on data.
Note: The number of countries is 168. The number of time periods is 30. The first 10 periods are discarded before regression. t-statistic greater than -1.65 indicates convergence. b-coefficient between 0 to 2 implies convergence in growth rates, $b < 0$ implies divergence, and $b > 2$ implies convergence in levels. Initial convergence clubs

are merged to form final convergence clubs using iterative merging proposed by Schnurbus et al. (2017). Convergence clubs are categorized as high and low-emission based on their relative transition path.

Figure 1 Relative transition path of convergence clubs

1.1 Per capita GHG emissions

1.2 Per capita CO_2 emissions

1.3 Per capita CH_4 emissions

1.4 Per capita N_2O emissions

Source: Authors' computation based on data.

Note: Convergence clubs having a relative transition path above the average are classified as high-emission clubs, while those below the average are classified as low-emission clubs.

Table 4 Determinants of GHG per capita emissions convergence clubs

Variables	**Model 1** **Per capita CH_4 emissions**		**Model 2** **Per capita N_2O emissions**	
	Coefficient (S.E.)	Marginal effect	Coefficient (S.E.)	Marginal effect
Panel (A) Estimation of other primary GHG component clubs equation				
Log of population	-0.38 (0.27)	-0.04	-0.11 (0.18)	-0.04
Log of primary energy consumption per capita	1.68 (0.81)*	0.21*	0.15 (0.68)	0.05
Log of GDP per capita	-0.96 (1.16)	-0.12	0.81 (0.96)	0.29
Political corruption index	-1.05 (0.95)	-0.13	0.77 (0.63)	0.27
KOF trade globalization index	-0.04 (0.01)*	-0.00*	-0.02 (0.01)*	-0.00**
Total natural resource rents	0.03 (0.01)*	0.00*	-0.00 (0.01)	-0.00
Constant	-1.17 (2.25)	-	-2.76 (1.84)	-
Panel (B) Estimation of GHG clubs equation				
Primary GHG component clubs	2.77 (1.41)*	0.51*	1.26 (0.19)***	0.34***
Log of population	0.31 (0.23)	0.05	0.28 (0.18)	0.07*
Log of primary energy consumption per capita	3.93 (1.26)**	0.73***	1.63 (0.64)*	0.44**
Log of GDP per capita	-0.66 (1.15)	-0.12	-0.35 (0.88)	-0.09
Political corruption index	1.21 (0.99)	0.22	-0.02 (0.65)	-0.00
KOF trade globalization index	-0.02 (0.01)*	-0.00*	-0.00 (0.01)	-0.00
Total natural resource rents	0.00 (0.02)	0.00	0.01 (0.01)	0.00
Constant	-13.17 (3.55)***	-	-6.33 (2.25)**	-

Number of observations	*117*	*117*
Panel (C) Likelihood ratio test of rho = 0		
Chi-square (1)	*5.29*	*6.91*
p-value	*0.02*	*0.00*
Panel (D) Wald test for overall fit		
Chi-square (13)	*65.19*	*75.23*
p-value	*0.00*	*0.00*

Source: Authors' computation based on data.
Note: *, **, *** indicate significance at 10%, 5%, and 1% level respectively.

Table 5 Robustness tests

Variables	**Model 1** **Per capita N_2O emissions**	**Model 2** **Per capita CH_4 emissions**	**Model 3** **Per capita overall emissions**
	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)
Panel (A) Estimation of primary GHG component clubs equation			
Log of population	-0.13 (0.19)	-0.61 (0.44)	-0.23 (0.19)
Log of primary energy consumption per capita	0.38 (0.76)	1.64 (1.12)	0.37 (0.68)
Log of GDP per capita	1.19 (1.00)	1.09 (1.89)	1.21 (0.99)
Political corruption index	0.99 (0.68)	-0.30 (1.35)	0.84 (0.66)
KOF trade globalization index	-0.04 (0.01)**	-0.07 (0.02)**	-0.04 (0.01)***
Total natural resource rents	-0.00 (0.01)	0.01 (0.03)	0.00 (0.01)
Constant	-4.27 (1.91)*	-6.90 (4.37)	-4.02 (1.94)*
Panel (B) Estimation of GHG clubs equation			
Primary GHG component clubs	1.57 (0.23)***	9.38 (0.00)***	1.08 (0.83)
Log of population	0.40 (0.20)*	-0.14 (0.38)	0.33 (0.21)*
Log of primary energy consumption per capita	2.44 (0.97)*	4.66 (2.05)*	1.78 (0.93)*
Log of GDP per capita	-1.12 (1.08)	-0.34 (2.03)	0.03 (1.04)
Political corruption index	0.34 (0.75)	1.40 (1.35)	0.20 (0.79)
KOF trade globalization index	0.01 (0.01)	-0.04 (0.02)*	-0.00 (0.01)
Total natural resource rents	0.01 (0.02)	0.03 (0.03)	0.02 (0.02)

