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# Cross-country distribution dynamics of carbon emissions and intensity: Before and after the global financial crisis

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This study aims to explore the levels of regional disparity in carbon emissions and intensity among different countries. Our study employs the distribution dynamics approach to uncover transition probabilities and the long-term evolution of relative per capita carbon emissions (REPC) and relative carbon intensity (REPGDP) across 204 countries. We split the analysis period into pre-crisis (2000-2007) and post-crisis (2007-2016) and divided countries into four income groups. The results indicate the emergence of new convergence clubs post-crisis in both REPC and REPGDP. Furthermore, the majority (many) of the low- (high) income countries congregate to extremely low (above the global average) REPC levels in the long run. Finally, using mobility probability plots, we identify low-

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(high-) income countries with REPC (REPGDP) levels of 2.3 (3.8) times the global average to have the highest probabilities of around 100 (65) per cent of diverging further above the worldwide average in the coming years. The study expands knowledge about convergence-divergence patterns in carbon emissions and intensity, which is crucial for energy management and effective climate policies. Moreover, it can aid in climate change projections and promote a fairer climate framework, encouraging high-emission countries to take greater responsibility

*Keywords*: Carbon emissions; Global financial crisis; Distribution dynamics; Convergence clubs; Income levels

*JEL Classifications*: C14; G01; O13; Q54

## 1 Introduction

Greenhouse gas (hereafter GHG) emitted into the atmosphere from burning fossil fuels significantly contributes to global climate change. Thus, effective control of the relentless growth of GHG emissions has become an irreplaceable mission for global society (Shahrour et al 2023). Accordingly, 196 countries signed the Paris Agreement in 2015 with the primary target of slowing down global warming to below 2°C (if possible 1.5°C) compared to pre-industrial levels (Cheng et al 2023). The signatories also pledged to define their climate actions known as Nationally Determined Contributions (hereafter NDCs). However, Climate Action Tracker (2021) forecasted that assuming all of the existing NDCs were delivered, the global temperature would still increase by 2.4°C. Furthermore, the NDCs are voluntary actions, thereby giving rise to countries under-committing, which, together with the implementation gap in numerous countries, makes reaching the global warming goals unlikely.

The knowledge of convergence-divergence patterns in carbon emissions is significant in energy management and formulation of efficient climate measures and policies (e.g., Kounetas 2018, Li and Wei 2021). Knowing the dynamic trajectory of emissions also helps facilitate climate change projections. Moreover, the convergence could result in a fairer climate framework, thereby increasing the odds of countries with high emissions assuming a greater responsibility for climate commitments (Aldy 2006, Delgado 2013, Erdogan and Solarin 2021). Indeed, the Kyoto and Paris Accords highlight the substantial positive impact of emissions convergence and shared environmental policies on the probability of reaching the desired goals.

Against this backdrop, the convergence in cross-country carbon emissions has attracted growing attention in the environmental economics literature (e.g., Rios and Gianmoena 2018, Li et al 2020). On the one hand, numerous studies test the presence of convergence in per capita carbon emissions measures (e.g., Westerlund and Basher 2008, Li et al 2020). On the other hand, the recent surveys by Acar et al (2018) and Payne (2020) show that the convergence of $CO_2$ intensity (per unit of GDP emissions) remains relatively unexplored, and the empirical results are mixed at best. Such gaps in the literature are worrying, given that many countries state carbon commitments in terms of either $CO_2$ emissions or $CO_2$ intensity[1] (Bhattacharya et al 2020). Furthermore, the two measures of a country's carbon emissions can take opposite routes (Parker and Bhatti, 2020).

In terms of research methods, many studies test the presence of sigma, beta, and stochastic convergence (e.g., Jobert et al 2010, Li and Lin 2013, Erdogan and Solarin, 2021). Other parametric, semi-parametric, and nonparametric methods have also been used to test absolute vis-à-vis conditional convergence (e.g., Brock and Taylor 2010, Delgado 2013), stochastic convergence (Chang and Lee 2008), spatial convergence (Rios and Gianmoena 2018), and club convergence (Parker and Bhatti 2020). However, fewer studies employ the distribution dynamics approach (hereafter DDA) developed by Quah (1993, 1997) (e.g., Aldy 2006, Criado and Grether 2011).

To the best of our knowledge, Kounetas (2018), Li et al (2021) and Wojewodzki et al (2023) are the only studies examining the convergence in both measures of carbon emissions using the DDA. However, they neither investigated the transitional dynamics of carbon emissions across countries focusing on different income levels nor examined the effect of the GFC. Moreover, Kounetas (2018) uses a relatively small sample limited to 23 EU countries, and his analysis does not include the MPP tool.

Considering the above-outlined gaps in environmental research, this study makes three new contributions to the environmental economics literature. To the best of our knowledge, we are first to examine the long-run, dynamic convergence-divergence pattern of (1) relative per capita carbon emissions (hereafter REPC) and (2) relative carbon intensity (hereafter REPGDP) across 204 countries[2]. Furthermore, we deliver a nascent analysis of the impacts of the 2008 global financial crisis (hereafter, GFC) and unprecedented expansionary fiscal and monetary policies on the future evolution of global REPC and REPGDP levels. For instance, we document worrying developments in transitional dynamics and long-run steady-state equilibria of both REPC and REPGDP measures post-GFC period compared with the pre-GFC period. Such findings might indicate the negative effect of GFC-related expansionary policies (e.g., massive borrowing, quantitative easing, and investment in carbon-intensive industries) on both carbon emissions measures' long-run steady-state equilibria and convergence process.

Third, this paper delves into the profound influence of carbon emissions and intensity on the distribution dynamics of nations grouped by income levels. Specifically, along with the

[1] For example, China and India have stated their emissions reduction goals regarding $CO_2$ intensity (Bhattacharya et al. 2020).

[2] REPC (REPGDP) is a ratio of country-specific annual per capita carbon emissions (intensity) to the average carbon emissions (intensity) of all sampled countries in a given year. Because of the global scope of this research (204 countries), we treat the sample's annual average value as a proxy for the global averages. Therefore, a country's REPC or REPGDP above (below) one implies that this country's REPC or REPGDP is above (below) the global average in a given year.

ergodic distribution, we also use a novel display tool of DDA introduced by Cheong and Wu (2018), the Mobility Probability Plot (hereafter, MPP). This new tool offers specific visual information regarding the probability mass distribution in the coming years. We document that the low- (high) income countries with REPC (REPGDP) values of around 2.3 (3.8) times the global average emissions have the most significant probabilities of around 100 (65) per cent of diverging further above the worldwide mean. This information, in turn, translates into a "policy priority list" of countries meriting the most urgent climate policies and actions.

The rest of this study is organised as follows. Section 2 provides an extensive review of relevant literature. Section 3 introduces data and research methods. Section 4 discusses the empirical results. The last section concludes the research findings and policy implications.

## 2 Literature Review

A burgeoning body of environmental literature has tested the convergence hypothesis of cross-country per capita carbon emissions. For example, Ezcurra (2007) use the DDA and find strong evidence of convergence towards the mean across 140 countries from 1960 to 1999. On the contrary, based on the same method and a panel of 166 countries from 1960 to 2002, Criado and Grether (2011) document an increased divergence and higher levels of $CO_2$ emissions in the long run. El-Montasser et al (2015) also report the results inconsistent with emissions convergence in a study of high-income G7 countries. Most recently, Lee et al (2023) employed stochastic convergence to analyse per capita emissions for 30 OECD countries from 1960 to 2018, revealing the lack of convergence.

On the contrary, Chang and Lee (2008) find significant evidence of stochastic convergence in a panel of 21 high-income OECD countries using the minimum LM unit root tests. More recently, Rios and Gianmoena (2018) test the spatial convergence clubs hypothesis vis-à-vis the conditional convergence hypothesis in a sample of 141 countries and document the emergence of three clubs. However, in a worldwide sample of countries, Fallahi (2020) show that per capita carbon emissions are non-stationary and highly persistent at both the global and regional levels.

Many researchers examine per capita carbon emissions, focusing on countries' economic development and income levels. For instance, in the sample of 100 countries, Nguyen Van (2005) employs the DDA and shows a long-run convergence only across 26 developed countries. Similarly, Aldy (2006) documents converge in emissions across only 23 developed OECD members but find an opposite pattern (divergence) among 88 countries. Payne and Aspergis (2021) identify three convergence groups among 27 low-income countries and five clubs among 38 lower-middle-income countries from 1972 to 2014. In a sample spanning from 1870 to 2002, Westerlund and Basher (2008) and Delgado (2013) find evidence of the convergence across developed and developing countries alike. Similarly, Ahmed et al (2017) study 162 countries and show convergent patterns in 20, 13 and 5 high-income, middle-income, and low-income countries, respectively. According to Li et al (2020), convergence is significantly faster across developed countries vis-à-vis developing countries.

