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Greening Prosperity Stripes across the Globe

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Abstract

This paper is motivated by the urgency of climate change mitigation and the crucial importance of communicating the need for it. Our approach relies on using a comparative visualization in colormap stripes for all countries across the globe that can easily be conveyed, compared and understood even by nonspecialists. It proposes a novel and simple measure of what is referred to as 'greening prosperity stripes' and defined as the ratio of real gross domestic product per capita to carbon dioxide emissions per capita, based on annual data from the World Bank since 1990. We illustrate our findings along various time-series and cross-section perspectives in the hope that the stripes images will raise awareness of environmental pollution and mobilize immediate climate policy action worldwide. Moreover, the greening prosperity indicator by country, possibly updated online every year, could be used to track progress toward the goal of net zero clearly and compellingly.

Keywords: real GDP per capita, CO2 emissions per capita, greening prosperity stripes, data visualization, public awareness, climate change mitigation

JEL codes: C82, F64, O44, Q51

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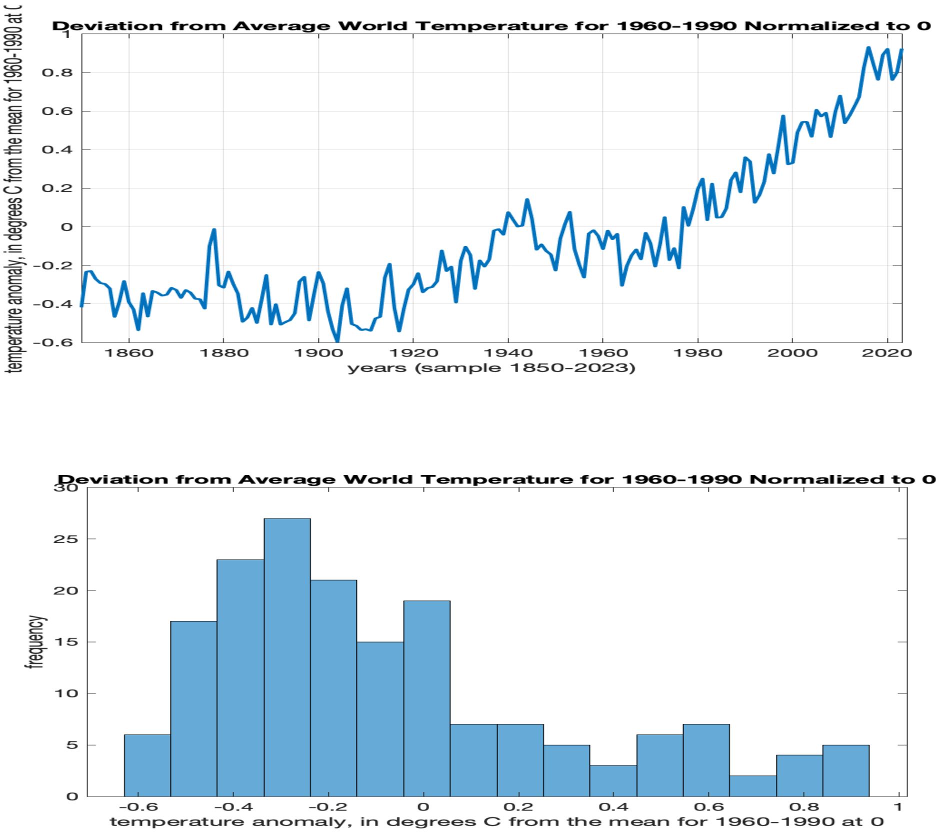
1 Introduction

As is by now well documented, 2023 has become the warmest year on record. The longest publicly available average temperature data at annual frequency for the world as a whole we are aware of can be accessed online via the UK Government's Met Office Hadley Centre for Climate Science and Services. These data cover the period 1850-2023 (174 years) and are plotted in Figure 1.

Figure 1: Global Annual Temperature 'Anomalies' since 1850



Note: The top panel provides a time-series view, while the bottom panel complements it by a frequency dimension for the same data. *Source*: UK Government's Met Office Hadley Centre for Climate Science and Services, `https://www.metoffice.gov.uk/hadobs/hadcrut5/data/current/download.html`.