Constant	-7.91 (2.52)**	-15.55 (5.35)**	-8.78 (3.25)**
Number of observations	*106*	*65*	*117*
Panel (C) Likelihood ratio test of rho = 0			
Chi-square (1)	*2.73*	*3.04*	*0.37*
p-value	*0.09*	*0.08*	*0.54*

Source: Authors' computation based on data.
Note: *, **, *** indicate significance at 10%, 5%, and 1% level respectively. Model 1 includes sample of countries in the low per capita CH_4 emissions club. Model 2 includes sample of countries in the low per capita N_2O emissions club.

Appendix

Table A.1 Summary Tables

S. No.	Study	Data	Target Variable(s)	Testing Procedure(s)	Empirical Finding(s)
Panel (A) GHG emissions					
1.	Belloc and Molina (2023)	114 countries (1990-2019)	Per capita GHG emissions	Club convergence (Phillips and Sul, 2007b; 2009)	Five convergence clubs
2.	El-Montassera et al. (2015)	G7 countries (1990-2011)	Per capita GHG emissions	Stochastic convergence (pair-wise univariate and panel unit root/stationarity tests)	Stochastic divergence
3.	José Presno et al. (2021)	28 EU countries (1990–2017)	GHG emissions (aggregate, ETS, and ESD)	Club convergence (Phillips and Sul, 2007b; 2009)	Four convergence clubs (1990-2017) and two convergence clubs (2005-2017) of aggregate GHG emissions; three convergence clubs of ETS and ESD GHG emissions (2005-2017)
4.	Payne et al. (2022)	183 countries (1990-2018)	Per capita GHG emissions	Stochastic convergence (newly developed test that jointly incorporates structural breaks and cross-correlations)	Stochastic convergence for some countries in different income groups
5.	Camarero et al. (2014)	27 EU countries (1990-2009)	Eco-efficiency measure of GHG emissions	Club convergence (Phillips and Sul, 2007b; 2009)	Six convergence clubs
6.	Marrero (2010)	27 EU countries (1990-2011)	Per capita GHG emissions	Conditional β-convergence (panel)	Conditional convergence

7.	Ursavas and Apaydin (2023)	G-7 countries (1997-2018)	Per capita GHG emissions	Club convergence (Phillips and Sul, 2007b; 2009)	Three convergence clubs
Panel (B) CO_2 emissions					
1.	Borowiec and Papiez (2024)	38 countries (1992-2019)	Per capita CO_2 emissions	Absolute β-convergence, conditional β-convergence (panel)	Absolute convergence; conditional convergence
2.	Fernández-Amador et al. (2019)	66 countries and 12 composite regions (1997-2014)	Per capita CO_2 emissions (production and consumption-based), per value-added CO_2 emissions (production and consumption-based)	Conditional β-convergence (bayesian structural model)	Conditional convergence for all emission indicators
3.	Bhattacharya et al. (2019)	70 countries (1990-2014)	Per GDP CO_2 emissions (production and consumption-based)	Club convergence (Phillips and Sul, 2007b; 2009)	Two convergence clubs of consumption-based CO_2 emissions; three convergence clubs of production-based CO_2 emissions
4.	Acar and Lindmark (2017)	28 OECD countries (1973-2010)	Per capita CO_2 emissions	Conditional β-convergence (panel)	Conditional convergence