The empirical literature suggests that the episodes of financial crises significantly influence global carbon emissions, intensity, and convergence patterns. In a study of fourteen Asian countries, Parker and Bhatti (2020) document different transition paths in the convergence process of per capita carbon emissions before and after the 1997 Asian financial crisis. The authors observe the emergence of four (three) convergence clubs pre- (post) crisis. According to Wang et al (2021), the shock of GFC brought an initial U-turn in an ongoing upward (downward) trend in global carbon emissions (intensity), followed by a return to the previous pattern between 2009 and 2011. Li et al (2020) argue that the GFC and unprecedented post-crisis policies adopted by different countries have led to cross-country divergence in emissions.

Recent surveys of empirical studies (Acar et al 2018, Payne 2020) agree that while the convergence hypothesis has been tested extensively for cross-country per capita carbon emissions, relatively few researchers have examined the convergence of $CO_2$ intensity. For instance, Lindmark (2004) graphically examines the patterns of carbon intensity across 56 countries during the 1870-1992 period and reports high-income countries converging with their low-income counterparts. Camarero et al (2013) use Phillips and Sul's (2007) convergence-club approach to identify four clubs of carbon intensity across 19 OECD countries and a non-convergent pattern in four industrialised countries. Zhu et al (2014) find evidence of convergence in a panel of 89 countries between 1980 and 2008. Zang et al (2018) examine a sample of 201 countries from 2003 to 2015 and document club convergence among all three groups of countries: low-, middle-, and high-income. According to Bhattacharya et al (2020), two convergence clubs exist in cross-country consumption-based carbon emissions. Moreover, their forecast based on a panel of 70 countries suggests that between 2014 and 2030, the number of convergence clubs in consumption-based carbon intensity will increase.

Nevertheless, the dynamic aspects of per capita $CO_2$ emissions vis-à-vis $CO_2$ intensity remain largely unexplored. Only three cross-country studies employ the DDA approach to carbon emissions and intensity at the same time. In a sample of 23 EU countries during the 1970-2010 period, Kounetas (2018) find no evidence of convergence. Li et al (2021) investigate the REPC and REPGDP measures in 178 countries. They document significant disparities in the transitional dynamics of both measures between 71 countries that signed the Belt and Road Initiative (hereafter BRI) cooperation with China and 107 non-BRI countries. Wojewodzki et al (2023) study transitional dynamics and evolution of per capita $CO_2$ emissions and $CO_2$ intensity across countries with different urbanisation levels and agrarian orientations. However, none of the three studies examine (1) the dynamics and future evolution of carbon emissions and intensity concerning countries' income levels and (2) the effect of the GFC on transitional dynamics and long-run steady-state equilibrium.

The existing body of environmental literature has yielded conflicting results[3] and left some critical gaps. We aim to fill the abovementioned gaps by investigating the transitional dynamics of carbon emissions and intensity in a global sample of 204 countries from 2000 to 2016. This study adopts the DDA approach and the MPP tool that Cheong and Wu developed (2018).

## 3 Methodology and Data

The data are compiled from the World Bank's World Development Indicators (WDI) database. Two measurements of carbon emissions are employed: relative $CO_2$ emissions per capita (REPC) and relative $CO_2$ intensity (REPGDP). REPC is measured as metric tons of $CO_2$ per capita in each country divided by the world average in a particular year. Similarly, REPGDP is measured as kg of $CO_2$ emissions per 2010 USD of GDP in each country divided by the world average for this year. Using relative values, the disparity amongst the nations can be displayed directly as a REPC or REPGDP value of 1, which indicates that a country's $CO_2$ emissions or intensity is equal to the global average. In contrast, a value smaller (greater) than 1 means the level below (above) the global average. The unbalanced panel covers 204 countries, starting in 2000 and ending in 2016[4]. That is because the data for 2017 and beyond were unavailable for many countries at the time of collection.

Table 1 presents annual descriptive statistics for both variables. We can observe one measure of central location (median) and one measure of dispersion (the coefficient of variation, hereafter, CV).

Table 1. Annual (2000-2016) descriptive statistics for the REPC and REPGDP variables

| **Variable** | **Year (2000-2016)** | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Global REPC* | 00 | 01 | 02 | 03 | 04 | 05 | 06 | 07 | 08 | 09 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
| Median | 0.59 | 0.59 | 0.59 | 0.58 | 0.53 | 0.54 | 0.59 | 0.55 | 0.55 | 0.60 | 0.55 | 0.56 | 0.55 | 0.57 | 0.57 | 0.57 | 0.58 |
| CV | 1.43 | 1.45 | 1.42 | 1.39 | 1.36 | 1.37 | 1.38 | 1.33 | 1.28 | 1.28 | 1.25 | 1.25 | 1.26 | 1.23 | 1.26 | 1.25 | 1.22 |
| *Global REPGDP* | | | | | | | | | | | | | | | | | |
| Median | 0.78 | 0.79 | 0.77 | 0.75 | 0.74 | 0.75 | 0.74 | 0.75 | 0.70 | 0.74 | 0.72 | 0.71 | 0.71 | 0.72 | 0.74 | 0.75 | 0.78 |
| CV | 1.07 | 1.03 | 1.04 | 1.03 | 1.00 | 0.95 | 0.94 | 0.93 | 0.90 | 0.84 | 0.84 | 0.86 | 0.92 | 0.94 | 0.82 | 0.79 | 0.79 |

Source: Authors' calculations based on the World Bank's World Development Indicators (WDI)

[3] Mixed results in prior studies can be attributed to different sample sizes and research methods. Specifically, studies using larger samples and dynamic analyses tend to find evidence against cross-country convergence.

[4] The number of countries is the lowest (199) in 2000, while 204 were covered between 2008 and 2016. This means that each country has a minimum of 9 consecutive annual observations.

Table 1 shows similar decreasing trends regarding the variability in global carbon emissions and intensities. Specifically, the CV values for REPC (REPGDP) dropped from 1.43 or 143% (1.07 or 107%) to 1.22 (0.79). This means a presence of sigma convergence in two major proxies for emissions over time, similar to the results of Zang et al (2018). This, in turn, constitutes good news from the perspective of desirable cross-country convergence to the global mean. However, the percentage change (decrease) in CV between 2000 and 2016 was larger (85%) for REPC than that for REPGDP (74%), at odds with the changes documented by Zang et al (2018) for the 2003-2015 period. Notwithstanding, global annual variability in the REPGDP has remained substantially larger than that of REPC throughout the sampled period.

As for the median values, these remained virtually unchanged between 2000 and 2016, ranging from 0.6 to 0.53 (0.79 to 0.7) in 2009 and 2004 (2001 and 2008) for the REPC (REPGDP) variable. Since the global annual mean value for both measures of relative carbon emissions equals one, we can conclude that the distribution of both variables is negatively skewed, especially for the REPC measure, due to its median values being significantly below one. This highlights relatively fewer (more) countries with REPC and REPGDP above (below) the global average during the investigation period.

Time series econometric analyses are frequently used in forecasting. However, it is essential to acknowledge that econometric models are limited in their ability to forecast the dependent variable, as they do not provide insights into the shape of the underlying distribution (Liu et al 2022). Instead, such methods only offer insights into several significant distribution features since they solely focus on predicting the dependent variable. Notwithstanding, since distribution is a two-dimensional entity, it is not feasible to predict the future distribution's overall shape solely through time series econometrics. Consequently, by ignoring information regarding, e.g., multimodal distributions, the econometric analysis may lead to contaminated or misleading results (Quah 1997, Maasoumi et al 2007). Likewise, traditional (econometric) methods cannot comprehensively overview the distribution pattern and its dynamic changes (Cheong and Wu 2018).

In contrast, the DDA developed by Quah (1993, 1997) focuses on examining the shape of the distribution and how it changes over time. Thus, while traditional econometric techniques can be utilised to calculate the slope parameter and assess the impact of a driving factor, the DDA allows for examining the effects of determinants on the entire distribution. This involves dividing the data into smaller datasets and applying the DDA to each subset individually. By comparing the distributions of these datasets, one can better understand the impacts of different driving factors[5].

[5] However, one limitation of the DDA is that the study of determinants can only be conducted one at a time.