The data in the top panel show the evolution of average world temperature in degrees Celsius (that is, northern and southern hemisphere of the globe equally weighted) every year since 1850. In representing the data on this figure, we have followed the convention in meteorology to depict what they call 'temperature anomalies', i.e., deviation of annual temperatures from what we usually denote in economics as a long-run 'steady state', and a recent one: that is, the deviation of the average temperature each year since 1850 from the mean for the period 1960-1990 (31 years), when the latter mean is normalized at 0. What strikes on the top-panel graph is the change in trend evident since the early 1980s, when the world has added by 2016 nearly 1 degree C on top of the mean for 1960-1990.

World average temperatures have fluctuated without displaying any trend up or down until about World War II, then a shift to a steady upward trend in the mean occurred around 1980.

The histogram in the bottom panel of Figure 1 presents the same data, but changing the perspective from a time-series representation into a probabilistic representation. It shows the empirical probability density of these temperature anomalies relative to the mean for 1960-1990 normalized at 0. One can easily observe the long and relatively thin upper (or right) tail of this distribution, depicting these anomalies that have been corresponding to the period since 1980 in the top-panel graph of the same figure.

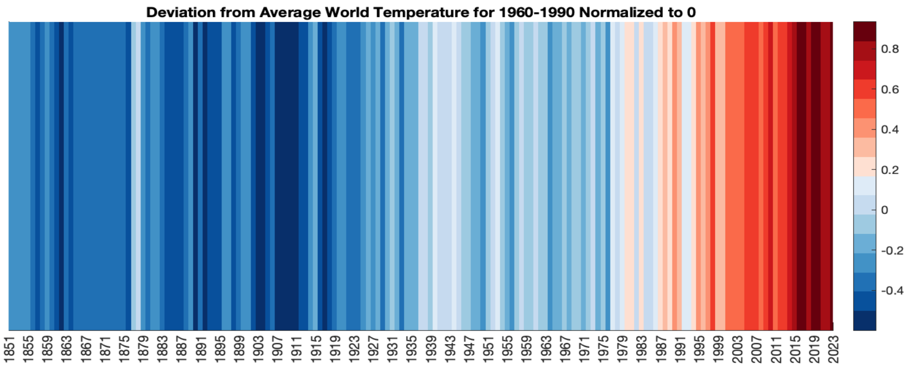
Against this background, and linking environmental pollution with macroeconomic data, the present work proposes a basic concept, namely, a 'greening prosperity' indicator, as well as its measurement and visualization, employing many intuitive panels of graphs that provide various comparative perspectives. It is motivated by the urgency of climate change mitigation and the crucial importance of explaining clearly the need for it. The proposed new indicator can readily be used to track progress by country along the goal of net zero greenhouse gas (GHG) emissions in the near future. Our approach focuses on versions of a comparative visualization in colormap stripes of real gross domestic product (GDP) per capita (pc), carbon dioxide (CO2) emissions pc and the resulting greening prosperity ratio pc (dividing the former indicator by the latter) for all countries across the globe. Its main advantage is that color stripes can easily be conveyed, compared by country and understood even by nonspecialists. The annual panel data we rely on are available online from the World Bank since 1990.

In this paper, we apply recent visualization approaches from meteorology, extending them into social science to capture linkages – or 'decoupling' – between economic growth and environmental pollution, and to compare greening prosperity within and across countries and over time, notably in stripes colormaps. Our new greening prosperity stripes, in effect, complement the world-famous University of Reading climate, or warming, stripes, which Ed Hawkins first introduced and popularized on the Internet in 2018 (Hawkins, 2018). To provide the basic idea of such visualizations, we present in Figure 2 an update of the celebrated warming stripes, keeping the same definition of the colors as in the original representation (16, from dark blue via light blue and light red to dark red – as can be seen in the right-hand side vertical axis of the graph).[1]

In Figure 2, the color stripes split the distance between the minimum and the maximum of the registered 'temperature anomaly' values (i.e., annual deviations away from the mean for 1960-1990 normalized at 0) into 16 nuances of the chosen spectrum. The

[1]The MATLAB R2023a code and the World Bank Excel data necessary for replication of all graphs and tables in the present paper are available via a zip archive on GitHub: `https://github.com/AlexanderMihailov`.

Figure 2: Reading Warming, or Climate, Stripes



Note: The figure represents a replication of the warming, or climate, stripes, popularized by Reading Meteorology Professor Ed Hawkins, `https://edhawkins.org/`. *Source*: UK Government's Met Office Hadley Centre for Climate Science and Services, `https://www.metoffice.gov.uk/hadobs/hadcrut5/data/current/download.html`.

accelerated global warming is clearly observed since about the mid-1990s, when the sequences of stripes turn into the reddish zone. We can also learn from this visualization that the coldest period of about 5 years the world has experienced since 1850 was just before World War I, 1907-1911. By contrast, the warmest years were 2016-2017, 2019-2020 and 2023.

