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Date: 28-07-2025

To
The Organizers,
PhD Student Workshop on Climate Finance
National Bureau of Economic Research
Cambridge, MA

Dear Professors Caroline Flammer and Stefano Giglio,

I am writing to express my interest in participating in the upcoming NBER PhD Student Workshop on Climate Finance, to be held on October 9-10, 2025. I am currently a Ph.D. candidate in the Jindal School of Government and Public Policy, O.P. Jindal Global University, India, working under the supervision of Professor Debajit Jha, and I expect to complete my Ph.D. by December 2026.

My current research focuses on the convergence of greenhouse gas (GHG) emissions across countries and the role of institutional policies in aligning national emission trajectories with global climate frameworks such as the Paris Agreement. Using a combination of advanced econometric techniques and high-dimensional policy datasets, I investigate the effectiveness of climate policy stringency, governance quality, and environmental regulation in driving emission transitions across different groups of countries.

My broader research agenda lies at the intersection of climate economics, environmental policy, and sustainable finance. Building on my Ph.D. thesis, I plan to pursue post-doctoral research exploring emissions transitions in the context of green finance, institutional investment flows, and global financial market responses to climate policy uncertainty. I am particularly interested in how finance mechanisms can support the decarbonization of emerging economies and facilitate equitable climate adaptation.

The opportunity to present my research and receive feedback from leading scholars in the field, as well as connect with peers engaged in related work, would be immensely valuable for advancing both my Ph.D. thesis and my future academic career. I am confident that participating in this workshop will greatly enhance the quality and impact of my research.

Please find attached a draft of my paper, titled “Does Income Convergence Lead to CO_2 Emissions Convergence? Revisiting Climate Finance Responsibilities of Annex II Donors”, along with my CV. Professor Debajit Jha, my primary advisor at O.P. Jindal Global University, is familiar with my work and would be happy to provide a reference upon request.

Thank you for considering my application. I look forward to the possibility of contributing to and learning from this important workshop.

Sincerely,
Keshav Sethi

KESHAV SETHI

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PROFILE

Possess relevant knowledge of economic concepts, statistics & econometrics. Skilled in macroeconomic empirical analysis using advanced econometric techniques to examine economic relationships over short- and long-term periods. Strong communication and interpersonal skills, effective both independently and in team settings.

EDUCATION

Ph.D., Economics — Aug 2023 – Present
Jindal School of Government and Public Policy, O.P. Jindal Global University, Sonipat, Haryana
CGPA: 7.37/8.0

M.A., Economics — Aug 2021 – Jul 2023
Jindal School of Government and Public Policy, O.P. Jindal Global University, Sonipat, Haryana
CGPA: 7.88/8.0

B.A. (Hons.), Economics — Jun 2018 – Jul 2021
Dr. Bhim Rao Ambedkar College, University of Delhi, Delhi
CGPA: 8.56/10.0

Senior Secondary (XII) — May 2017 – May 2018
Lilawati Vidya Mandir Senior Secondary School, Central Board of Secondary Education, Delhi
Percentage: 88.8%

Secondary (X) — May 2015 – May 2016
Lilawati Vidya Mandir Senior Secondary School, Central Board of Secondary Education, Delhi
CGPA: 9.2/10.0

RESEARCH INTERESTS

Macroeconomics, Growth Economics, Applied Econometrics, Environmental Economics

WORK EXPERIENCE

Intern (Tax Technology) — Dec 2022 – Feb 2023
Ernst and Young, Gurgaon, Haryana

Intern (Ministry of Jal Shakti) — Jun 2022 – Aug 2022
Ministry of Statistics and Programme Implementation, Government of India, Delhi

Research Intern — Dec 2021 – Feb 2022
Institute of Studies in Industrial Development, Indian Council of Social Science Research, Delhi

ACADEMIC ACHIEVEMENTS

M.A., Economics Gold Medallist — Aug 2023
B.A., (Hons.) Economics Academic Merit — Jul 2021
Senior Secondary (XII) Merit in Economics — Dec 2018

TEACHING ASSISTANT POSITIONS

Macroeconomics-1 (Undergraduate) — Spring 2022
Jindal School of Government and Public Policy, O.P. Jindal Global University, Sonipat, Haryana
Course Instructor: Dr. (Prof.) Debajit Jha

Growth Empirics and Policy (Graduate) — Spring 2024
Jindal School of Government and Public Policy, O.P. Jindal Global University, Sonipat, Haryana
Course Instructor: Dr. (Prof.) Debajit Jha

Indian Economy (Undergraduate) — Fall 2024
Jindal School of Government and Public Policy, O.P. Jindal Global University, Sonipat, Haryana
Course Instructor: Dr. (Prof.) Debajit Jha

Time Series Analysis (Undergraduate & Graduate) Spring 2025
Jindal School of Government and Public Policy, O.P. Jindal Global University, Sonipat, Haryana
Course Instructor: Dr. (Prof.) Debajit Jha

CERTIFICATIONS

Data Analytics for Business — Jun 2019 – Jul 2019
Shaheed Sukhdev College of Business Studies, University of Delhi, Delhi

Introduction to Managerial Economics — Aug 2019 – Nov 2019
Indian Institute of Management, Bangalore (Online)
Percentage: 79%

Business Statistics — Jan 2020 – Apr 2020
Indian Institute of Technology, Roorkee (Online)
Percentage: 90%

Managerial Economics — Jul 2021 – Oct 2021
Indian Institute of Technology, Bombay (Online)
Percentage: 75%

Effective Business Communication — Aug 2022 – Nov 2022
Indian Institute of Management, Bangalore (Online)
Percentage: 77.1%

COMPUTER SKILLS

STATA, R, Gretl, E-Views, LaTeX, Tableau, CorelDraw, Microsoft Office, QGIS

PUBLICATIONS

Guin, P., Bhan, N., & Sethi, K. (2025). Mortality due to heatstroke and exposure to cold: Evidence from India. *Temperature*, 12(2), 179-199.

WORKING PAPERS

Jha, D., & Sethi, K. (2023). Identifying Policy Priorities for Asian Economies: A Growth Convergence and Transition Based Framework. Available at SSRN 4557622.

Roy, S., & Sethi, K. (2024). A Bayesian Approach to Inequality-Growth Nexus.

Sethi, K., & Jha, D. (2024). Decoding Emission Puzzle: How Methane and Nitrous Oxide Drive GHG Convergence Clubs.

Jha, D., & Sethi, K. (2025). Convergence of Global CO2 Emissions: An Empirical Study of Potential Determinants.

Sethi, K., & Jha, D. (2025). Assessing the Impact of Global Environmental Agreements on CO2 Emissions Convergence: Evidence from Pre- and Post-1990 Periods.