Furthermore, the DDA possesses a significant advantage over traditional econometric analysis regarding its resilience to outliers. This stems from the fact that the computation of the DDA relies on the probability of entities transitioning between different states, which is contingent upon the occurrence of the entities rather than their measured values. In stark contrast, traditional econometric analysis is susceptible to the influence of outliers, as it relies on calculating the slope parameter, which can be significantly affected by outliers. Moreover, one of the tools of the DDA is the ergodic distribution, which represents the future trend's steady-state distribution (Wei et al 2020). This analytical technique can comprehensively depict the underlying trend and the future evolution and intensity of, for example, carbon emissions.

Quah's DDA can be divided into two major categories: the traditional Markov transition matrix analysis and the stochastic kernel approach. One issue of the traditional Markov transition matrix analysis is the arbitrary boundary of the state associated with the selection of grid values. In contrast, demarcation can be achieved objectively in the stochastic kernel approach, which can be viewed as an improvement of the traditional Markov transition matrix approach. As a result, this study employs the stochastic kernel approach. The bivariate kernel estimator can be represented as the equation (1).

$$\hat{f}(x,y) = \frac{1}{nh_1h_2}\sum_{i=1}^{n} K\left(\frac{x-X_{i,t}}{h_1}, \frac{y-X_{i,t+1}}{h_2}\right) \tag{1}$$

where $n$ stands for the number of observations, and $x$ ($y$) stands for the relative $CO_2$ emissions of an entity at period t (t+1). $X_{i,t}$ ($X_{i,t+1}$) represents an observed value of relative $CO_2$ emissions at time t (t+1). Furthermore, terms $h_1$ and $h_2$ correspond to the bandwidths computed using the approach established by Silverman (1986), and $K$ is the normal density function. Due to the data sparseness, we use the adaptive kernel with flexible bandwidth, which was first proposed by Silverman (1986). There are two steps in implementation. It involves the computation of a pilot estimate at the beginning, and then the bandwidth is adjusted by a factor that reflects the kernel density. Under restrictive assumptions that the studied variable's distribution at time $t+\tau$ depends on $t$ only, the process is of first order and doesn't change over time; the relationship between the distributions at periods $t$ and $t+\tau$ can be represented by the equation (2).

$$f_{t+\tau}(z) = \int_0^{\infty} g_\tau(z|x) f_t(x)dx \tag{2}$$

where $g_\tau(z|x)$ represents the transition probability kernel, which plots the distribution from period $t$ to $t+\tau$, while the term $f_t(x)$ stands for the kernel density function of the variable's distribution at period $t$. Moreover, the term $f_{t+\tau}(z)$ captures the $\tau$-period-ahead density function of $z$ conditional on $x$. Because annual transitions are used in the analysis, the sample size will be larger, and the estimation results will be more reliable. Given that it exists, the ergodic density function can be calculated from equation (3).

$$f_{\infty}(z) = \int_{0}^{\infty} g_{\tau}(z|x) f_{\infty}(x) dx \qquad (3)$$

where $f_{\infty}(z)$ represents the ergodic density function given infinite $\tau$. The ergodic distribution can be viewed as a forecast of the steady-state distribution of relative $CO_2$ emissions. The MPP display tool was developed by Cheong and Wu (2018) to interpret detailed mobility probability, which can be used in conjunction with the traditional distribution dynamics approach. The MPP is obtained through the computation of $p(x)$ representing the net upward mobility probability as per equation (4).

$$p(x) = \int_{x}^{\infty} g_{\tau}(z|x) dz - \int_{0}^{x} g_{\tau}(z|x) dz \qquad (4)$$

The MPP is expressed in percentages ranging from -100 to 100 and plots the net upward mobility probability against the REPC and REPGDP variables. A positive (negative) value highlights that the entity has a net probability of an upward (downward) shift in the distribution of the analysed variable (Wei et al 2020). The MPP has advantages over traditional display tools of distribution dynamics, such as three-dimensional plots or contour maps of transition probability kernels. Specifically, the MPP offers detailed information about the transitional dynamics of the variable even if the distribution's probability mass is highly concentrated. Moreover, we can superimpose several MPPs in one graph, which, in turn, facilitates effective comparisons of the REPC and REPGDP transitional dynamics between pre- and post-GFC periods as well as across countries grouped by income levels. Due to its merits, the MPP has been employed to study transitional dynamics of energy consumption (Shi et al 2021a, b), per capita GDP (Wu et al 2021), housing affordability (Liu et al 2022), information transparency (Williams et al 2022), and credit ratings (Lee et al 2021).

## 4 Empirical Results and Discussions

To better understand the transitional dynamics of carbon emissions and intensities worldwide, this section presents and discusses ergodic distributions and the MPPs of the REPC and REPGDP variables. As for the order of presentation, first, we divide the dataset into two subperiods: pre-GFC (2000-2007) and post-GFC (2008-2016). Next, we split the overall sample into four subgroups based on countries' income levels following the World Bank's classification.

### 4.1 Carbon emissions and intensities before and after the GFC

The GFC was followed by unprecedented fiscal and monetary policies undertaken by many developing (e.g., China) and developed (e.g., the US and the UK) governments to revive their economies. This section analyses the transitional dynamics and future evolution of the REPC variable before the GFC (2000-2007) and afterwards (2007-2016). Figure 1 presents the ergodic distributions of the REPC variable. It should be remembered that the ergodic distribution presents the future long-run steady-state equilibrium under the assumption that the transitional dynamics remain the same. Moreover, the vertical (horizontal) axis represents the proportion (REPC values).

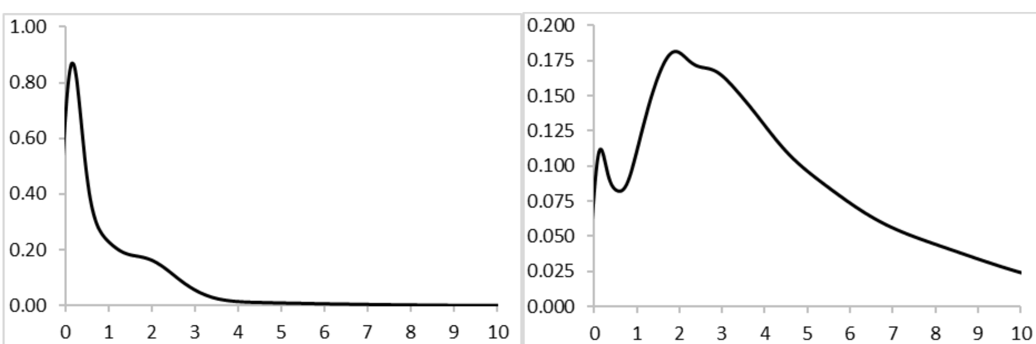
Figure 1 shows two striking differences between the two periods in the future evolution of REPC. First, the pre-GFC (post-GFC) distribution is bi-modal (tri-modal), i.e., we can observe the emergence of an additional convergence club in the long-run steady-state equilibrium based on the post-GFC period. Specifically, panel A's major and minor peaks correspond to a REPC value of around 0.2 and 2, respectively. However, in the post-GFC distribution, the three peaks occur at the REPC values of 2 (major peak), 0.2, and 2.7 (minor peaks). Second, the distribution in panel B is significantly more spread out. For instance, the post-crisis major peak has a height of 0.18, while the pre-crisis major peak has a height of 0.85.

The emergence of an additional (third) convergence club in the post-GFC period indicates increased heterogeneity in countries' REPC in the long run and aligns with Rios and Gianmoena (2018), who show the emergence of three convergence clubs in a worldwide study. This suggests that the disparities in emissions widened (Criado and Grether, 2011), potentially due to varying responses to the financial crisis (e.g., investments in carbon-intensive industries, reduced taxes, ultra-low interest rates and quantitative easing) and subsequent economic developments.

Furthermore, significantly more spread-out post-crisis ergodic distribution and the emergence of additional convergence clubs at higher (nearly three times the average) REPC

Figure 1 Ergodic distributions for REPC before and after GFC

A Pre-crisis (2000-2007)    B Post-crisis (2007-2016)




Notes: The horizontal and vertical axes show the value of the REPC variable and the proportion, respectively.