The 'greening prosperity stripes', which we discuss hereafter, are useful because colors have the power to impress and get through to even a nonspecialized public worldwide (as suggested in the psycholigy literature, e.g., Gao and Xin (2006), Wilms and Oberfeld (2018)), thus raising awareness and potentially mobilizing action. Our hope is that the proposed innovative visualization will highlight clearly how significant environmental pollution has become and how far even the advanced countries still remain from a desirable goal of a genuine green(ing) prosperity, no matter the trend of 'decoupling' of economic growth from CO2 emissions observed since the 1990s in most of them. Realizing this dangerous state of affairs will remind us that we should act decisively as early as now in order to mitigate and reverse the negative – and recently extreme – influences of climate change on life on our planet.

The rest of the paper is organized as follows. Section 2 provides an overview of the key related literature in economics. Section 3 defines formally the theory and measurement issues related to the new macroeconomic indicator we propose. Section 4 provides a set of innovative colormap graphs, depicting various perspectives and comparisons that are easily communicated and understood in quantifying the greening prosperity indicator by country and major World Bank country groupings over the years from 1990 through 2020. The same section also summarizes our main findings and suggests some interpretations. Section 5 discusses the immediate policy implications of our work, and section 6 concludes. A supplementary online appendix presents additional data sources and graph representations in Section A.1, also plotting in Section A.2 the conventional time-series and cross-section analogs to our colormap stripes in the main text.

2 Literature

There is a substantial literature, at least since the early 1990s, on the relationship between economic growth, or – less so – life expectancy, and CO2 emissions. But not a single paper has ever linked these two variables, approximating social welfare and environmental pollution, respectively, in a ratio by country, like we do in what follows. Our aim is to define an intuitive visual representation of the mentioned ratio that could serve as a widely accepted indicator of greening prosperity and thereby measure progress toward the goal of net zero. This is exactly the gap in the literature our current paper fills in. In this section, we briefly highlight key approaches and findings in a selection of closely related studies, mostly to set up the background for analyzing and interpreting our comprehensive comparative visualizations later on.

It may seem a bit surprising to the younger generations, but the scientific literature on the so-called 'greenhouse effect' is about two centuries old. Dobes et al. (2014) trace down its origins to Fourier (1827/2013) and Tyndall (1861), while in economics Arrhenius (1896) was the first to raise the issue about the effect of anthropogenic carbon emissions on the global climate. The same authors divide and survey the subsequent literature in economics into three strands: (i) on trends in climate change, the oldest chronologically – e.g., Keeling et al. (1976) measured the concentration of atmospheric CO2 at Mauna Loa Observatory, Hawaii, to document the effects of the combustion of coal, petroleum, and natural gas on the distribution of CO2 in the atmosphere, finding that the annual average CO2 concentration rose by 3.4% between 1959 and 1971; (ii) on mitigation of climate change, with the field of environmental economics gaining more visibility following the first oil price shock in the 1970s, e.g., d'Arge et al. (1982), Edmonds and Reilly (1983a), Edmonds and Reilly (1983b)); and (iii) on adaptation to climate change, with the policy concerns regarding urgent global action becoming more and more acute since the late 1980s and the early 1990s, e.g., the DICE and RICE models of Nordhaus (1993) and Nordhaus and Yang (1996), as well as, more recently, Stern (2008) and many studies that followed.

Perhaps the earliest formalized awareness of the concern about limited and exhaustible natural resources was proposed in the seminal paper by Hotelling (1931). Devarajan and Fisher (1981) revisit Hotelling's contribution on the occasion of its 50th anniversary and write that "Hotelling had a two-fold purpose in writing the 1931 paper: (1) to assess the policy debates arising out of the conservation movement and (2) to develop a theory of natural resources" (p. 66). According to these authors, a second wave in the literature on exhaustible resources spurred in the 1970s. Then in the 1990s Grossman and Krueger (1991, 1993, 1995) put the beginning of a third wave in this literature, defining the environmental Kuznets curve (EKC), first in their 1991 NBER working paper, by analogy with the work of Kuznets (1955) relating economic growth to income inequality (see also Acemoglu and Robinson (2002) on the political economy of the original Kuznets curve). According to the EKC hypothesis, as also claimed in the survey by Dinda (2004), p. 431 (abstract), there exists "an inverted-U-shaped relationship between different pollutants and per capita income, i.e., environmental pressure increases up to a certain level as income goes up; after that, it decreases." Dinda (2004) provides an overview of the EKC literature, its history, insights, policy as well as its conceptual and methodological critiques, and summarizes this literature (up to 2004) in the sense that "evidence for the existence of EKC is inconclusive." (p. 450).