LANGUAGES KNOWN

English, Hindi, Punjabi

Does Income Convergence Lead to CO_2 Emissions Convergence? Revisiting Climate Finance Responsibilities of Annex II Donors

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Abstract

This study examines the relationship between income convergence and CO_2 emissions convergence across 20 Annex II countries from 1900 to 2022, focusing on its relevance to climate finance responsibilities. It argues that do similar income levels necessarily imply similar emission levels across countries over time? If yes, then similar financial obligations seem justified. But if not, then it opens the door to further negotiations between countries. The paper addresses this critical policy question using the convergence framework. Using Johnson (2020) time-varying convergence method, alongside wavelet coherence and quantile-on-quantile regression techniques, we analyze how income convergence relates to CO_2 emissions convergence over time. Results reveal that income convergence and CO_2 emissions convergence are interconnected, but not linearly. Strong linkages exist in specific historical periods, particularly post-WWII and after the 1990s, while divergences appear in others. The findings suggest that similar income levels do not guarantee similar CO_2 emissions levels. Hence, climate finance obligations should account for differences in CO_2 emissions across countries, rather than relying solely on economic capacity. Hence, the study offers new empirical evidence supporting differentiated climate finance responsibilities.

Keywords: Climate finance, CO_2 emissions, income, convergence, climate change

1. Introduction

We have been experiencing episodes of extreme weather events globally for the past centuries.[1] However, in recent decades, the frequency and intensity of these events, such as heatwaves, floods, droughts, etc., have increased significantly. This increase is closely linked to climate change, particularly global warming, which refers to long-term shifts in temperatures and weather patterns. The global discourse identified human emissions of greenhouse gases (GHG), particularly carbon dioxide (CO_2), which constitutes more than 75% of GHG emissions, as the main contributor to climate change due to positive radiative forcing (Sonwani and Saxena, 2022). Hence, a lot of climate change negotiations initiated after the 1970s placed the urgent need to mitigate the adverse effects of these issues.[2] Over time, the attention of the global community shifted from recognizing environmental degradation to assigning differentiated responsibilities for its mitigation. In this context, the role of Annex II countries, comprising the economically advanced nations, is pivotal. These countries, identified under the United Nations Framework Convention on Climate Change (UNFCCC), are mandated not only to reduce their GHG emissions but also to financially support developing countries through mechanisms such as the Green Climate Fund (GCF).[3] Therefore, their historical responsibility for emissions due to early industrialization and higher current economic capacity underpin their obligation to financially assist developing nations in combating and adapting to climate change.

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[1] There have always been natural changes in the Earth's climate, times when it was much colder or warmer. For example, during the Ice Age, large parts of the world were covered in ice. Later, periods like the "Little Ice Age" and the "Medieval Warm Period" also showed climate changes. Even Mars has had climate changes, which scientists believe were caused by big changes in its orbit and tilt. (Haberle et al., 2013; Lackner et al., 2022).

[2] The First World Climate Conference held in 1979, marked the beginning of global climate discussions. This was followed by the establishment of the World Climate Programme in 1980 and the Intergovernmental Panel on Climate Change (IPCC) in 1988. Subsequent decades saw major developments such as the UN Framework Convention on Climate Change (UNFCCC) in 1992, the Kyoto Protocol (1997), and the Paris Agreement (2015), with several Conferences of Parties (COPs) shaping the global climate governance.

[3] The UNFCCC lists 40 countries as Annex I Parties, which are expected to bear a greater burden in mitigating GHG emissions compared to other nations. Out of these, 24 are designated as Annex II countries (Tribett et al., 2017). For more details, please visit https://unfccc.int/parties-observers.

The criterion for assigning financial obligations in global climate negotiations raises an important concern: do similar income levels necessarily imply similar emission levels across countries over time? If yes, then financial obligations seem justified. But if not, then it opens the door to further negotiations between countries.

It is plausible that a high-income country may emit relatively low through investments in green technologies and cleaner industrial practices. Countries may emit high levels during their industrial phases (known as the scale effect), but as their economies advance, they often transition towards green industrialization (known as the composition and technique effect), as described in the Environmental Kuznets Curve hypothesis (Grossman and Krueger, 1995). Scholars such as Brock and Taylor (2004) and Ordas Criado et al. (2011) also showed that emissions reduce or reach a finite steady state in the long run, despite a positive growth in income across countries.[4] For example, Iceland, Denmark, and the Netherlands are among the countries most prepared for a low-carbon future, according to the World Economic Forum (Masterson, 2022). In such cases, imposing financial responsibilities on all high-income countries, without accounting for differences in emissions, may be unjust to those nations that have achieved economic growth while maintaining lower emissions. This disparity may lead to negotiations where countries with lower emissions and high growth argue that those with both high emissions and high income should bear a greater share of the financial burden. Additionally, such countries may argue that a significant portion of their economic resources has already been invested in domestic green technologies and infrastructure, limiting their capacity to contribute to international climate finance. For example, US, UK, and Germany have many times justified large-scale domestic green investments as a main reason for a limited role in international climate finance (Buchner et al., 2023). Thus, we can make a case for

[4] They showed that the growth rate of emissions per capita will decrease in the long run due to pollution abatement technologies and diminishing returns to capital.

countries that historically emitted at high levels but have transitioned to lower emissions through green investments, or emitted at relatively lower levels during early industrialization (historically), to provide funds differently internationally if their emissions are becoming different over time despite having similar income levels as other countries. This paper addresses this critical policy question using the convergence framework.

In the convergence framework, we try to understand whether differences in income (emissions) across countries reduce over time or not. If such differences reduce, then countries become similar in terms of income (emissions). However, it is important to see that if the reduction of differences in income across countries translates to a reduction of differences in emissions across countries over time. This will help us understand how income convergence is related to emissions convergence over time. As a result, we can form common (or differentiated) policies across countries related to climate finance. Previous studies on income convergence (e.g., Kar et al., 2013; 2018; Kar and Jha, 2025; Jha and Sethi, 2023) and emissions convergence (e.g., Acar and Lindmark, 2017; Akram et al., 2024; Bhattacharya et al., 2020) have largely focused on identifying the convergence dynamics across countries for a specific time period and hence they are not able to study the relationship between two convergence trends over time. To the best of our knowledge in this field, none of the existing studies identified the convergence dynamics across countries over a period of time. This becomes a significant gap to address.

In order to address this, we undertake a historical empirical investigation into the convergence dynamics of income per capita and CO_2 emissions per capita, using a dataset of 20 Annex II countries spanning 1900–2022. This long-run analysis captures critical phases of convergence dynamics during industrialization, post-war reconstruction, globalization, and the modern climate policy era. We use a novel econometric technique by Johnson (2020), i.e., modification to Phillips and Sul (2007; 2009) (PS) log t test. This technique will help us identify the convergence dynamics over time. Later, to examine the relationship between income per capita

convergence and CO_2 emissions per capita convergence, we use wavelet coherence (WTC) and quantile-on-quantile regression (QQR). These techniques allow us to examine non-linear relationships between these two convergence trends.