5.	Marrero et al. (2021)	22 EU countries (1990-2014)	Per capita CO_2 emissions	Club convergence (Phillips and Sul, 2007b; 2009), absolute β-convergence, conditional β-convergence (panel), σ-convergence (trend analysis of SD), stochastic convergence (panel unit root tests)	Absolute convergence (Phillips and Sul, 2007b; 2009); absolute convergence (β); conditional convergence; decreasing trend in SD; stochastic convergence
6.	Tiwari and Mishra (2017)	18 Asian countries (1972-2010)	Per capita CO_2 emissions	Absolute β-convergence (panel), σ-convergence (trend analysis of CV, non-parametric distribution dynamics approach)	Absolute convergence; decreasing trend for CV; distributions exhibit convergence
7.	Dogah and Churchill (2022)	7 ASEAN countries (1960-2018)	Per capita CO_2 emissions (aggregate and fuel-specific)	Club convergence (Phillips and Sul, 2007b; 2009)	Two convergence clubs for most emission indicators; absolute convergence for aggregate CO_2 emissions (2000-2018)
8.	Solarin (2019)	27 OECD countries (1961-2013)	Per capita CO_2 emissions	Absolute β-convergence (cross-section), σ-convergence (trend analysis of SD and CV), stochastic convergence (univariate unit root tests)	Absolute β-convergence; decreasing trend for SD; decreasing trend for CV; stochastic convergence for most countries
9.	Belloc and Molina (2023)	114 countries (1990-2019)	Per capita CO_2 emissions	Club convergence (Phillips and Sul, 2007b; 2009)	Absolute convergence
10.	Oliveira and Bourscheidt (2017)	39 countries (1996-2007)	Per capita CO_2 emissions (sectoral)	Conditional β-convergence (panel)	Conditional convergence for agriculture, food, non-durable goods manufacturing, and service sectors

11.	Camarero et al. (2014)	27 EU countries (1990-2009)	Eco-efficiency measure of CO_2 emissions	Club convergence (Phillips and Sul, 2007b; 2009)	Four convergence clubs
12.	Infante et al. (2024)	10 countries (January 2000 to December 2021)	CO_2 emissions	Stochastic convergence (fractional integration test)	Stochastic convergence
Panel (C) CH_4 emissions					
1.	Fernández-Amador et al. (2022)	66 countries and 12 composite regions (1997-2014)	Per capita CH_4 emissions (aggregate and sectoral), per value-added CH_4 emissions (aggregate and sectoral)	Conditional β-convergence (bayesian structural model)	No conditional convergence for all aggregate emission indicators; conditional convergence for most sectors
2.	Belloc and Molina (2023)	114 countries (1990-2019)	Per capita CH_4 emissions	Club convergence (Phillips and Sul, 2007b; 2009)	Two convergence clubs
3.	de Oliveira and Bourscheidt (2017)	39 countries (1996-2007)	Per capita CH_4 emissions (sectoral)	Conditional β-convergence (panel)	Conditional convergence for agriculture, food, and services sectors
4.	Camarero et al. (2014)	27 EU countries (1990-2009)	Eco-efficiency measure of CH_4 emissions	Club convergence (Phillips and Sul, 2007b; 2009)	Five convergence clubs
5.	Infante et al. (2024)	10 countries (January 2000 to December 2021)	CH_4 emissions	Stochastic convergence (fractional integration test)	Stochastic convergence for some countries
Panel (D) N_2O / NO_2 emissions					

1.	Belloc and Molina (2023)	114 countries (1990-2019)	Per capita N_2O emissions	Club convergence (Phillips and Sul, 2007b; 2009)	Two convergence clubs
2.	Camarero et al. (2014)	27 EU countries (1990-2009)	Eco-efficiency measure of N_2O emissions	Club convergence (Phillips and Sul, 2007b; 2009)	Four convergence clubs
3.	Infante et al. (2024)	10 countries (January 2000 to December 2021)	NO_2 emissions	Stochastic convergence (fractional integration test)	Stochastic convergence for some countries