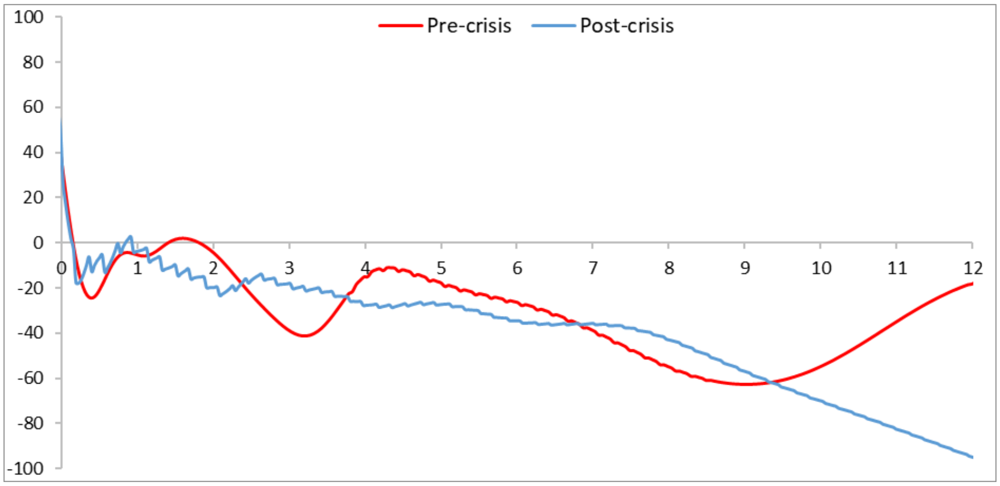
values pose opportunities and challenges for global climate policy efforts, respectively (Li et al 2020). On a positive note, substantially more dispersed post-crisis distribution signalises improved flexibility regarding desirable carbon emissions reduction and convergence to the mean. Conversely, achieving consensus and coordination among countries to reduce carbon emissions may be more complex, as countries converging towards significantly above-average REPC may have divergent interests and priorities. This, in turn, highlights the need for policymakers to tailor their approaches to address the specific circumstances and drivers of carbon emissions in countries experiencing different convergence dynamics. Overall, Figure 1 suggests a shifting landscape in global REPC patterns, requiring nuanced and adaptive approaches in formulating and implementing climate policy.

Figure 2 presents the MPPs of cross-country REPC pre- and post-GFC, which allows us to directly compare the distributional dynamics and probability mass of emissions in all countries. The findings are mixed regarding desirable reduction and convergence in $CO_2$ emissions. On the one hand, the post-GFC MPP lies underneath the pre-GFC MPP for countries with REPC values from 1.2 to 2.3, 3.8 to 7 and above 9.3. Based on the post-crisis sample period, this translates to a greater probability of reducing carbon emissions in years to come for countries with such emissions levels. Therefore, decision-makers could focus on reinforcing existing policies or implementing new measures to strengthen or sustain this positive trend. The policies could include incentivising renewable energy investments, implementing stricter emissions regulations, or promoting energy efficiency measures tailored to these countries' needs.

Such an encouraging pattern is particularly pronounced for the outliers with the highest REPC values of around 12. Specifically, we can observe that the probability of future carbon emissions converging towards the global average increases from 17% before the GFC to approximately 100% after the crisis. Such a maximum probability constitutes a so-called "development trap", i.e., good news from the perspective of $CO_2$ emissions convergence; that is because the biggest emitters, upon approaching this threshold level, would encounter a decline in their REPC in the following year. The concept of a "development trap" highlights the importance of recognising when a country's REPC approaches such a threshold level and ensuring that appropriate measures are in place to sustain and reinforce emission reduction efforts during this critical development phase. This could involve providing targeted support to the identified countries, such as technological transfers, capacity-building programs, or financial incentives for transitioning to cleaner energy sources.

On the other hand, countries with above-average REPC values from 2.3 to 3.8 and 7 to 9.3 are less likely to reduce their $CO_2$ emissions in the coming years during the post-GFC period than in the pre-GFC period. This means that policymakers may need to reassess existing strategies and consider implementing tailored policies to address specific challenges hindering

Figure 2 MPPs for REPC before and after GFC




Notes: The horizontal and vertical axes show the value of the REPC variable and the MPP, respectively.

emission reduction efforts in these countries. This could include enhancing access to clean energy technologies, promoting sustainable land-use practices, or providing financial incentives for adopting low-carbon technologies.

Figure 3 shows ergodic distributions of global, country-level annual carbon intensities (REPGDP). We can observe a high resemblance between both graphs in panels A and B. The only apparent difference can be ascribed to the appearance of two additional minor peaks around the REPGDP value of 0.4 and 1 in panel B. This means the emergence of two additional clubs in the post-GFC period, consistent with Bhattacharya et al (2020), who predict that assuming a “business as usual scenario” between 2014 and 2030, the number of convergence clubs in cross-country carbon intensity would increase. Such results also corroborate Li et al (2020) argument that the GFC and extraordinary post-crisis policies adopted by governments worldwide have led to cross-country divergence in carbon emissions. These findings could offer valuable insights to policymakers. By identifying and monitoring countries belonging to emerging clubs, policymakers can gain a deeper understanding of the factors influencing variations in carbon intensity. This understanding can then inform the design of tailored policies and implementation of targeted measures to address each club member’s specific challenges and opportunities, such as promoting cleaner technologies, enhancing energy efficiency, or fostering sustainable development practices.

Additionally, the emergence of a peak around the REPGDP value of one suggests that some countries are likely to converge to the global average carbon intensity level in the long run. Policymakers can view this as a positive development and leverage it to inform and guide their environmental strategies. This could involve sharing best practices, providing technical assistance, or facilitating knowledge exchange to support countries in transitioning towards more sustainable and environmentally friendly practices. Additionally, policymakers may consider implementing policies that incentivise and reward countries for achieving or maintaining carbon intensity levels close to the global average.

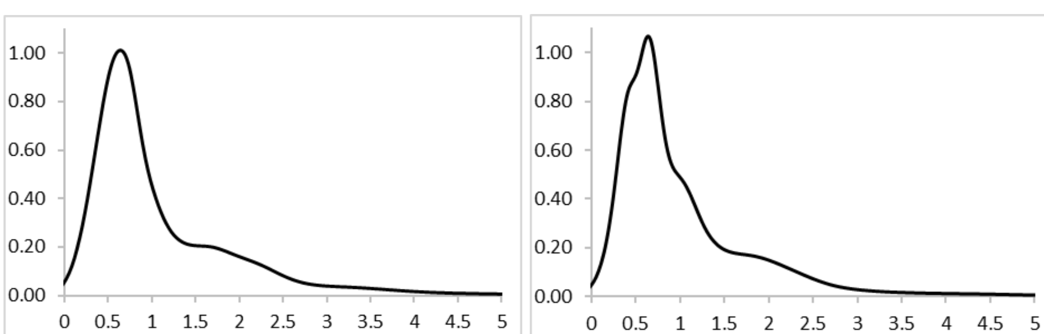
Figure 4 highlights that two MPPs are near-identical for REPGDP values below 2.65. Additionally, only countries with REPGDP values far below the global average for both subperiods have a significant positive net probability of moving upward (closer to the global average value of one). However, the two plots are highly divergent for the remaining range of relative carbon intensities. Specifically, the post-GFC MPP lies above the pre-GFC MPP for the range of REPGDP values from 3.3 to 4.9. This suggests a reduced probability of lowering carbon relative intensities (convergence to the mean) for countries with such emissions levels in years to come. Therefore, such countries' decision-makers should focus on identifying the culprits behind this worrying trend and implementing new, more efficient measures to reverse

On a positive note, we can observe significantly greater and generally increasing probabilities of reducing carbon intensities (negative values on the vertical axis) post-crisis compared to pre-crisis for countries with the most extreme relative $CO_2$ intensities (above 5). This is good news from the perspective of global convergence in emissions, which would motivate countries to fulfil their environmental commitments and facilitate the adoption of unified environmental policies or new initiatives (Erdogan and Solarin 2021).

Moreover, focusing on the post-GFC MPP (blue-coloured plot), we can identify three intersections (and two tangent points) with the horizontal axis around the REPGDP values of 0.67, 0.92 and 1 (0.48 and 1.7). These broadly correspond with the location of four post-crisis peaks in panel b of Figure 3. This, in turn, underscores that the shape of the ergodic distribution is primarily determined by transitional dynamics, as indicated by the MPP. Thus, Figure 4 further supports the policies proposed in the previous paragraphs.