Our results show that income per capita convergence and CO_2 emissions per capita convergence are related to each other at different points in time, non-linearly. This shows that climate finance responsibilities should be differentiated across these countries. This study is methodologically novel in applying a technique to examine the convergence dynamics of variables over time and thus producing a time series that captures the convergence trend. Additionally, it contributes to policy-oriented climate economics by evaluating whether climate finance policies should be common or differentiated across countries.

The rest of the sections are organized as follows. Section 2 reviews the literature on income convergence and CO_2 emissions convergence. Section 3 provides the data description and explains the methods used in the study. Section 4 presents the empirical findings, and finally, Section 5 concludes with policy prescriptions.

2. Literature Review

In this section, we present the literature evidence on income convergence, followed by CO_2 emissions convergence. The idea of convergence originated from neo-classical growth theory (e.g., Solow, 1956) implies that per capita income differences among countries must be reduced in the long run. This framework assumes that there is a single steady state for all economies (or absolute convergence) (e.g., Baumol, 1986; Delong, 1988; Barro and Sala-i-Martin, 1992; Martin, 1995).[5] However, empirical work has not been very kind to this proposition.[6] Studies in this scholarship found that there is no tendency for poor countries to grow faster than rich

[5] Any temporary shock can cause an economy to deviate from its steady state position but due to diminishing returns to capital economy rests in its steady state in the long run.
[6] See Romer (1986) and Lucas (1988) for conclusive evidence against the absolute convergence hypothesis.

ones, over any reasonably long time. Whatever convergence one can find is conditional: it depends on policies, institutions, and other country-specific circumstances (Rodrik, 2011).[7] Later, the endogenous growth framework (e.g., Romer, 1986) demolished the assumption of a single steady state and introduced the idea of increasing returns to scale in technology and research and development (R&D), due to which initial conditions differ across countries, as it generates spillover effects.[8] So, there will be persistence of per capita income differences if there is structural heterogeneity (e.g., human capital, technological advancements, etc.) present across countries. These two schools of thought provide the foundation for traditional methodologies, i.e., beta (β) (regression-based approach) and sigma (σ) (dispersion-based approach) convergence, which are often considered summary measures and are widely criticized in the modern empirical growth literature that centers on the idea of club convergence.[9]

Club convergence literature (e.g., Durlauf and Johnson, 1995; Galor, 1996) argues that due to differences in initial conditions across countries, there is a possibility of multiple equilibria, i.e., economies may converge to steady states of numerous clubs, rather than converging to a unique steady state. Empirically, club convergence (conditional) would emerge, i.e., countries with identical structural parameters will converge to the same steady-state equilibrium if their initial conditions are similar as well (Jha and Sethi, 2023).[10] A popular methodology by Phillips and Sul (2007; 2009) is based on this concept to estimate income clubs in a cross-section of

[7] See Barro (1991) and Mankiw et al. (1992) to understand that economies with low initial incomes tend to grow faster than economies with high initial incomes, after controlling for rates of human capital accumulation, savings, and population growth.
[8] Romer (1986) argued that investment in education can lead to increasing returns to scale. Similarly, Lucas (1988) showed that human capital is the engine of economic growth through the expansion of R&D and the promotion of innovation and new products.
[9] See Friedman (1992) and Quah (1993a; 1993b; 1996; 1997). Follow the data and methodology section for more discussion on the shortcomings of beta and sigma convergence.
[10] The distribution dynamics approach by Quah (1996; 1997) is also based on the idea of club convergence and polarization. It uses a stochastic kernel to identify specific sections of the distribution that are more prone to transitions (in probabilistic terms). See Kar et al. (2011), Epstein et al. (2003), and Castro (2003) for studies based on this approach.

countries (e.g., Kar and Jha, 2021; Kar et al., 2018; Tomal, 2022). This notion of convergence received significant attention in the existing literature after the development of the PS technique.[11]

As an alternative, one might examine the time series characteristics of the data to understand the concept of stochastic convergence, which was put forth by Carlino and Mills (1993) and Bernard and Durlauf (1995; 1996) regarding the convergence of income among the countries.[12] Many unit root/stationarity tests have been developed (e.g., the Augmented Dickey-Fuller (ADF) unit root test of Dickey and Fuller, 1979, and Said and Dickey, 1984) to test for stochastic convergence of income across countries. However, the major drawback of this approach is that it does not account for structural breaks and cross-section dependence in the model for accurate predictions (Perron, 1989; Banerjee et al., 2004). Nevertheless, not simply GDP or income, but a wide range of disciplines have extensively studied this concept by employing a highly diverse set of statistical tools that address these limitations (e.g., Napolitano et al., 2018; Fallahi, 2017; Barassi et al., 2011; Lee et al., 2008).[13]

Hence, the convergence behavior can be categorized into four types of tests: absolute and conditional β convergence, σ convergence, club convergence, and stochastic convergence. All of these tests have been extensively used in the income convergence literature to examine the convergence patterns across different country samples and time periods.

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[11] The application of the PS technique has not only been restricted to studying basic macroeconomic indicators like GDP or income but also in other fields such as house/rent prices (e.g., Apergis and Payne, 2012; Kim and Rous, 2012), consumer price index (e.g., Fritsche and Kuzin, 2011; Kim and Kim, 2015), total factor productivity (e.g., Hamit-Haggar, 2013; Rath and Akram, 2019), public finance (e.g., Apergis and Cooray, 2014; Apergis, 2015), stock market (e.g., Apergis et al., 2014; Kerkemeier and Kruse-Becher, 2022) and many more. See Tomal (2023) for a detailed literature review on this technique.

[12] This technique requires that shocks to income relative to the mean are temporary. If there is a unit root in income relative to the mean, then it implies non-stationarity, and shocks have permanent effects, thereby refuting stochastic convergence.

[13] See Payne et al. (2022) for a new testing approach that jointly incorporates structural breaks and cross-correlations in the convergence model. See also Phillips and Sul (2003), Moon and Perron (2004), and Bai and Ng (2004) for methodologies based on stochastic convergence.