Brock and Taylor (2005) write in their book chapter abstract that "[t]he relationship between economic growth and the environment is, and will always remain, controversial." Their review article discusses and evaluates the theoretical literature linking environmental quality to economic growth, focusing on three questions: "(1) what is the relationship between economic growth and the environment? (2) how can we escape the limits to growth imposed by environmental constraints? and (3) where should future research focus its efforts?". They claim to have identified major unresolved theoretical questions and to have presented the results of recent empirical work (up to 2005).

Bengochea-Morancho et al. (2001) study the relationship between economic growth and CO2 emissions in the European Union (EU). They employ a panel data analysis for 1981–1995 to estimate the relationship between GDP growth and CO2 emissions in 10 EU countries. Their results do not support a uniform policy to control emissions, but indicate instead that a reduction in emissions should be achieved by taking into account the specific economic situation and the industrial structure of each EU member state. However, Alaganthiran and Anaba (2022) claim to have established that a 1% increase in economic growth in a sample of 20 Sub-Saharan African countries increases CO2 emissions by approximately 0.02%.

Alternative measures of environmental inequality in the 50 US states, differentiated by their exposure to industrial air pollution, are examined by Boyce et al. (2016). They find substantive differences in rankings by different measures and conclude that no single indicator is sufficient for addressing the entire range of equity concerns that are relevant to environmental policy; instead multiple measures are needed.

As far as life expectancy is concerned, as another common indicator of well-being complementing GDP pc, Das and Debanth (2023) note that life expectancy has a probable connection with CO2 emission in two opposite ways: (i) more CO2 emissions lead to more production of output and higher income level which is likely to affect the life expectancy of people in a positive way; (ii) conversely, CO2 emissions are an important air pollutant and may reduce the span of human life. Their paper aims to investigate the net impact of CO2 on life expectancy in India. The main finding is that India has already surpassed its optimal atmospheric concentration of CO2 and thereby should adopt CO2 reduction strategies.

Employing a new dataset on comparable global CO2 production and consumption inventories over 1997-2011, Fernández-Amador et al. (2017) study the relationship between real GDP pc and CO2 emissions pc associated with both production and consumption activities. They claim to have focused on the entire carbon chain, which includes linkages between production-based emissions in one country and final consumption in another, via cross-border value chains. By estimating polynomial and threshold models that account for problems of reverse causality and identification, they find that the income elasticity for both inventories is regime-dependent and reflects small carbon efficiency gains from economic development.

With regard to a related issue, namely, income inequality, Grunewald et al. (2017) report empirical findings according to which for low- and lower middle-income economies higher income inequality is associated with lower per capita CO2 emissions, while in upper middle-income and high-income economies higher income inequality increases per capita CO2 emissions. Their results, thus, do not support an EKC related to income inequality. By contrast, the empirical findings in Santillán-Salgado et al. (2020) suggest a validation of the EKC, measured by CO2 emissions per capita and GDP per capita. Moreover, they argue that CO2 emissions have a long-term relationship with economic growth, energy use, electricity use, urbanization, and inequality. Yet, according to the same study, in a short run CO2 emissions depend mostly on a subset of the mentioned factors, namely, economic growth, urbanization, and income inequality.

Ritchie (2021) points to the recent widely discussed 'decoupling' between economic growth and CO2 emissions, i.e., that it is possible for an economy to grow without increasing CO2 emissions. She notes that UK CO2 emissions peaked in 1972, but this does not consider imported emissions – such as arising from UK import products that are manufactured abroad. If these imported emissions are taken into account, then UK emissions have peaked in 2007. Ritchie (2021) also claims that the biggest source of these 'imported' emissions is China, followed by the EU. Emissions produced directly by the UK have declined, notably due to "a combination of environmental policies and a shift of the UK economy from more carbon-intensive manufacturing to less carbon-intensive service-based industries." She presents estimates according to which when looking at the UK's CO2 emission intensity, which continues to fall, the energy generation (negative 67%), manufacturing (negative 43%), water supply (negative 38%), and transport (negative

33%) sectors saw the biggest falls between 1990 and 2017. The change from coal to renewable energy has further contributed to UK CO2 emissions continued decrease.