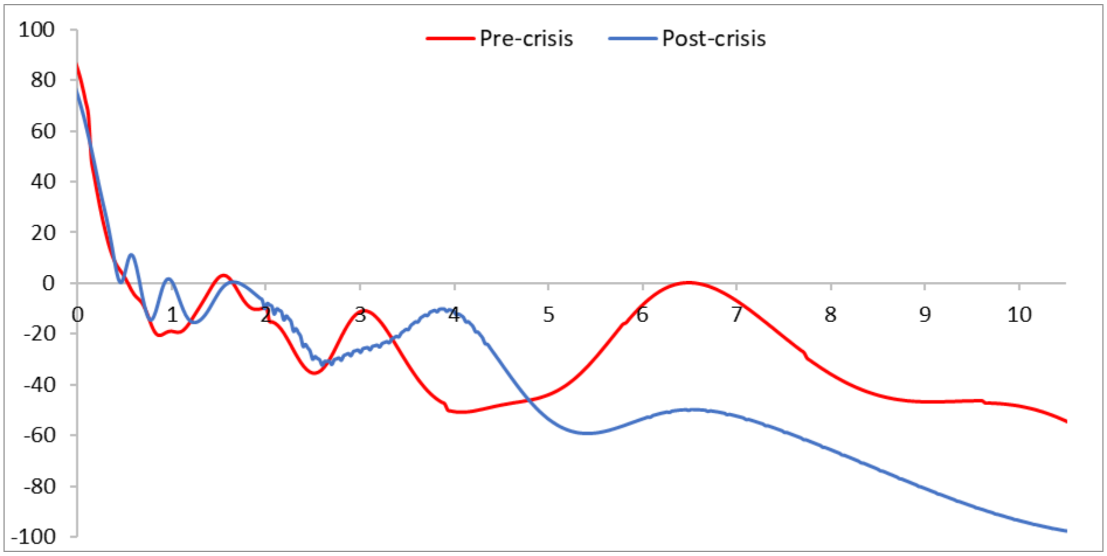
Figure 3 Ergodic distributions for REPGDP before and after GFC

A Pre-crisis (2000-2007) B Post-crisis (2007-2016)



Notes: The horizontal and vertical axes show the value of the REPGDP variable and the proportion, respectively.

Figure 4. MPPs for REPGDP before and after GFC



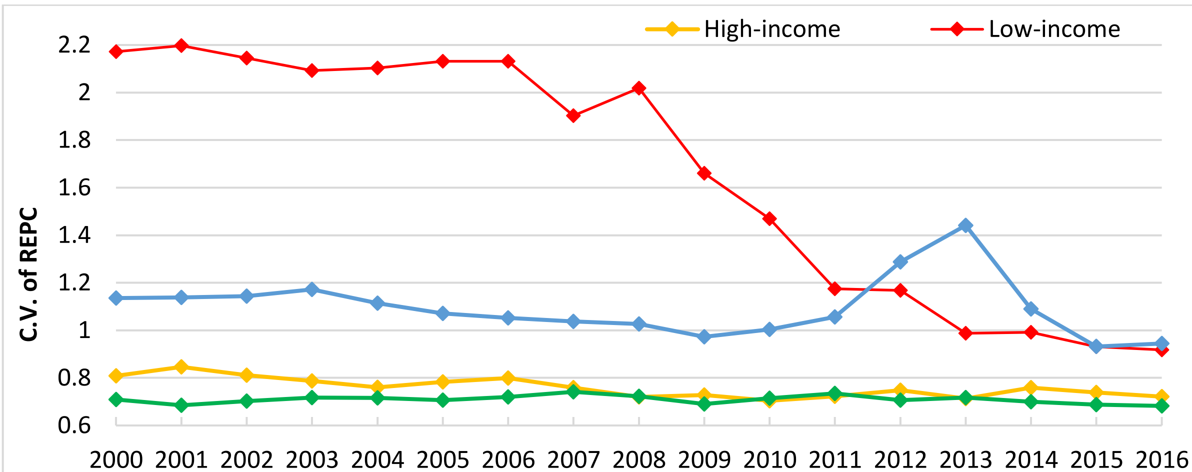

Notes: The horizontal and vertical axes show the value of the REPGDP variable and the MPP, respectively.

## 4.2 Carbon emissions and intensities across countries with different income levels

In a seminal study, Grossman and Krueger (1991) find evidence of the Environmental Kuznets Curve (hereafter EKC) hypothesis, i.e., an inverted U-shaped relationship between economic growth and environmental indicators (e.g., air pollution). Since then, the EKC has been tested empirically in studies on carbon emissions, but the results remain inconclusive and mixed (e.g., Atasoy 2017, Nam et al 2020).

Figure 5 plots the annual CVs of the REPC variable for countries grouped by their income levels according to the World Bank's classification updated annually. We can observe a rapid global cross-group convergence resulting primarily from a massive decrease in variability among the poorest countries, especially post-2006 (from 2.13 to 0.94). Interestingly, the lower-middle-income countries displayed a reversed (increased) trend between 2009 and 2013, which could be associated with unprecedented expansionary policies (monetary and fiscal alike) of many developing economies (e.g., China) to resist the GFC of 2008 (Wang et al 2021). The smallest decrease in CV during the sampled period encountered a group of upper-middle-income countries (from 0.71 to 0.68) followed by the high-income economies (from 0.81 to 0.72).

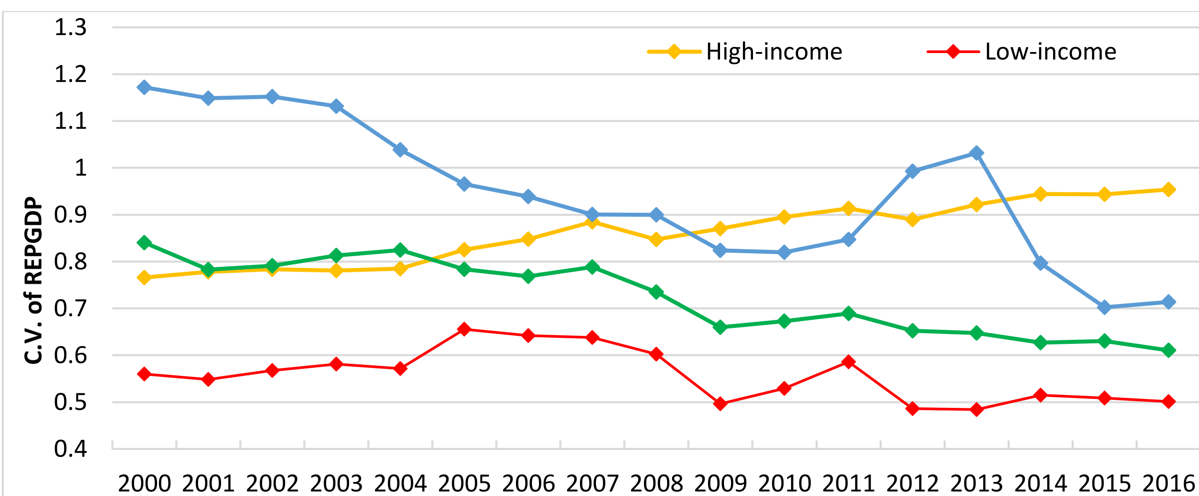
Figure 5. Time trends in annual CVs of REPC variable by different income groups




Source: Authors' calculations based on the World Bank's World Development Indicators (WDI)

The picture painted in Fig 6. largely contrasts that in Fig 5. First, we can observe that the lowest variability, with an overall decreasing trend over time, can be attributed to the low-income countries.

Figure 6. Time trends in annual CVs of REPGDP variable by different income groups




Source: Authors' calculations based on the World Bank's World Development Indicators (WDI)

On the contrary, the annual CVs for the most affluent economies (yellow-coloured plot) followed an increasing trend (from 0.76 to 0.95), translating into a robust divergence between 2000 and 2016. While we can observe a similar reversed (increasing) pattern in the blue-coloured plot (lower-middle-income) to that in Figure 5, this group of countries made the most significant progress regarding within-group convergence in carbon emissions.

While Figure 5 and 6, based on the sigma convergence tool (CV), are highly informative, they are limited in their ability to forecast the dependent variable, as they do not provide insights into the shape of the underlying distribution. Given the above backdrop, we are the first to employ the ergodic distribution and the MPP to analyse REPC and REPGDP across countries divided into four groups based on income levels[6].