In the literature on emission convergence, which mostly focuses on CO_2 emissions, all of these tests are also frequently used. This shows that the studies on emissions convergence borrow similar approaches from the literature on income convergence. We now present the cross-country studies on CO_2 emissions convergence. Strazicich and List (2003) (SL) made a seminal contribution to this area by identifying evidence of stochastic and conditional β-convergence of CO_2 per capita emissions in 21 industrialized countries from 1960 to 1997 following panel unit root test and cross-section regression. Lee et al. (2008), following Sen (2003) reinvestigated the result of SL (2003) by allowing for a structural break and got the same results. Westerlund and Basher (2008) (WB) identified stochastic convergence of CO_2 per capita emissions for 28 countries (16 developed and 12 developing) using panel unit root tests that allow for cross-sectional dependence for the period 1870 to 2002. The evidence of convergence was also confirmed by Karakaya et al. (2019) using Pesaran (2007) approach which augments the standard ADF test by allowing for cross-section dependence.[14] Moreover, Christidou et al. (2013) used a century-long data (1870 to 2006) of per capita CO_2 emissions for 36 countries and found evidence of stochastic convergence. On the other hand, some studies provide mixed results in terms of stochastic convergence of CO_2 per capita emissions (i.e., convergence evidence in subsamples) by employing a variety of unit root and stationarity tests (e.g., Aldy, 2006; Yavuz and Ylanci, 2013; Barassi et al., 2011; Erdogan and Solarin, 2021; Ahmed et al., 2016). Some studies in this literature used the PS technique to examine club convergence. Panapoulou and Pantelidis (2009) were the first to apply this technique to per capita CO_2 emission data, using a sample of 128 countries and found absolute convergence from 1960 to 1975, while two convergence clubs from 1975 to 2003. Recently, Belloc and Molina (2023) also pointed out the evidence of absolute convergence in CO_2 per capita

[14] Using Carrion-i-Silvestre et al. (2005) methodology which accounts for structural breaks and cross-sectional dependence in the convergence model, Romero-Ávila (2008) and Lee and Chang (2009) provide strong evidence of stochastic convergence in CO_2 per capita emissions for 23 and 21 countries respectively over the period 1960–2002, thereby confirming SL (2003) and WB (2008) findings.

emissions using a sample of 114 countries from 1990 to 2019, following the PS technique.[15] In addition to club convergence, studies used β-convergence analysis and rendered evidence of absolute as well as conditional convergence across countries (e.g., Borowiec and Papiez, 2024; Fernández-Amador et al, 2018; Li and Lin, 2013; Jobert et al., 2010; Brannlund et al., 2017; Acar and Lindmark, 2017; Berk et al., 2022; Brock and Taylor, 2004). Moreover, three comprehensive surveys of the literature on GHG emissions convergence (Payne, 2020; Lee et al., 2021; Pettersson et al., 2013) reveal that the majority of studies indicate mixed results in CO_2 emissions across countries.

Hence, from the above discussion, we can conclude that studies on income convergence and CO_2 emissions convergence provided different dynamics of convergence based on country samples, time periods, and methods used.

3. Data and Methods

In this study, we have collected data on two variables, namely income per capita and CO_2 emissions per capita. The income per capita data is measured in international $ at 2011 prices and collected from Maddison Project Database (2023). The CO_2 emissions per capita data account for territorial emissions, measured in tonnes, and collected from Global Carbon Budget (2024). The dataset covers 20 Annex II countries for the period 1900 to 2022. The methods used in the present study are discussed in subsequent sub-sections.

3.1 Parameter variation in Log t test by Johnson (2020)

The original PS method identifies four possible convergence outcomes: absolute convergence, conditional convergence, club convergence, and absolute divergence. It is a regression-based approach, commonly referred to as the log t test, which provides convergence estimates for a specific period. Johnson (2020) modified the original PS log t test to generate convergence

[15] See also Belloc and Molina (2022) for evidence of absolute CO_2 per capita convergence in 19 Latin American countries from 1970 to 2018 using PS technique.

estimates over time, thereby allowing us to capture convergence dynamics as a time series. The details about PS technique are as follows. This test accommodates cross-sectional heterogeneity in the behaviour of the panel units. This is done by decomposing X_{it} into a short-run idiosyncratic components, α_i, and a common component, μ_t, as follows:

$$X_{it} = \alpha_i \mu_t + \epsilon_{it} \qquad (1)$$

The short-run heterogeneity in the panel is captured together by α_i and the error term ϵ_{it}.

PS express the above equation in the form of a time-varying dynamic factor model where the idiosyncratic elements (α_i and ϵ_{it}) are rearranged and presented together as b_{it}. This b_{it} represents the distance between an individual unit, X_{it}, from the time-varying common component, μ_t. This has been presented in equation 2 as follows.

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

This shows that the units of the panel can take different transition paths depending on economy-specific characteristics presented by b_{it}.

However, there is a problem: the number of unknows is more than the number of observations in equation 2, hence, not possible to estimate b_{it}. PS suggests a solution in the form of using a relative transition coefficient h_{it} rather than using X_{it} to study convergence:

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

Here h_{it} traces out the transition path the same way b_{it} was doing. The only difference is that now the transition paths are derived by eliminating the common component, μ_t, dividing X_{it} by the cross-section average at each point in time.

Convergence in this framework is achieved when $h_{it} \rightarrow 1$ as $t \rightarrow \infty$. Hence, in this framework, the long-run convergence ($h_{it} \rightarrow 1$) is achieved even after allowing for short-run cross-sectional heterogeneity in the transition paths of individual economies. This is the most important advantage of the log t test over the traditional regression-based framework (Phillips and Sul, 2009), which is based on the assumption of cross-sectional homogeneity in the panel units.

PS also defines the cross-sectional variance of h_{it} as:

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

Where the null hypothesis of convergence translates into $H_t \rightarrow 0$ as $t \rightarrow \infty$.

In order to formalize the null hypothesis, b_{it} has been assumed to follow a semi-parametric decay model of the form:

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

In equation (5), b_i is the long-run value of b_{it} and is a constant. σ_i represents an idiosyncratic scale parameter and ζ_{it} is an independent and identically distributed random variable across the cross-section i. However, it may also be a weakly dependent time series. *L(t)* is a slowly decaying function and satisfies the condition $L(t) \rightarrow \infty$ as $t \rightarrow \infty$. β is the rate at which the variation in the cross-section converges to zero over time.

Therefore, the null hypothesis of convergence can be expressed as:

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

The null hypothesis suggests that over time there will a convergence of the idiosyncratic transition elements (b_i) to a common value b. The alternative hypothesis is defined as follows:

$$H_A = Either\ i)\ b_i = b\ for\ all\ i\ and\ \beta < 0\ (Divergence)$$

$$Or \quad ii)\ b_i \neq b\ for\ some\ i\ and\ \beta \geq 0\ (Club\ Convergence)$$

Note that case ii) in the alternative hypothesis indicates towards a possibility of formation of convergence clubs. Thus, rejection of the null hypothesis of convergence implies two possibilities: divergence or club convergence. In the case of convergence clubs, the transition paths b_i are expected to converge towards more than one long-run values. This is how PS accommodated the possibility of multiple equilibria in the convergence test.

Finaly, PS proposed a regression model to test whether the cross-sectional variance (H_t) of the relative transition coefficient h_{it} converges to zero in the long run. The regression model takes the following form:

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

This regression model is known as log t-test, where $\hat{b} = 2\beta$, where β is the rate (speed) of convergence. H_1 represents the variance of h_{it} at the initial period t = 1, and H_t is the variance of h_{it} at any given point in time. $\log(\frac{H_1}{H_t})$ presents a measure of this convergence because convergence of h_{it} require (H_1/H_t) to go down over time. PS suggests that we can take the value of $L(t)$ to be equal to $\log(t)$. In order to focus more on the later part of the time series, we use a truncated sample to estimate equation (6). The truncation is done using a parameter r representing the proportion of the total sample T. The truncated sample thus goes from rT (or its closest integer value) to T. In principle, can be any value between 0 and 1 i.e., $r \in [0, 1]$. However, PS suggests value of $r \in [0.2, 0.3]$ based on Monte Carlo simulations, which helps achieve a balance between power properties of the test and the limit distribution. For small to moderate size, samples ($T \leq 50$), PS recommends r to be equal to 0.3, while 0.2 when ($T \geq 100$). In our study, we use r = 0.2, as our sample size is greater than 100. In this framework,

the null hypothesis of convergence, i.e. $\beta \geq 0$ is tested using an autocorrelation and heteroscedasticity consistent one-sided t-test.