3 Methodology

Similarly to the resource and environmental economics literature just outlined, the measurement and theory of macroeconomic indicators and price and quantity indexes is now more than a century old too: see, e.g., Mitchell (1913), Fisher (1921), Kuznets (1934), Leontief (1936), Burns and Mitchell (1946), Koopmans (1947), Kaldor (1961). Our aim here is not to provide a survey of its rich and well-known history of contributions, but rather to focus directly on designing an indicator that captures prosperity as gradually 'greening' (or 'browning') over time – for the world as an average as well as for each country and major country grouping. We want this indicator to be simple and intuitive to understand, i.e., to be graphically representable as a colormap image of a sequence of stripes with color nuances defined from brown to green.

3.1 Theory

Mathematically, we aim at an indicator that is some function of variables changing over time $y_t(...)$. The arguments of the function may potentially be several, and the functional forms may potentially be several too. The simplest and most obvious approach we pursue hereafter is to impose a general function of two arguments $y_t(x_t, z_t)$, where x_t is some measure of prosperity and z_t is some measure of the degree of environmental pollution, and the respective partial derivatives are as follows:

$$\frac{\partial y_t(x_t, z_t)}{\partial x_t} > 0 \text{ and } \frac{\partial y_t(x_t, z_t)}{\partial z_t} < 0 \tag{1}$$

The specific functional form satisfying the above conditions can be, in its simplest expression, just a ratio

$$y_t(x_t, z_t) = \frac{x_t}{z_t} \tag{2}$$

where x_t, some measure of prosperity in real value per capita, will tend to grow over time, while z_t, some measure of environmental pollution in real value per capita, will tend to decrease over time, reaching a minimum of a unit, the latter defined as virtually zero pollution. So, as $z_t \to 1$, $y_t \to x_t$, with the limit defining completely green – i.e., unpolluted, clean or 'undiscounted' (by pollution) – prosperity in real value per capita.

To translate the above prosperity indicator discounted by the degree of pollution into a colormap stripes image, one needs to define a function capturing the global minimum and the global maximum in a dataset, represented as a matrix $\mathbf{M}$, ideally a balanced panel of countries (and country groups) as rows, $\mathbf{M_j}$, of the matrix, $j = 1, 2, ..., J-1, J$, and years as columns of the matrix, $\mathbf{M_t}$, $t = 1, 2, ..., T-1, T$. Then each element of the matrix, m_{jt}, is a country-year observation, each row of the matrix, $\mathbf{M_j}$, is a country j evolving over time, and each column of the matrix, $\mathbf{M_t}$, is a cross-section in year t. Now there are two straightforward ways to define the stripes, depending on their desired number $n = 1, 2, ..., N-1, N$ in a colormap image.

One can determine the range, R, between the *global* maximum, $Max(m_{jt})$, and the *global* minimum, $Min(m_{jt})$, in the dataset matrix $\mathbf{M}$ as

$$R \equiv Max(m_{jt}) - Min(m_{jt}),\ \text{for all } j = 1, ..., J \text{ and all } t = 1, ..., T \tag{3}$$

and then allocate to it the respective number of desired colors (and nuances) as *stripe* S

$$S \equiv \frac{R}{N} \tag{4}$$

Alternatively, one can wish instead to focus on a *particular country* stripes s as they are evolving over time, and the respective definitions then involve the particular country vector only in defining the *country* (or *local*) maximum, $\max(m_j)$, and minimum, $\min(m_j)$, range r_j, and stripe s_j

$$r_j \equiv \max(m_j) - \min(m_j),\ \text{for a given } j \text{ and } t = 1, ..., T \qquad \text{and} \tag{5}$$

$$s_j \equiv \frac{r_j}{N} \tag{6}$$

The above is a *time-series* stripe representation or visualization, i.e., for a country j over time. Another perspective can present the *cross-section* stripe representation or visualization, i.e., for all countries in a given year t, with respectively defined variables $\max(m_t)$, $\min(m_t)$, r_t, and s_t

$$r_t \equiv \max(m_t) - \min(m_t),\ \text{for a given } t \text{ and } j = 1, ..., J \qquad \text{and} \tag{7}$$

$$s_t \equiv \frac{r_t}{N} \tag{8}$$

3.2 Measurement

We now define our indicators of 'greening prosperity'. One theoretical and general definition consistent with equation (2) could be