Table 2.A List of countries included in the sample

Club convergence (168), 1990-2019	Determinants analysis (117), 1990-2019
Afghanistan | Albania | Algeria | Angola | Argentina | Armenia | Australia | Austria | Azerbaijan | Bahamas | Bahrain | Bangladesh | Barbados | Belarus | Belgium | Belize | Benin | Bhutan | Bolivia | Botswana | Brazil | Brunei | Bulgaria | Burkina | Burundi | Central African Republic | Cambodia | Cameroon | Canada | Cape Verde | Chad | Chile | China | Colombia | Comoros | Congo | Costa Rica | Cote d'Ivoire | Croatia | Cuba | Cyprus | Czechia | Dominican Republic | Democratic Republic of Congo | Denmark | Djibouti | Dominica | Ecuador | Egypt | El Salvador | Equatorial Guinea | Estonia | Eswatini | Ethiopia | Fiji | Finland | France | Gabon | Gambia | Georgia | Germany | Ghana | Greece | Guatemala | Guinea | Guinea Bissau | Guyana | Haiti | Honduras | Hungary | Iceland | India | Indonesia | Iran | Iraq | Ireland | Israel | Italy | Jamaica | Japan | Jordan | Kazakhstan | Kenya | Kuwait | Kyrgyzstan | Laos | Latvia | Lebanon | Lesotho | Liberia | Libya | Lithuania | Luxembourg | Madagascar | Malawi | Malaysia | Mali | Malta | Mauritania | Mauritius | Mexico |	Albania | Algeria | Argentina | Australia | Austria | Bangladesh | Barbados | Belgium | Benin | Bhutan | Bolivia | Botswana | Brazil | Bulgaria | Burkina Faso | Burundi | Cameroon | Cape Verde | Central African Republic | Chad | Chile | China | Colombia | Congo | Costa Rica | Cote d'Ivoire | Cyprus | Democratic Republic of Congo | Denmark | Dominican Republic | Ecuador | Egypt | El Salvador | Eswatini | Ethiopia | Fiji | Finland | France | Gabon | Gambia | Germany | Ghana | Greece | Guatemala | Guinea | Guinea-Bissau | Guyana | Haiti | Honduras | India | Indonesia | Ireland | Italy | Jamaica | Japan | Jordan | Kenya | Kuwait | Laos | Lebanon | Lesotho | Luxembourg | Madagascar | Malawi | Malaysia | Mali | Mauritania | Mauritius | Mexico | Mongolia | Morocco | Mozambique | Myanmar | Namibia | Nepal | Netherlands | New Zealand | Nicaragua | Niger | Nigeria | Norway | Oman | Pakistan | Panama | Papua New Guinea | Paraguay | Peru | Philippines | Poland | Portugal | Romania | Russia | Rwanda | Saudi Arabia | Senegal | Sierra Leone | Singapore | South

Moldova | Mongolia | Montenegro | Morocco | Mozambique | Myanmar | Namibia | Nepal | Netherlands | New Zealand | Nicaragua | Niger | Nigeria | North Korea | Norway | Oman | Papua New Guinea | Pakistan | Panama | Paraguay | Peru | Philippines | Poland | Portugal | Qatar | Romania | Russia | Rwanda | Samoa | Saudi Arabia | Senegal | Serbia | Sierra Leone | Singapore | Slovakia | Slovenia | Somalia | South Africa | South Korea | South Sudan | Spain | Sri Lanka | Sudan | Sweden | Switzerland | Syria | Tajikistan | Tanzania | Thailand | Togo | Tonga | Tunisia | Turkey | Turkmenistan | United Arab Emirates | United Kingdom | United States | Uganda | Ukraine | Uruguay | Uzbekistan | Vanuatu | Venezuela | Vietnam | Yemen | Zambia | Zimbabwe	Africa | South Korea | Spain | Sri Lanka | Sudan | Sweden | Switzerland | Tanzania | Thailand | Togo | Tunisia | Turkey | Uganda | United Arab Emirates | United Kingdom | United States | Uruguay | Vietnam | Zambia | Zimbabwe