The t-statistic value of higher than -1.65 implies that the null hypothesis of convergence cannot be rejected at the 5% significance level. While t-statistic value of higher than -1.65 confirms convergence, the convergence can take the form 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 $\hat{b} = 2\beta$). While values of $\hat{b} \geq 2$ imply absolute convergence, values of $\hat{b}$ in the range $2 \geq \hat{b} \geq 0$ imply conditional convergence. Thus, in the case where convergence cannot be rejected, PS enables us to distinguish between two sub-cases of convergence, i.e., absolute and conditional convergence. This aspect of the PS methodology has been used in a number of recent studies (e.g., Marrero et al, 2021; Ajit and Ghosh, 2024).

The value of t-statistic less than -1.65 implies the null hypothesis of convergence is rejected at the 5% significance level. If the null hypothesis of convergence is rejected, the next step is to identify clusters, sub-groups, or clubs. PS uses a clustering algorithm to identify the possibility of club convergence. It is a data-driven method. PS automatically clusters data based on repeating log t-test several times in different groups of time series. These clubs are initial clubs. There is a possibility that some of the initial clubs can be merged together. For that, PS suggested a merging algorithm to get the final convergence clubs.

The result of the PS can vary depending on the filter that has been used to separate out the trend component from the aggregate data. PS suggests using the HP filter. Tomal (2024) pointed out two limitations of the standard HP filter. The first limitation is related to end-point bias, i.e., the disproportionate impact 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. If λ is too big, the HP-filtered trend leaves behind a residual trend that distorts the cyclical component. Conversely, if λ is too small, the fitted trend becomes overly flexible, mimicking 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 repeated application of the standard HP filter until the surplus trend residuals are completely removed from the cyclical component. Hence, the club convergence results derived from using the boosted HP filter are more reliable. In the present paper, we have used the boosted HP filter.

However, as mentioned earlier, PS does not allow its log t regression parameter to vary over time. Consequently, the convergence estimates are for a specific period rather than capturing changes over time. As a result, parameter variation in log t regression is necessary to understand the convergence dynamics over time. The modifications of standard PS, performed by Johnson (2020) for long-run analysis, are given below.

$$log\left(\frac{H_1}{H_t}\right) - 2logL(t) = p + b\,log\,t + u_t,\ for\ t = [rT], [rT]+1, \dots, T \qquad (7)$$

$$\log\left(\frac{H_1}{H_t}\right) - 2logL(t) = m(log\,t) + u_t,\ for\ t = [rT], [rT]+1, \dots, T \qquad (8)$$

The equation (8) is estimated with the help of the local linear regression approach as described in Loader (1999). It allows 'b' (PS convergence parameter) to vary over time, thus giving us the value of b at each point in time.

3.2 Wavelet coherence technique

Wavelet coherence (WTC) is a technique for analyzing the time-frequency relationship between two time series. Unlike traditional methods such as correlation or regression, which assume a constant relationship across time, wavelet coherence allows us to examine how the strength and direction of the relationship between two variables vary across both time and frequency (or scale).

In this study, we analyze the co-movement between income per capita convergence and CO_2 emissions per capita convergence for 20 Annex II countries from 1925 to 2022 using the wavelet coherence method. This technique is particularly suited to data, which often displays non-stationarity and multiscale dynamics.

In the wavelet coherence analysis, time is represented on the horizontal axis, while frequency is displayed on the vertical axis, where lower frequencies correspond to higher scales. The wavelet coherence plot highlights regions in the time-frequency space where the two time series co-vary, indicating the strength of their co-movement. These regions are color-coded: warmer colors (such as red) represent areas of significant interrelation between the two variables, whereas cooler colors (such as blue) indicate periods of weak or no dependence. Areas beyond the cone of influence, typically marked in grey, represent regions where results may be less reliable due to edge effects.

The phase difference between the two series is illustrated using directional arrows on the plot. A zero-phase difference indicates that the two series move together at a particular scale (i.e., they are in phase). Arrows pointing to the right indicate an in-phase relationship, where both series move in the same direction. In contrast, arrows pointing to the left indicate an anti-phase relationship, where the series move in opposite directions. The orientation of the arrows also conveys lead-lag relationships: arrows pointing to the right-down or left-up suggest that the first variable leads the second, whereas arrows pointing to the right-up or left-down indicate that the second variable leads the first. This visualization allows for a detailed assessment of both the strength and timing of the relationship between the variables across different time scales. Therefore, high coherence indicates strong correlation at a particular time and frequency. While low coherence indicates weak or no relationship at that point in time and frequency.

3.3 Quantile-on-Quantile Regression (QQR)

The quantile-on-quantile regression (QQR) introduced by Sim and Zhou (2015) is a method that allows us to study the relationship between two variables across their entire distributions, rather than focusing only on the conditional mean or individual quantiles. This is particularly relevant when the variables under consideration exhibit non-linear, asymmetric, or heterogeneous behavior.

In this study, we apply QQR to examine how income per capita convergence affects CO_2 emissions per capita convergence across different quantiles of both variables, using annual data for 20 Annex II countries over the period 1925–2022. While traditional quantile regression (Koenker and Bassett, 1978) estimates the effect of explanatory variables across quantiles of the dependent variable, QQR takes this further by allowing interaction between the quantiles of both the dependent and independent variables. The output of the QQR analysis is typically presented as a surface or heatmap of $\beta(\theta, \tau)$ coefficients across different combinations of quantiles θ (for Y) and τ (for X). For example, a positive and significant $\beta(\theta, \tau)$ at high θ and high τ implies that high income per capita convergence speed is associated with higher CO_2 emissions per capita convergence speed.

4. Empirical Results

In this section, we first present the convergence trends obtained from the Johnson (2020) technique for income per capita and CO_2 emissions per capita across 20 Annex II countries during the period 1925 to 2022. Then, we present the results of WTC and QQR, examining the relationship between the two convergence trends. Figure 1 presents the convergence trend of income per capita, where the solid blue line represents the estimated PS convergence parameter over time and the dotted lines represent the confidence band.