$$G_{Yt} \equiv \frac{Y_t}{E_t} \tag{9}$$

where G_{Yt} is some measure of 'greening prosperity' per capita, defined as, or relative to, Y_t, which is some measure of well-being or welfare per capita, and E_t, which is some measure of pollution of the environment per capita. For both the numerator and the denominator in the above ratio there seem to be at least two obvious candidates. For the numerator, one could use either real GDP pc (comparable internationally) or life expectancy (comparable internationally). For the denominator, one could use a general measure of pollution, such as caused by GHG, which are several,[2] or the largest share of these GHG, which belongs convincingly (as the numbers just mentioned in the footnote indicate) to CO2 emissions. Accordingly, the general definition in equation (9) may specialize as:

$$GPBpc_{Yt} \equiv \frac{RGDPpc_t}{GHGEpc_t} \tag{10}$$

where $GPBpc_{Yt}$ is greening prosperity defined *broadly* in terms of real GDP pc, $RGDPpc_t$, 'discounted' (or 'deflated') by (or 'corrected' for or 'cleaned' from) GHG emissions pc, $GHGEpc_t$; or:

$$GPNpc_{Yt} \equiv \frac{RGDPpc_t}{CO2Epc_t} \tag{11}$$

where $GPNpc_{Yt}$ is greening prosperity defined *narrowly* in terms of real GDP pc, $RGDPpc_t$, now divided by CO2 emissions pc, $CO2Epc_t$. An alternative definition of welfare and the related greening prosperity indicator may use the same two versions of the denominator, as in equations (10) and (11), but with a different measure in the numerator, namely, life expectancy:

$$G_{Lt} \equiv \frac{L_t}{E_t} \tag{12}$$

where G_{Lt}, the measure of greening prosperity, is now defined – and, hence, denoted in the subscript – by life expectancy L_t in the numerator. Then, depending on the broad or narrow definition of the denominator, we would obtain, respectively:

$$GPBpc_{Lt} \equiv \frac{L_t}{GHGEpc_t} \qquad \text{and} \tag{13}$$

[2]The Kyoto Protocol to curb GHG emissions, signed by 39 developed economies in 1997, covered carbon dioxide, accounting for 82% of all emissions in 1995, according to UNEP (1999/revised 2002), methane (with 12%), nitrous oxide (with 4%), hydro-fluorocarbons, perfluorocarbons and sulphur hexafluoride, as cited in, e.g., Bengochea-Morancho et al. (2001) and updated online at UNEP (1999/revised 2002): `https://www.unep.org/resources/report/climate-change-information-kit.`

$$GPNpc_{Lt} \equiv \frac{L_t}{CO2Epc_t} \tag{14}$$

To not dilute too much our visualizations and interpretations in this first pass of the proposed greening prosperity stripes in the present paper, we choose hereafter to focus on the – measurement or empirical – definition in equation (11). This is also because the data for CO2 emissions are more widely available for all countries in the world than the corresponding, and more encompassing, GHG emissions. We, nevertheless, keep in mind the alternative definitions in the equations above for future exploration.[3]

One advantage of our choice to define greening prosperity as in equation (11) is that it is thereby measured in a way allowing for an intuitive interpretation, namely, real GDP pc (in constant PPP international USD) 'discounted' by the degree of CO2 emissions (in metric tons). To define the goal of 'net zero', the metric tons in the typical measure of CO2 emissions could be expressed as kilograms (x 1'000) – or even grams (x 1'000'000) – and the minimum defined at unity: the net zero greening prosperity ratio, then, has a denominator of 1 and, thus, does not discount anymore the value of real GDP pc.

3.3 Sample Selection in Colormap Representations by Country over Time

Figure 3 presents the World Bank list of all 218 countries in the world, plus 48 country groupings or regions (with their number of ordering, name and country/group code), which we use in the comprehensive comparative visualization diagrams that follow. While the GDP pc data in constant USD of 2015 are the longest time-series (TS) available for all countries in the world (see the online appendix for illustrations), when it comes to a more comparable measurement of the same indicator for the same total of all countries, the World Bank provides a shorter TS in international constant US dollars of 2017 and applying the methodology of purchasing-power parity (PPP) exchange-rate conversion. This TS exists and is publicly available online for all countries in the world in annual frequency since 1990. To ensure a higher degree of precision and comparability in our study, we employ exactly this World Bank time series, starting in 1990.