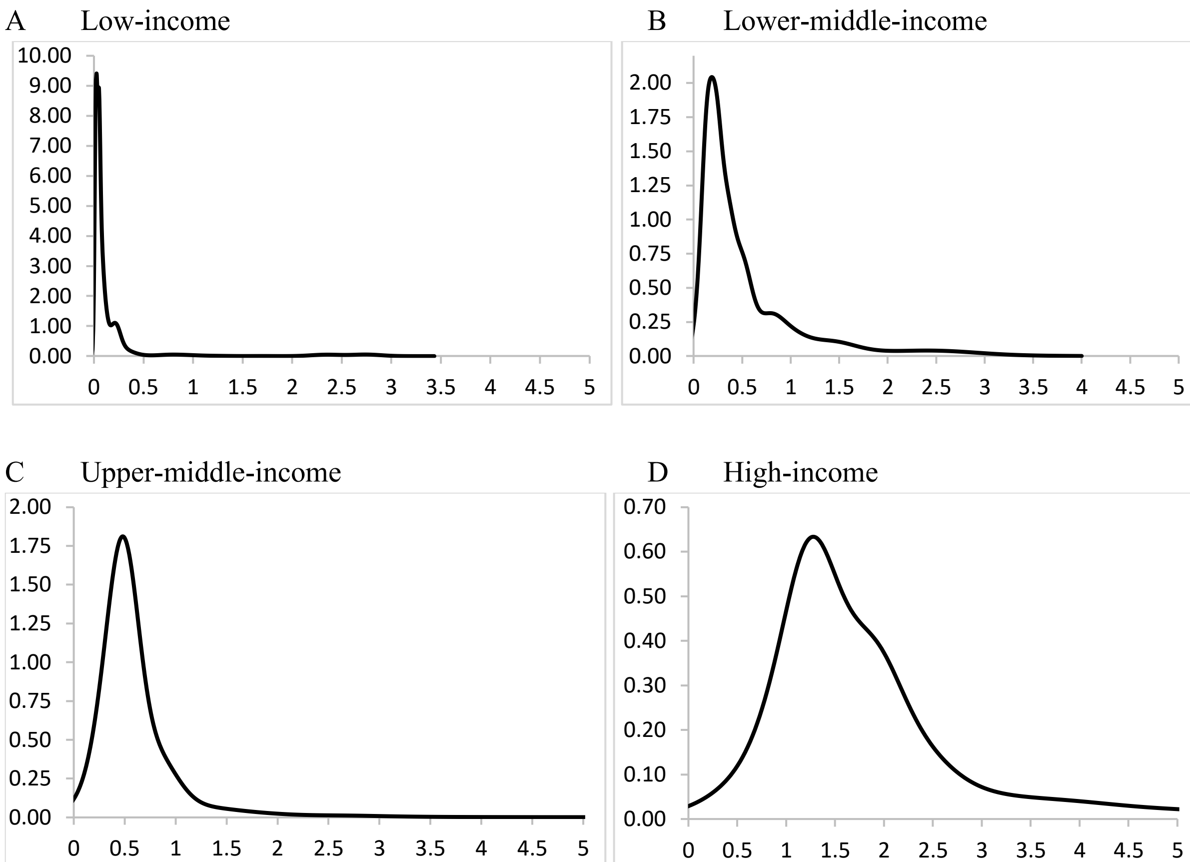
Figure 7 indicates that most low-income and many lower-middle-income countries congregate around minimal REPC levels in the long-run steady-state equilibrium. On the other hand, most high-income economies converge to above the global average REPC levels. Such apparent divergent long-run trend between the poorest and wealthiest countries is grim news and at odds with the EKC. This, together with pre/post-GFC analysis (see Fig. 1), suggests that the GFC and expansionary policies introduced by many industrialised countries could result in a long-run increase in REPC and the persistent income gap between the rich and the poor.

Figure 7 also highlights by far the most (least) significant convergence process for the low- (high-) income group of countries captured by the tallest (shortest) and the least (most) spread out ergodic distribution. Such findings starkly contrast with the evidence reported by Li and Lin (2013). Furthermore, we can observe that except for upper-middle-income countries, multiple convergence clubs emerge, whilst all peaks in panels A and B (D) are situated below (above) the global average REPC equal to one. Thus, assuming the transitional dynamics remain unchanged, we can expect only conditional convergence in REPC across the three groups of countries: low-, lower-middle-, and high-income. Such a finding contrasts that of Zang et al (2018), who examined a sample of 201 countries from 2003 to 2015 and found evidence of club convergence only among high-income countries.

In addition, we can observe that ergodic distributions become more spread out as we move up the income ladder, i.e., from panel A to panel D. This observation, in turn, is contrary to the results of Li et al (2020) and suggests the least and the most significant convergence process across the richest and the poorest countries, respectively. The findings in Fig 7. highlight the complex relationship between income levels and carbon emissions, emphasising the need for targeted policies and international cooperation to address climate change effectively across diverse economic contexts.

[6] See Table A1 in the Appendix for the list of countries by their income levels as of the end of 2016. During the 2000-2016 period, numerous (a few) countries have moved into higher (lower) income brackets in line with the World Bank's annual classification. As of 2016, 30, 53, 55, and 66 low-, lower-middle, upper-middle, and high-income countries are in the sample.

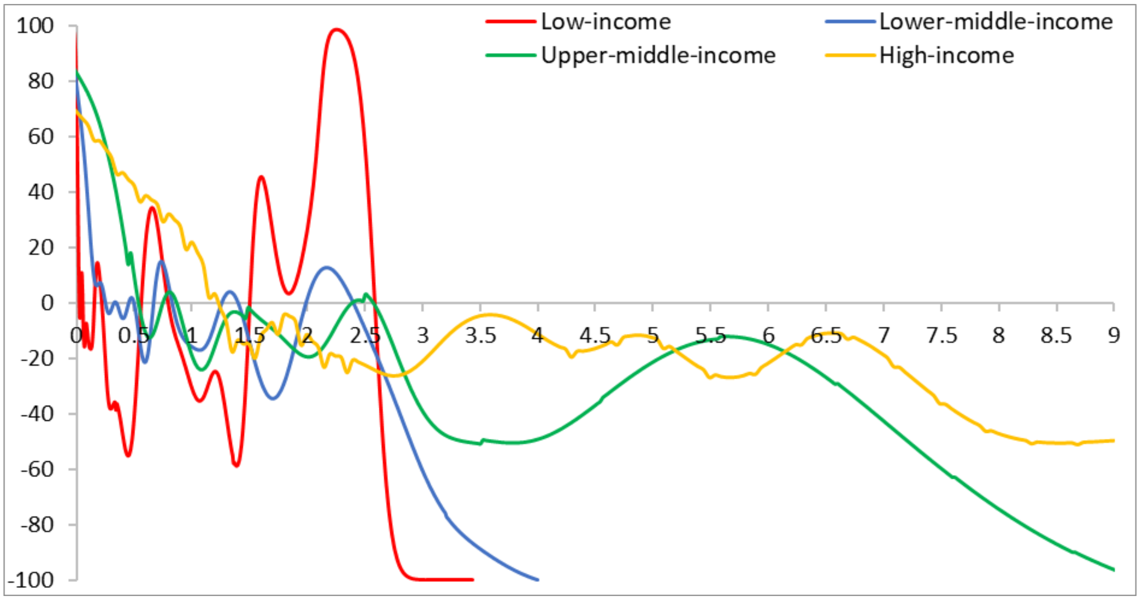
Figure 7. Ergodic distributions for REPC by different income groups




Notes: The horizontal and vertical axes show the value of the REPC variable and the proportion, respectively.

Figure 8 shows that the MPP for the high (low) income countries is the least (the most) volatile, translating into the least (the most) significant aggregate net mobility probability in years to come. The weakest aggregate net mobility probability suggests a lower likelihood of substantial shifts in high-income countries' per capita carbon emissions patterns over time. Instead, we can expect a relatively stable or stagnant emissions trajectory, with gradual or incremental changes in REPC. This, in turn, could result from the interplay of established infrastructure, mature economies, and strict environmental regulations that limit rapid changes in carbon emissions of the high-income countries. On the contrary, more volatile aggregate net mobility probability signals a more dynamic and evolving REPC landscape, reflecting rapid changes in economic activities, rapid industrialisation, technological transitions, policy interventions, and limited regulatory oversight across many low-income countries.

Figure 8. MPPs for REPC by different income groups




Notes: The horizontal and vertical axes show the value of the REPC variable and the MPP, respectively.

Additional important implications can be drawn from identifying (1) the sections of MPPs above the global average REPC values positioned above the horizontal axis and (2) the intersections and tangent points between the MPPs and the horizontal axis. That is because (1) it enables us to pinpoint carbon emitters above the global average with a specific range of REPC levels and exact probabilities to diverge further away/above the global average in the coming years. Similarly, (2) indicates sticky and above the global average REPC values around which the entities from different income groups would congregate in years to come.

Given limited resources and environmental policy goals of convergence/reduction in $CO_2$ emissions (Wei et al 2022, Wei et al 2023), countries with above-average REPC levels and net upward mobility probabilities ranging from 100 to zero should be placed on the policy priority list. Figure 9 indicates that for the low- (lower-middle) income countries, the alarming ranges of REPC occur from 1.5 to 2.6 (1.25 to 1.4 and 2 to 2.45), while for the upper-middle- (high) income countries around a REPC value of 1.5 and from 2.45 to 2.6 (below 1.25). However, the top spot in the policy priority list should be reserved for low-income countries with REPC values of around 2.3. This is because the MPP representing these entities reaches the maximum positive net mobility probability of 100 at a REPC value of 2.3. This, in turn, implies that upon reaching such a REPC level, the country's emissions have a 100 per cent probability of moving even further above the global average in years to come.