The PS convergence parameter of per capita income across Annex II countries reveals significant fluctuations over the past century. Initially, during the period from 1925 to 1945, the PS convergence parameter remained below zero, indicating divergence in income per capita levels across these countries. This was likely a result of economic instability due to wartime destruction, and varying stages of industrial development and reconstruction needs during the interwar and World War II period. Following this, between 1945 and 1973, there was a sharp reversal as the PS convergence parameter rose into the level convergence zone (above 2), peaking in the late 1960s. This period reflected strong income per capita equalization across Annex II countries, driven by rapid industrialization in Western Europe, the influence of the U.S. Marshall Plan, the establishment of the Bretton Woods economic order, and robust multilateral cooperation among advanced economies. This era, often referred to as the "Golden Age of Capitalism," was marked by rapid economic growth and narrowing income per capita disparities among developed nations. However, from 1973 onwards, the trend reversed once again. The aftermath of the oil crisis and subsequent global recessions led to a gradual decline in the PS convergence parameter. Between the mid-1980s and early 2000s, the parameter fluctuated around zero or slightly below, suggesting that convergence had stalled and divergence had re-emerged. Structural changes in the global economy, neoliberal policy shifts, and technological transformations contributed to differential economic growth rates among high-income countries during this phase. From 2000 to 2015, a clear phase of divergence emerged. The PS convergence parameter remained significantly below zero, reaching its lowest point between 2010 and 2015. This period reflects the impacts of the 2008 global financial crisis, uneven recovery patterns among Annex II countries, and structural slowdowns in European economies compared to North America and the Asia-Pacific region. In the most recent period, 2015 to 2022, the PS convergence parameter shows tentative signs of recovery, though it remains negative. This suggests that while divergence is slowing, convergence has

not been restored. Post-crisis recoveries and some fiscal efforts may explain this marginal improvement, though the disruptions caused by the COVID-19 pandemic likely constrained further progress.

From a long-term perspective, this analysis reveals that income per capita convergence across Annex II countries has not been consistent. While strong convergence characterized the mid-20th century, the past four decades have largely been marked by divergence. This persistent divergence carries important policy implications. Specifically, it challenges the assumption that all high-income Annex II countries possess equal financial capacity to shoulder similar climate finance obligations under mechanisms like the Green Climate Fund. Divergence in income levels suggests that differentiated responsibilities within Annex II might be more appropriate, reflecting variations in economic capacity.

Figure 1: Income per capita convergence trend over time

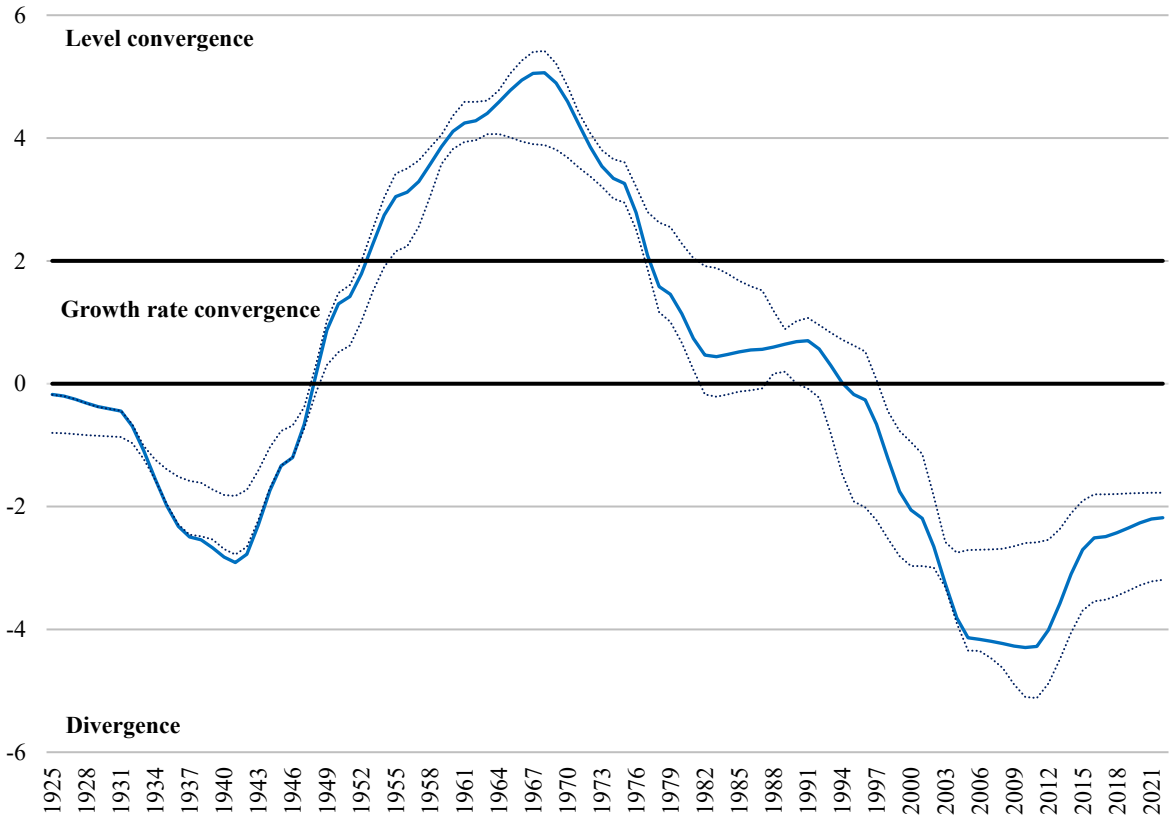
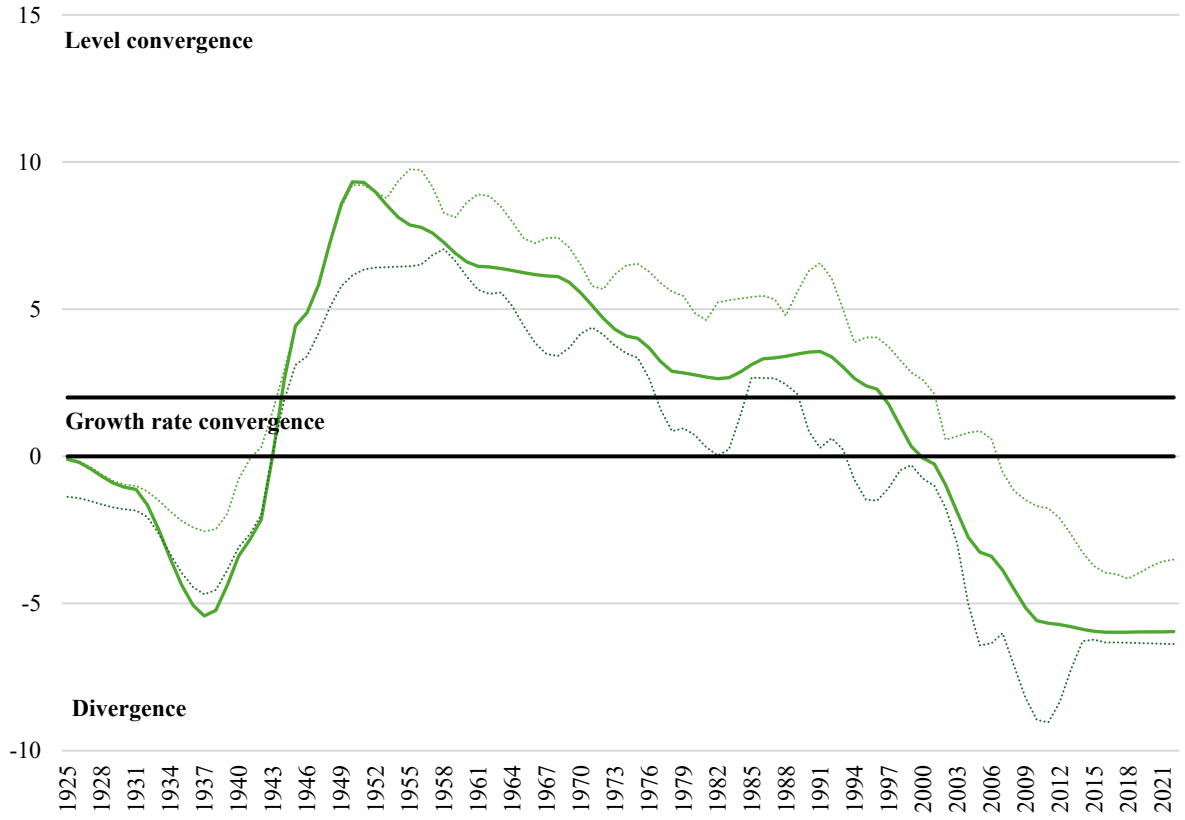