Our colormap visualizations by country over time that will be discussed in what follows depict graphs of GDP pc at PPP in international USD of 2017, CO2 emissions pc and the resulting greening prosperity ratios, or stripes, for the period 1990-2020 in two panels (each with 12 subplots), i.e., for 18 countries and 6 country groups, using annual data that is publicly available from the World Bank. Our whole sample includes one

[3]Some figures where life expectancy replaces real GDP pc in the denominator of the greening prosperity indicator are provided in the online appendix.

low-income country (Mozambique), one lower middle-income country (India), five upper middle-income countries (China and Brazil in the first subsample of 12 subplots and Bulgaria, Mexico and Russia in the second subsample), 11 high-income countries (US, UK, Australia and Japan in the first subsample and Germany, France, Italy, Poland, Switzerland, Canada and Saudi Arabia in the second subsample), and six country groups (the world, high-income countries, low-income countries and the EU in the first subsample and upper middle-income countries and lower middle-income countries in the second subsample). In selecting the countries and the country groups for key illustrations, we have been guided by the importance of their respective economies, and/or the extent to which they pollute the environment, and/or to represent the diversity of their societies and institutions, originating in different geographical continents and in various stages of economic development.

In a next step, we expand our sample to the 'population' (in the statistical sense, here) of all countries and groups in the World Bank database, as listed in Figure 3. We, in effect, present additional perspectives of the colormaps, now in terms of cross-sections for selected years. This allows us to see the maximal values attained by our green prosperity pc indicator as well as its drivers, in the numerator and the denominator, for these selected years. We provide four snapshots, or cross-sections, of the world along our three variables of interest, starting with the initial year for which we have got the data, 1990, and then moving forward in 10-year increments, to depict gradually the evolution of the cross-section in 2000, 2010 and, finally, 2020, the last year of the available World Bank data 'population'.

3.4 Descriptive Statistics for the World and Its Four Major Groups of Countries

Before going into further disaggregation, presenting our sample of 24 countries and country groups in individual graphs, we here provide some more general discussion of Table 1. This table lists statistical information with regard to the world as a whole and its four major constituent subgroups, according to the classification by the World Bank.

Starting with the world as a whole, one sees that the mean and median GDP pc at PPP in international USD of 2017 have been close together around the value of 12'550 as an average over the 31 years spanning our time period of analysis, 1990-2020. The world has also emitted, on average for the same period, CO2 of some 4.3 metric tons pc (again, the mean and median are pretty close). Consequently, the average greening prosperity ratio for the world during the same period has resulted in about 2'900 'discounted' USD of 2017. One can, therefore, infer that CO2 emissions pc (the denominator in the ratio) have reduced GDP pc (the numerator in the ratio) by more than 4 times.