Table 3.A List of countries in per capita GHG emissions convergence clubs

Club-1 (77)	Club-2 (71)	Club-3 (20)
Algeria | Argentina | Armenia | Australia | Austria | Azerbaijan | Bahamas | Bahrain | Barbados | Belarus | Belgium | Belize | Bolivia | Brazil | Brunei | Bulgaria | Canada | Chad | Chile | China | Cyprus | Czechia | Denmark | Ecuador | Equatorial Guinea | Estonia | Finland | Georgia | Germany | Greece | Guyana | Iceland | India | Iran | Iraq | Ireland | Israel | Japan | Kazakhstan | Kuwait | Kyrgyzstan | Laos | Latvia | Lebanon | Libya | Lithuania | Luxembourg | Malaysia | Mauritius | Mexico | Moldova | Mongolia | Netherlands | New Zealand | Norway | Oman | Panama | Paraguay | Peru | Poland | Qatar | Russia | Saudi Arabia | Serbia | Singapore | Slovakia | Slovenia | South Africa | South Korea | Thailand | Turkey | Turkmenistan | United Arab Emirates | United States | Uruguay | Venezuela | Vietnam |	Angola | Albania | Bangladesh | Benin | Bhutan | Botswana | Burkina | Central African Republic | Cambodia | Cameroon | Cape Verde | Colombia | Congo | Costa Rica | Croatia | Cuba | Dominican Republic | Dominica | Egypt | El Salvador | Eswatini | Ethiopia | Fiji | France | Gabon | Ghana | Guatemala | Guinea | Honduras | Hungary | Indonesia | Italy | Jamaica | Jordan | Kenya | Mali | Malta | Mauritania | Montenegro | Morocco | Myanmar | Namibia | Nepal | Nicaragua | Niger | North Korea | Papua New Guinea | Pakistan | Philippines | Portugal | Romania | Samoa | Senegal | South Sudan | Spain | Sri Lanka | Sudan | Sweden | Switzerland | Syria | Tajikistan | Tanzania | Tonga | Tunisia | United Kingdom | Uganda | Ukraine | Uzbekistan | Vanuatu | Zambia | Zimbabwe	Afghanistan | Burundi | Comoros | Cote d'Ivoire | Democratic Republic of Congo | Djibouti | Gambia | Guinea Bissau | Haiti | Lesotho | Liberia | Madagascar | Malawi | Mozambique | Nigeria | Rwanda | Sierra Leone | Somalia | Togo | Yemen

Table 4.A List of countries in CH_4 per capita emissions convergence clubs

Club-1 (4)	Club-2 (13)	Club-3 (151)
Bahrain | Burundi | Mongolia | Turkmenistan	Australia | Barbados | Chad | Guyana | Iraq | Kazakhstan | Kuwait | Libya | New Zealand | Paraguay | Qatar | Russia | Uruguay	Afghanistan | Albania | Algeria | Angola | Argentina | Armenia | Austria | Azerbaijan | Bahamas | Bangladesh | Belarus | Belgium | Belize | Benin | Bhutan | Bolivia | Botswana | Brazil | Brunei | Bulgaria | Burkina | Central African Republic | Cambodia | Cameroon | Canada | Cape Verde | Chile | China | Colombia | Comoros | Congo | Costa Rica | Cote d'Ivoire | Croatia | Cuba | Cyprus | Czechia | Dominican Republic | Democratic Republic of Congo | Denmark | Djibouti | Dominica | Ecuador | Egypt | El Salvador | Equatorial Guinea | Estonia | Eswatini | Ethiopia | Fiji | Finland | France | Gabon | Gambia | Georgia | Germany | Ghana | Greece | Guatemala | Guinea | Guinea Bissau | Haiti | Honduras | Hungary | Iceland | India | Indonesia | Iran | Ireland | Israel | Italy | Jamaica | Japan | Jordan | Kenya | Kyrgyzstan |

		Laos | Latvia | Lebanon | Lesotho | Liberia | Lithuania | Luxembourg | Madagascar | Malawi | Malaysia | Mali | Malta | Mauritania | Mauritius | Mexico | Moldova | Montenegro | Morocco | Mozambique | Myanmar | Namibia | Nepal | Netherlands | Nicaragua | Niger | Nigeria | North Korea | Norway | Oman | Papua New Guinea | Pakistan | Panama | Peru | Philippines | Poland | Portugal | Romania | Rwanda | Samoa Saudi Arabia | Senegal | Serbia | Sierra Leone | Singapore | Slovakia | Slovenia | Somalia | South Africa | South Korea | South Sudan | Spain | Sri Lanka | Sudan | Sweden | Switzerland | Syria | Tajikistan | Tanzania | Thailand | Togo | Tonga | Tunisia | Turkey | United Arab Emirates | United Kingdom | United States | Uganda | Ukraine | Uzbekistan | Vanuatu | Venezuela | Vietnam | Yemen | Zambia | Zimbabwe