Figure 2 presents the PS convergence parameter of CO_2 emissions per capita across 20 Annex II countries from 1925 to 2022. The green solid line in the figure represents the estimated parameter, while the dotted lines denote the confidence intervals. Between 1925 and 1945, the PS convergence parameter remains negative, pointing to divergence in CO_2 emissions per capita across Annex II countries. A sharp dip around 1938–1940 reflects heightened disparities during this period, likely due to disruptions caused by World War II. While some countries intensified industrial production for war efforts, others suffered from destruction and economic collapse, exacerbating emissions differences. Post-World War II, from 1945 to 1970, a strong trend of level convergence emerges. The PS convergence parameter rises sharply and peaks above 9 around 1950, indicating that CO_2 emissions per capita became increasingly similar across these economies. This convergence can be attributed to coordinated post-war industrial reconstruction, widespread reliance on fossil fuels (especially coal and oil), and expansion of manufacturing sectors in Western economies. This period reflects the "Golden Age of Fossil Energy," where energy consumption and production practices became relatively standardized among developed nations. From 1970 to 1995, however, the convergence trend weakened. The PS convergence parameter shows a steady decline, although it largely remains above zero, suggesting continued but slower convergence in CO_2 per capita emissions. Differentiated energy transitions during this phase, such as the adoption of nuclear energy, varied pollution control strategies, and early environmental awareness (e.g., WCC-1) following the oil shocks of the 1970s, likely contributed to slowing convergence. Countries began to diversify energy sources and implement differing industrial and environmental policies, leading to variations in emissions levels. Between 1995 and 2005, the PS convergence parameter stabilized within the range of 0 to 2, signalling a phase of growth rate (or conditional) convergence. During this period, countries with higher per capita emissions likely began reducing emissions more rapidly, while those with historically lower per capita emissions saw slower growth. This phase

reflects the initial effects of global climate policies such as the Kyoto Protocol (1997), which encouraged coordinated mitigation efforts. From 2005 onward, the convergence pattern changed dramatically. The PS convergence parameter turns sharply negative, remaining below -5 after 2010, with a particularly steep decline around 2015–2017. This indicates strong divergence in per capita CO_2 emissions among Annex II countries. Several factors likely explain this trend: unequal adoption rates of renewable energy, differing speeds of decarbonization, structural differences in national energy systems and industrial sectors, and varied policy responses. Furthermore, post-2008 financial crisis rebounds and the uneven economic recovery from the COVID-19 pandemic may have exacerbated these emissions disparities.

Figure 2: CO_2 emissions per capita convergence trend over time



Overall, the convergence analysis of CO_2 emissions per capita reveals a complex and evolving picture. While Annex II countries experienced a period of strong convergence during the mid-

20th century, recent decades are characterized by clear divergence in per capita emissions levels. This highlights significant structural and policy differences in emissions reduction pathways, emphasizing the need for differentiated climate strategies even among advanced economies.

Table 1: Summary of Convergence Results

Period	Income per capita convergence	CO_2 emissions per capita convergence	Inference
1945–1970	Strong (Level)	Strong (Level)	High economic and energy structure similarity
1970–1990	Weakening	Weakening	Beginning of structural decoupling
2000–2020	Divergence	Divergence	Green growth and fossil dependence divergence

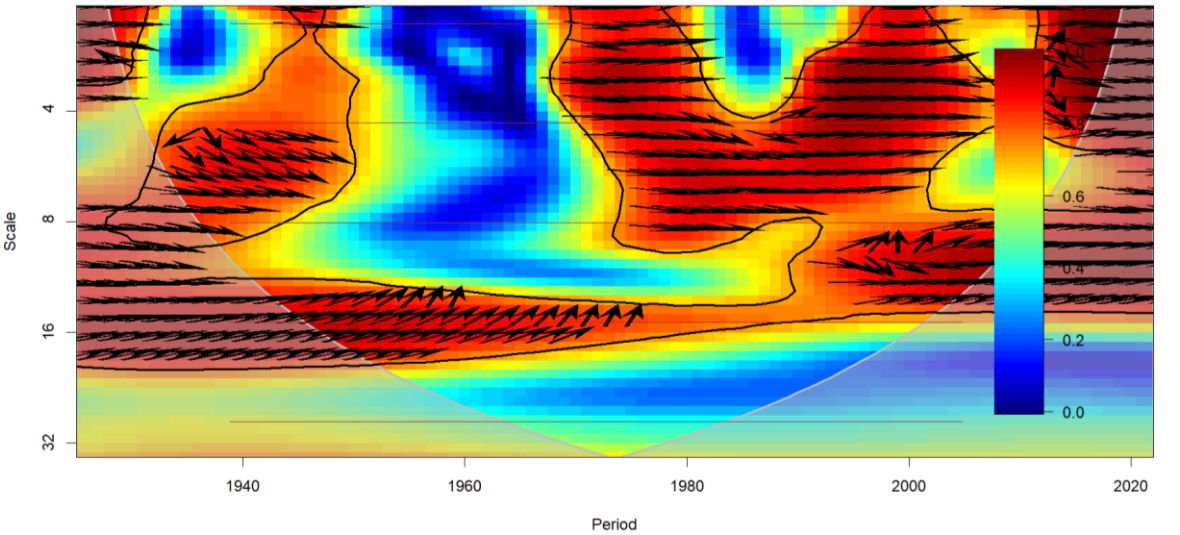
Figure 3 presents the wavelet coherence (WTC) analysis, which examines the dynamic time-frequency relationship between income per capita convergence and CO_2 emissions per capita convergence across 20 Annex II countries. Several key insights emerge from the WTC plot. Notably, high coherence zones (red areas) highlight periods where income per capita convergence and CO_2 emissions per capita convergence are strongly interrelated. Two prominent phases of strong coherence can be observed. The first spans approximately from 1945 to 1965 across mid-to-long-term scales (scale 4–16). This period reflects a strong in-phase relationship, suggesting that post-World War II income per capita convergence significantly drove CO_2 emissions per capita convergence, likely due to coordinated industrial growth and similar energy consumption patterns among developed countries. The second phase of high coherence is evident from 1995 to 2022, particularly across scales 8–16.