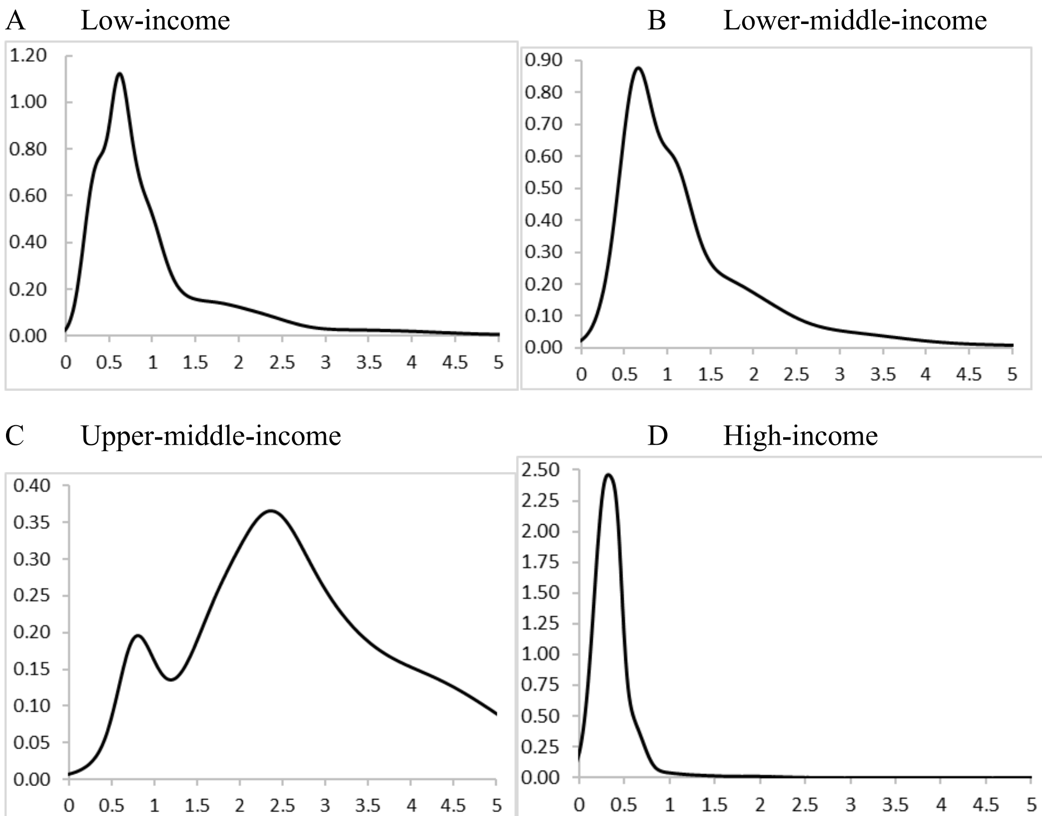
Moreover, Figure 8 indicates that low- and upper-middle-income countries experience a development trap in their REPC. This is a positive piece of information because it means that whenever low- and upper-middle-income countries achieve REPC values of 2.9 and 4, they will encounter a reduction in REPC and a downward move within the distribution in the following years. However, the green and yellow plots representing more affluent economies approach the development trap at higher REPC levels of 9 and 21.5, respectively.

Summing up, findings based on the first measure of $CO_2$ emissions (REPC) are essential from the perspective of future environmental policies aiming at emissions reduction and convergence. For instance, the results imply the onus on high-income countries to reduce their per capita carbon emissions. Furthermore, more significant variability in the REPC observed across the rich countries suggests they would have more spare capacity and flexibility in reducing $CO_2$ emissions. On the other hand, the poorer countries appear to have ample time before converging to the global average, except for the outliers with a net mobility probability of 100 at a REPC value of 2.3, identified in Figure 8.

Figure 9 shows that the ergodic distribution for the low-income (lower-middle-income) group is denser (more spread out), with more entities converging around lower (higher) REPGDP values corresponding to three peaks located at 0.35, 0.6 and 1.8 (0.7, 1.1 and 2). Furthermore, the distribution in panel C for the upper-middle-income countries is the most dispersed, with many countries congregating around REPGDP values far above the mean (2.4). However, the most concentrated is the ergodic distribution for the wealthiest group of countries, with a single peak significantly below the global mean (REPGDP value of 0.32) and a long, thin right tail. Concerning the emergence of convergence clubs, these appear in panels A to C only, signifying conditional (absolute) convergence at best across low- and medium-income (high-income) countries. Such observation only partially corroborates Zang et al (2018) results of clubs across all income groups in their study of 201 countries.

Overall, findings from Figure 9 suggest that the onus is on the upper-middle-income emitters to reduce carbon intensity because some countries from this income group converge toward the long-run carbon intensities significantly above the global average. Such a finding corroborates Dong et al (2020), who document that the upper-middle-income is the primary source of worldwide $CO_2$ emissions post-2008 financial crisis. Moreover, the results suggest that middle-income economies incur relatively higher environmental externalities (emissions per USD of GDP) for their economic development (Zang et al 2018, Wang et al 2021). Nevertheless, the most dispersed ergodic distribution for upper-middle-income countries implies greater flexibility in reducing carbon intensity. Policymakers could leverage this flexibility to implement policies and strategies tailored to specific country contexts, including investment in clean technologies, renewable energy, energy efficiency, and sustainable infrastructure.

Figure 9. Ergodic distributions for REPGDP by different income groups

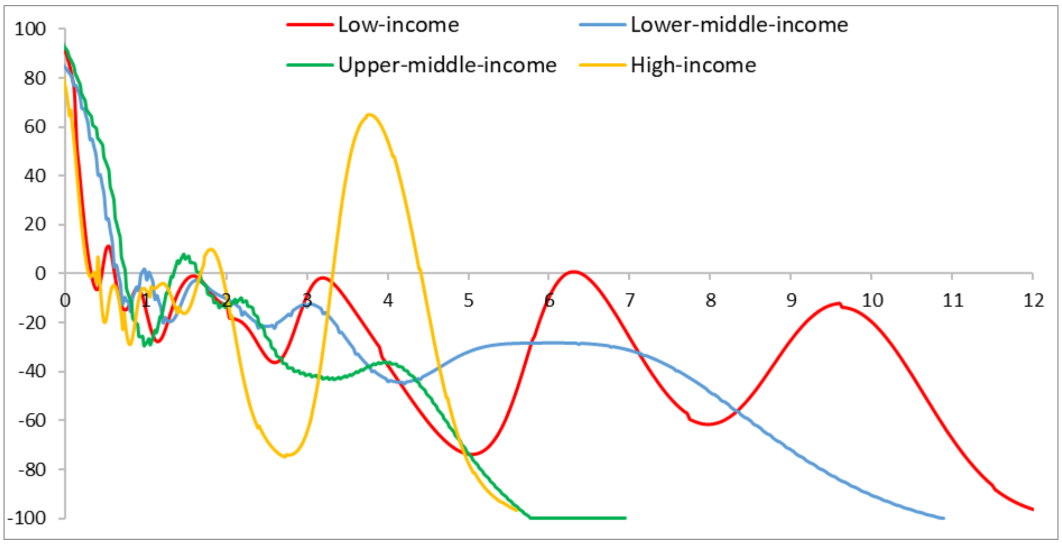



Notes: The horizontal and vertical axes show the value of the REPGDP variable and the proportion, respectively.

The MPPs in Figure 10 indicate that countries with REPGDP values below 0.35, irrespective of income levels, experience a positive net probability of moving upward in the distribution in future years. From the policy perspective, Figure 10 is interesting because it pinpoints the countries with specific above-the-global average REPGDP values and positive net probability of moving higher in the future distribution. Therefore, assuming the emissions reduction goals are based on $CO_2$ intensity, such countries merit special attention, i.e., they should enter the climate policy priority list.

We can observe that low-income countries with a range of REPGDP values around 1.65, 3.15, and 6.3 should be placed on the priority list due to the stickiness of their above-average relative emissions. By the same token, high-income countries with relative carbon intensities between 3.3 and 4.5 are also problematic. In particular, industrialised economies with REPGDP values around 3.8 have the most significant (65%) probability of further diverging from and above the global average regarding their REPGDP in years to come. This, in turn, places them high on the policy priority list. On the contrary, two middle-income groups appear to be the least problematic.

Figure 10**.** MPPs for REPGDP by different income groups




Notes: The horizontal and vertical axes show the value of the REPGDP variable and the MPP, respectively.