Table 5.A List of countries in N_2O per capita emissions convergence clubs

Club-1 (97)	Club-2 (31)	Club-3 (40)
Angola | Albania | Argentina | Armenia | Australia | Austria | Azerbaijan | Bahamas | Belarus | Belgium | Belize | Bolivia | Botswana | Brazil | Bulgaria | Burkina | Central African Republic | Cambodia | Cameroon | Canada | Chad | Chile | China | Colombia | Congo | Costa Rica | Croatia | Czechia | Denmark | Dominica | Equatorial Guinea | Estonia | Ethiopia | Finland | France | Georgia | Germany | Greece | Guinea | Guinea Bissau | Guyana | Hungary | Iceland | Indonesia | Iran | Ireland | Italy | Kazakhstan | Kenya | Laos | Latvia | Lithuania | Luxembourg | Madagascar | Malawi | Malaysia | Mali | Mauritania | Mexico | Moldova | Mongolia | Mozambique | Myanmar | Namibia | Netherlands | New Zealand | Nicaragua | Niger | Norway | Papua New Guinea | Paraguay | Poland | Romania | Russia | Senegal | Serbia | Singapore | Slovakia	Algeria | Benin | Brunei | Cuba | Cyprus | Dominican Republic | Djibouti | Ecuador | Egypt | Eswatini | Gabon | Guatemala | Honduras | Israel | Kuwait | Kyrgyzstan | Libya | Morocco | Nepal | Oman | Pakistan | Panama | Peru | Qatar | Rwanda | South Africa | Switzerland | Thailand | Tunisia | Uganda | Vietnam	Afghanistan | Bahrain | Bangladesh | Barbados | Bhutan | Burundi | Cape Verde | Comoros | Cote d'Ivoire | Democratic Republic of Congo | El Salvador | Fiji | Gambia | Ghana | Haiti | India | Iraq | Jamaica | Japan | Jordan | Lebanon | Lesotho | Liberia | Malta | Mauritius | Montenegro | Nigeria | North Korea | Philippines | Portugal | Samoa | Saudi Arabia | Sierra Leone | South Korea | Sri Lanka | Syria | Tajikistan | Togo | United Arab Emirates | Yemen

| Slovenia | Somalia | South Sudan | Spain | Sudan | Sweden | Tanzania | Tonga | Turkey | Turkmenistan | United Kingdom | United States | Ukraine | Uruguay | Uzbekistan | Vanuatu | Venezuela | Zambia | Zimbabwe		

Table 6.A Alternate specifications of primary GHG component clubs and GHG clubs equations

6.A.1 Per capita CH_4 emissions

Variables	**Model 1**	**Model 2**	**Model 3**
	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)
Panel (A) Estimation of primary GHG component clubs equation			
Log of population	-0.61 (0.27)*	-0.59 (0.23)*	-0.46 (0.25)*
Log of primary energy consumption per capita	1.70 (0.89)*	1.58 (0.73)*	1.67 (0.76)*
Log of GDP per capita	-2.16 (1.18)*	-1.87 (0.98)*	-0.96 (1.20)
Political corruption index	-	0.22 (0.76)	-0.45 (0.70)
KOF trade globalization index	-	-	-0.03 (0.01)*
Total natural resource rents	-	-	-
Constant	1.71 (1.73)	0.95 (1.95)	-1.12 (2.33)
Panel (B) Estimation of GHG clubs equation			
Primary GHG component clubs	1.18 (0.83)	2.27 (0.75)**	2.37 (0.67)***
Log of population	0.21 (0.21)	0.15 (0.20)	0.26 (0.22)
Log of primary energy consumption per capita	2.79 (0.98)**	3.79 (1.01)***	3.79 (0.86)***
Log of GDP per capita	-1.41 (1.09)	-1.46 (1.02)	-0.52 (1.05)
Political corruption index	-	1.85 (0.80)*	1.24 (0.68)*
KOF trade globalization index	-	-	-0.02 (0.01)*
Total natural resource rents	-	-	-
Constant	-6.10 (1.58)***	-10.73 (2.28)***	-12.97 (2.72)***

Number of observations	*117*	*117*	*117*
Panel (C) Likelihood ratio test of rho = 0			
Chi-square (1)	*2.98*	*3.30*	*4.31*
p-value	*0.08*	*0.06*	*0.03*

Source: Authors' computation based on data.
Note: *, **, *** indicate significance at 10%, 5%, and 1% level respectively.