The lead-lag dynamics depicted by the arrows offer further insights. During most of the strong coherence phases, arrows point to the right and slightly upward, indicating that income per capita convergence typically leads CO_2 emissions per capita convergence. This pattern is especially clear between the 1950s and 1980s, suggesting that reductions in income per capita

disparities precede and potentially drive reductions in CO_2 emissions per capita disparities. In more recent periods (post-2000), some arrows point to the right and slightly downward, hinting at a possible feedback loop where CO_2 emissions per capita convergence may influence income per capita convergence, potentially through mechanisms such as climate policies or carbon taxation.

Periods of low coherence (blue regions) are also evident, most notably between 1965 and 1985. This phase corresponds with historical events like the oil crises of the 1970s and periods of stagflation, during which economic instability and divergent energy strategies among countries may have weakened the link between income per capita convergence and CO_2 emissions per capita convergence.

Figure 3: WTC plot

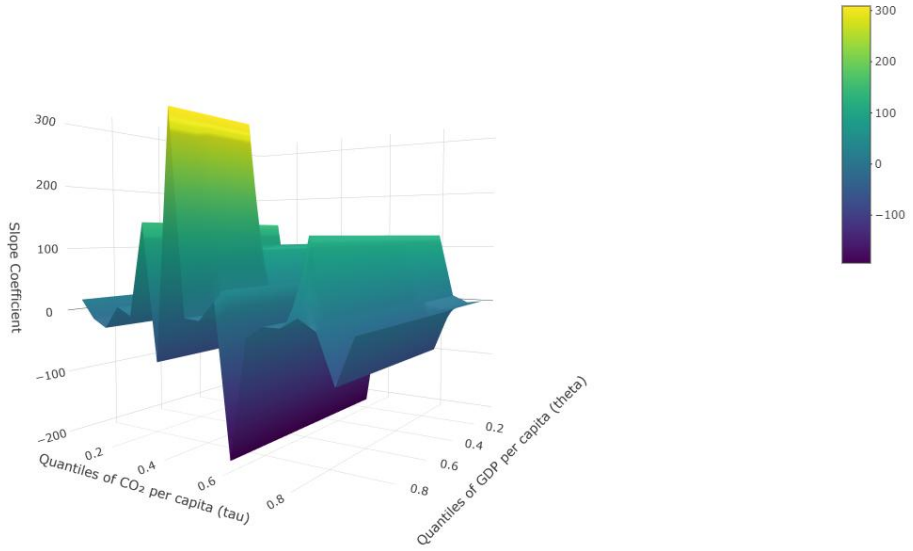


From a policy perspective, the WTC plot underscores two important conclusions. First, the persistent relationship between income per capita and CO_2 emissions per capita convergence over long-term scales suggests that structural economic factors, such as energy systems and industrial development, fundamentally shape emissions trajectories. Second, the sustained high coherence observed since the early 1990s likely reflects the growing influence of global climate

governance, shared policy norms, and the adoption of green technologies among developed economies.

In the QQR surface plot (Figure 4), the X-axis represents the quantiles of income per capita convergence (θ), the Y-axis reflects the quantiles of CO_2 emissions per capita convergence (τ), and the Z-axis depicts the estimated slope coefficient, indicating the strength and direction of the association between the two convergence trends.

Figure 4: QQR plot



The surface plot reveals strong heterogeneity in the relationship between income and emissions convergence, as evidenced by the highly nonlinear and asymmetric surface. A clear positive relationship is observed within the central quantiles of both variables. Specifically, when both income per capita convergence and CO_2 emissions per capita convergence fall within their middle quantiles (approximately 0.4 to 0.6), the slope coefficient becomes strongly positive. In contrast, the lower and upper quantiles exhibit marked divergences. In the lower quantiles of CO_2 emissions per capita convergence ($\tau < 0.2$) combined with higher quantiles of income per capita convergence ($\theta > 0.8$), the slope coefficients turn negative, as seen in the purple zones of the surface plot.

This indicates that certain countries, despite showing strong income per capita convergence, are not exhibiting similar trends in CO_2 emissions per capita convergence. This divergence may be attributed to early adoption of green technologies and cleaner industrial practices. Similarly, in the upper quantiles of CO_2 emissions per capita convergence, coupled with lower quantiles of income per capita convergence, the surface rises significantly. This indicates that some countries with relatively lower income per capita, although economically lagging in Annex II group, are rapidly converging in emissions, possibly due to intensified industrial activities without stringent environmental regulations.

5. Conclusion

This study examined the historical relationship between income per capita convergence and CO_2 emissions per capita convergence across 20 Annex II countries from 1900 to 2022 using Johnson (2020) time-varying convergence method, wavelet coherence analysis, and quantile-on-quantile regression.

The findings reveal a non-uniform relationship between income and emissions convergence. While several historical periods show clear evidence of joint convergence—particularly during the post-World War II industrial recovery and the post-1990 global climate negotiations—there are also distinct phases where the trajectories of income per capita and CO_2 emissions per capita diverged significantly. Specifically, in recent decades, despite income convergence among Annex II countries, emissions convergence has weakened, with countries following divergent decarbonization pathways. This reflects the adoption of differentiated energy policies across countries.

Wavelet coherence analysis demonstrates that income per capita convergence typically leads CO_2 emissions per capita convergence. The presence of strong coherence during specific historical windows indicates periods where economic growth facilitated coordinated emissions

outcomes. However, the absence of such coherence in other periods highlights the role of policy divergence and energy transitions in disrupting this relationship. The quantile-on-quantile regression results further reinforce the presence of nonlinear and heterogeneous dynamics.

From a policy perspective, the study challenges the conventional framework of assigning equal financial obligations to all Annex II countries based solely on income levels. The evidence suggests that countries with similar economic capacities, but different emissions performances should not bear identical climate finance responsibilities. High-income countries that have transitioned to lower emissions through early adoption of green technologies or maintained historically low emissions due to cleaner industrial development may argue for differentiated financial contributions. Conversely, countries with both high income and persistently high emissions may be expected to shoulder a larger share of the climate finance burden.

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