## 5 Conclusion and Policy Implications

The main findings of this study can be summarised in three points. First, the post-GFC period ergodic distributions are characterised by the emergence of additional convergence clubs in relative per capita carbon emissions (REPC) and relative carbon intensity (REPGDP). Besides, the post-GFC distribution is significantly more spread out, suggesting that the global long-run convergence process in REPC ex-post-GFC becomes less significant. Such results, in turn, might imply the adverse effects of GFC and post-crisis expansionary policies aimed at economic recovery undertaken by developing and developed countries (e.g., in China and the US). Overall, the results are pessimistic from the perspective of global warming and environmental policies because the more significant number of clubs makes future international climate negotiations and ambitious targets more complex and challenging.

Second, regarding countries grouped by income levels, the results are very different based on the analyses for the REPC vis-à-vis the REPGDP variable. For instance, a solid divergent trend exists in the long-run distribution of REPC. With a vast majority (most) of the poorest (richest) countries congregating at extremely low (above the global average) REPC levels. From the perspective of environmental policies aiming at reduction/convergence in global $CO_2$ emission, the results based on the REPC variable suggest that the onus should be majorly on the industrialised (high-income) countries. However, using the REPGDP variable, the convergence process is the least significant among upper-middle-income countries, with many countries clustering around REPGDP values far above the mean (2.4). Therefore, based on the REPGDP measure, upper-middle-income countries should bear a more significant share of the future carbon emissions commitments.

Third, using the MPP tool, we identify countries with specific REPC and REPGDP levels that merit a place in the environmental policy priority list. Specifically, low-income countries with REPC values of around 2.3 have around 100 per cent probability of moving further up in the distribution in future years. By the same token, high-income countries with REPGDP values around 3.8 have the most significant (65 per cent) probabilities of diverging further from and above the global average. Therefore, in line with the global warming environmental policies aiming at $CO_2$ emissions reduction/convergence, the above countries should be at the top of the priority list.

This study offers several policy implications. First, the results deliver nascent evidence supporting the usefulness of the MPP display tool. For instance, an MPP-based "policy priority list" can inform policy prioritisation efforts by highlighting areas where emissions abatement is most urgently required. Policymakers, in turn, could employ this information to allocate limited resources and prioritise interventions targeting specific countries exhibiting unfavourable emissions trends, thereby maximising the effectiveness of climate mitigation efforts globally. Therefore, we advocate the periodic/annual implementation of the MPP framework as an integral part of the global reference system, helping countries update, optimise and manage their climate policies and carbon regulations.

Second, we analysed the transitional dynamics and long-run trends in two variables: (1) REPC, which focuses on carbon emissions per capita, and (2) REPGDP, which accounts for emissions relative to economic output. Thus, the documented divergence in the forecast trends between REPGDP and REPC has several implications for multilateral climate negotiations and global environmental policies. (1) countries with high per capita emissions (as reflected in REPC) may argue for policies prioritising emission reductions based on individual consumption patterns. Conversely, countries with high carbon intensity relative to GDP (as indicated by REPGDP) may advocate for policies that focus on reducing emissions associated with economic activities. Balancing these competing interests will be crucial for achieving equitable and effective climate agreements. (2) the results suggest the need for sector-specific approaches to emission reduction. For instance, economies with high carbon intensity may need to decarbonise specific sectors (e.g., energy production, industry, or transportation). Tailoring mitigation efforts to address sector-specific challenges can enhance the effectiveness of climate policies and facilitate smoother negotiations. Meanwhile, countries with high REPC may require policies targeting lifestyle changes, consumption patterns, and urban development.

Third, estimating the distribution of the DDA and the MPP methods among all the countries can help commensurate intergovernmental cooperation plans by prioritising carbon tax policies across the countries. For instance, findings based on the pre- versus post-crisis dynamics in global $CO_2$ emissions align with predictions that assuming a "business as usual scenario" will increase the number of clubs in cross-country carbon intensity (REPGDP) and emissions per capita (REPC) alike. We advocate that policymakers consider these projections when designing long-term environmental policies and strategies. This could include implementing proactive measures to mitigate carbon intensity growth, such as setting ambitious emission reduction targets, promoting renewable energy adoption, or implementing carbon pricing mechanisms. Furthermore, the research outcomes depict the future development trend of national carbon emissions and intensity, thereby guiding the government to allocate capital and technical resources more efficiently to promote energy transition. Climate change cooperation organisations can encourage and prioritise their investment in these countries and regions and improve knowledge diffusion, particularly in regions with outdated and imbalanced carbon emissions and intensity.

The study employs the visual tools of the DDA method, which is inherently limited due to restrictive assumptions of no changes in the transitional dynamics of the study variable. This, in turn, may influence the accuracy of transition probabilities and long-term evolution projections. Moreover, due to data limitations, our sample spans between 2000 and 2016. However, the unprecedented changes in the global social and political economy, such as the COVID-19 worldwide pandemic and the outbreak of the military conflict in Ukraine, substantially impact the energy market and the trajectory of global emissions. Given the above backdrop, exploring the potential structural changes and convergence patterns in carbon emissions and intensities for the most recent period is imperative.

Moreover, by focusing on carbon emissions among countries with different income levels, we possibly overlook other factors influencing emissions disparities, such as socioeconomic, political, and environmental variables. The analysis of pre-crisis and post-crisis periods may not capture all relevant economic or ecological shocks impacting emissions trajectories. Consequently, future research could expand the scope of study to incorporate a broader range of factors influencing carbon emissions convergence-divergence patterns, such as technological advancements, policy interventions, and socio-economic indicators.

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## Appendix

**Table A1.** 204 countries grouped by income level

| Income levels | Countries |
|---|---|
| High-income | Andorra, Antigua and Barbuda, Aruba, Australia, Austria, Bahamas, Bahrain, Barbados, Belgium, Bermuda, British Virgin Islands, Brunei Darussalam, Canada, Cayman Islands, Chile, Cyprus, Czech Republic, Denmark, Estonia, Faeroe Islands, Finland, France, French Polynesia, Germany, Gibraltar, Greece, Greenland, Hong Kong, Hungary, Iceland, Ireland, Israel, Italy, Japan, Kuwait, Latvia, Liechtenstein, Lithuania, Luxembourg, Macao, Malta, Netherlands, New Caledonia, New Zealand, Norway, Oman, Palau, Poland, Portugal, Qatar, Saudi Arabia, Seychelles, Singapore, Slovak Republic, Slovenia, South Korea, Spain, St. Kitts and Nevis, Sweden, Switzerland, Trinidad and Tobago, Turks and Caicos Islands, United Arab Emirates, United Kingdom, United States, Uruguay |
| Upper-middle-income | Albania, Algeria, Argentina, Azerbaijan, Belarus, Belize, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, China, Colombia, Costa Rica, Croatia, Cuba, Dominica, Dominican Republic, Ecuador, Equatorial Guinea, Fiji, Gabon, Grenada, Guyana, Iran, Iraq, Jamaica, Kazakhstan, Lebanon, Libya, Malaysia, Maldives, Marshall Islands, Mauritius, Mexico, Montenegro, Namibia, Nauru, North Macedonia, Panama, Paraguay, Peru, Romania, Russian Federation, Samoa, Serbia, South Africa, St. Lucia, St. Vincent and the Grenadines, Suriname, Thailand, Tonga, Turkey, Turkmenistan, Tuvalu, Venezuela |
| Lower-middle-income | Angola, Armenia, Bangladesh, Bhutan, Bolivia, Cabo Verde, Cambodia, Cameroon, Congo, Rep., Côte d'Ivoire, Djibouti, Egypt, El Salvador, Eswatini, Georgia, Ghana, Guatemala, Honduras, India, Indonesia, Jordan, Kenya, Kiribati, Kosovo, Kyrgyz Republic, Lao PDR, Lesotho, Mauritania, Micronesia, Moldova, Mongolia, Morocco, Myanmar, Nicaragua, Nigeria, Pakistan, Papua New Guinea, Philippines, São Tomé and Principe, Solomon Islands, Sri Lanka, Sudan, Syria, Tajikistan, Timor-Leste, Tunisia, Ukraine, Uzbekistan, Vanuatu, Vietnam, West Bank and Gaza, Yemen, Zambia |
| Low-income | Afghanistan, Benin, Burkina Faso, Burundi, Central African Republic, Chad, Comoros, Congo, Dem. Rep., Eritrea, Ethiopia, Gambia, Guinea, Guinea-Bissau, Haiti, North Korea, Liberia, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Rwanda, Senegal, Sierra Leone, Somalia, Tanzania, Togo, Uganda, Zimbabwe |

Note: The list of countries follows the World Bank's classification as of the end of 2016.