6.A.2 Per capita N_2O emissions

Variables	**Model 1**	**Model 2**	**Model 3**
	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)
Panel (A) Estimation of primary GHG component clubs equation			
Log of population	-0.17 (0.17)	-0.25 (0.17)	-0.11 (0.17)
Log of primary energy consumption per capita	-0.23 (0.61)	-0.14 (0.61)	0.16 (0.59)
Log of GDP per capita	0.04 (0.82)	0.42 (0.84)	0.80 (0.82)
Political corruption index	-	1.32 (0.58)*	0.77 (0.59)
KOF trade globalization index	-	-	-0.02 (0.01)*
Total natural resource rents	-	-	-
Constant	0.96 (1.22)	-1.35 (1.61)	-2.76 (1.62)*
Panel (B) Estimation of total GHG clubs equation			
Primary GHG component clubs	-0.38 (1.87)	-0.43 (1.56)	1.22 (0.15)***
Log of population	0.14 (0.23)	0.07 (0.25)	0.27 (0.17)*
Log of primary energy consumption per capita	1.88 (0.80)*	2.09 (0.78)**	1.64 (0.60)**

Log of GDP per capita	-0.57 (0.91)	-0.26 (1.00)	-0.30 (0.81)
Political corruption index	-	1.21 (1.01)	0.07 (0.62)
KOF trade globalization index	-	-	-0.00 (0.00)
Total natural resource rents	-	-	-
Constant	-5.49 (2.59)*	-7.99 (2.23)***	-6.40 (1.89)**
Number of observations	*117*	*117*	*117*
Panel (C) Likelihood ratio test of rho = 0			
Chi-square (1)	*0.00*	*0.00*	*6.53*
p-value	*0.92*	*0.92*	*0.01*

Source: Authors' computation based on data.
Note: *, **, *** indicate significance at 10%, 5%, and 1% level respectively.

Table 7.A Variables and data sources

S. No.	Variable	Definition	Sources
Panel (A) Main variables			
1.	Per capita GHG emissions	Measured in tonnes of carbon dioxide-equivalents per capita	Climate Analysis Indicators Tool compiled by *Our World in Data*
2.	Per capita CO_2 emissions	Measured in tonnes per person	Carbon Budget (2022) compiled by *Our World in Data*
3.	Per capita CH_4 emissions	Measured in tonnes of carbon dioxide-equivalents per capita	Climate Analysis Indicators Tool compiled by *Our World in Data*
4.	Per capita N_2O emissions	Measured in tonnes of carbon dioxide-equivalents per capita	Climate Analysis Indicators Tool compiled by *Our World in Data*
Panel (B) Determinants			
5.	Log of population	Logarithm of the population of each country or region (in lakhs)	*Our World in Data* based on different sources
6.	Log of energy per capita	Logarithm of primary energy consumption per capita, measured in kilowatt-hours per person per year	Energy Institute Statistical Review of World Energy (2023) compiled by *Our World in Data*
7.	Log of GDP per capita	Logarithm of GDP per capita PPP, measured in constant international $ at 2017 prices	World Bank
8.	Political corruption index	Extent to which the executive, legislative, judiciary, and bureaucracy engage in bribery and theft, and the making and implementing of laws are susceptible to corruption. Ranges from 0 to 1, and the higher value indicates more corruption	V-Dem
9.	Total natural resource rents	Difference between the price of a commodity and the average cost of producing it. Total natural resources rents are the sum of oil rents, natural gas	World Bank

		rents, coal rents, mineral rents, and forest rents, measured as a percentage of GDP	
10.	KOF globalization trade index	Measures the economic, social, and political dimensions of globalization. Ranges from 0 to 100, and the higher value indicates the higher the level of globalization	KOF Swiss Economic Institute

Figure 1.A Relative transition paths of per capita GHG emissions convergence clubs

Club-1

Club-2

Club-3

Source: Authors' computation based on data

Figure 2.A Relative transition paths of per capita CO_2 emissions convergence club

Club-1

Source: Authors’ computation based on data.

Figure 3.A Relative transition paths of per capita CH_4 emissions convergence clubs

Club-1

Club-2

Club-3

Source: Authors' computation based on data

Figure 4.A Relative transition paths of N_2O per capita emissions convergence clubs

Club-1

Club-2

Club-3

Source: Authors' computation based on data