Figure 3: World Bank Database (Online): All Countries and Groups in the World

Abs No.	Country (no highlight) or group (yellow highlight)	Code	Rel No.	Abs No.	Country (no highlight) or group (yellow highlight)	Code	Rel No.	Abs No.	Country (no highlight) or group (yellow highlight)	Code	Rel No.
1	Aruba	ABW	1	91	Grenada	GRD	78	181	New Zealand	NZL	149
2	Africa Eastern and Southern	AFE	1	92	Greenland	GRL	79	182	OECD members	OED	33
3	Afghanistan	AFG	2	93	Guatemala	GTM	80	183	Oman	OMN	150
4	Africa Western and Central	AFW	2	94	Guam	GUM	81	184	Other small states	OSS	34
5	Angola	AGO	3	95	Guyana	GUY	82	185	Pakistan	PAK	151
6	Albania	ALB	4	96	High income	HIC	14	186	Panama	PAN	152
7	Andorra	AND	5	97	Hong Kong SAR, China	HKG	83	187	Peru	PER	153
8	Arab World	ARB	3	98	Honduras	HND	84	188	Philippines	PHL	154
9	United Arab Emirates	ARE	6	99	Heavily indebted poor countries (HIPC)	HPC	15	189	Palau	PLW	155
10	Argentina	ARG	7	100	Croatia	HRV	85	190	Papua New Guinea	PNG	156
11	Armenia	ARM	8	101	Haiti	HTI	86	191	Poland	POL	157
12	American Samoa	ASM	9	102	Hungary	HUN	87	192	Pre-demographic dividend	PRE	35
13	Antigua and Barbuda	ATG	10	103	IBRD only	IBD	16	193	Puerto Rico	PRI	158
14	Australia	AUS	11	104	IDA & IBRD total	IBT	17	194	Korea, Dem. People's Rep.	PRK	159
15	Austria	AUT	12	105	IDA total	IDA	18	195	Portugal	PRT	160
16	Azerbaijan	AZE	13	106	IDA blend	IDB	19	196	Paraguay	PRY	161
17	Burundi	BDI	14	107	Indonesia	IDN	88	197	West Bank and Gaza	PSE	162
18	Belgium	BEL	15	108	IDA only	IDX	20	198	Pacific island small states	PSS	36
19	Benin	BEN	16	109	Isle of Man	IMN	89	199	Post-demographic dividend	PST	37
20	Burkina Faso	BFA	17	110	India	IND	90	200	French Polynesia	PYF	163
21	Bangladesh	BGD	18	111	Not classified	INX	21	201	Qatar	QAT	164
22	Bulgaria	BGR	19	112	Ireland	IRL	91	202	Romania	ROU	165
23	Bahrain	BHR	20	113	Iran, Islamic Rep.	IRN	92	203	Russian Federation	RUS	166
24	Bahamas, The	BHS	21	114	Iraq	IRQ	93	204	Rwanda	RWA	167
25	Bosnia and Herzegovina	BIH	22	115	Iceland	ISL	94	205	South Asia	SAS	168
26	Belarus	BLR	23	116	Israel	ISR	95	206	Saudi Arabia	SAU	169
27	Belize	BLZ	24	117	Italy	ITA	96	207	Sudan	SDN	170
28	Bermuda	BMU	25	118	Jamaica	JAM	97	208	Senegal	SEN	171
29	Bolivia	BOL	26	119	Jordan	JOR	98	209	Singapore	SGP	172
30	Brazil	BRA	27	120	Japan	JPN	99	210	Solomon Islands	SLB	173
31	Barbados	BRB	28	121	Kazakhstan	KAZ	100	211	Sierra Leone	SLE	174
32	Brunei Darussalam	BRN	29	122	Kenya	KEN	101	212	El Salvador	SLV	175
33	Bhutan	BTN	30	123	Kyrgyz Republic	KGZ	102	213	San Marino	SMR	176
34	Botswana	BWA	31	124	Cambodia	KHM	103	214	Somalia	SOM	177
35	Central African Republic	CAF	32	125	Kiribati	KIR	104	215	Serbia	SRB	178
36	Canada	CAN	33	126	St. Kitts and Nevis	KNA	105	216	Sub-Saharan Africa (excluding high income)	SSA	38
37	Central Europe and the Baltics	CEB	4	127	Korea, Rep.	KOR	106	217	South Sudan	SSD	179
38	Switzerland	CHE	34	128	Kuwait	KWT	107	218	Sub-Saharan Africa	SSF	39
39	Channel Islands	CHI	35	129	Latin America & Caribbean (excluding high income)	LAC	22	219	Small states	SST	40
40	Chile	CHL	36	130	Lao PDR	LAO	108	220	Sao Tome and Principe	STP	180
41	China	CHN	37	131	Lebanon	LBN	109	221	Suriname	SUR	181
42	Cote d'Ivoire	CIV	38	132	Liberia	LBR	110	222	Slovak Republic	SVK	182
43	Cameroon	CMR	39	133	Libya	LBY	111	223	Slovenia	SVN	183
44	Congo, Dem. Rep.	COD	40	134	St. Lucia	LCA	112	224	Sweden	SWE	184
45	Congo, Rep.	COG	41	135	Latin America & Caribbean	LCN	23	225	Eswatini	SWZ	185
46	Colombia	COL	42	136	Least developed countries: UN classification	LDC	24	226	Sint Maarten (Dutch part)	SXM	186
47	Comoros	COM	43	137	Low income	LIC	25	227	Seychelles	SYC	187
48	Cabo Verde	CPV	44	138	Liechtenstein	LIE	113	228	Syrian Arab Republic	SYR	188
49	Costa Rica	CRI	45	139	Sri Lanka	LKA	114	229	Turks and Caicos Islands	TCA	189
50	Caribbean small states	CSS	5	140	Lower middle income	LMC	26	230	Chad	TCD	190
51	Cuba	CUB	46	141	Low & middle income	LMY	27	231	East Asia & Pacific (IDA & IBRD countries)	TEA	41
52	Curacao	CUW	47	142	Lesotho	LSO	115	232	Europe & Central Asia (IDA & IBRD countries)	TEC	42
53	Cayman Islands	CYM	48	143	Late-demographic dividend	LTE	28	233	Togo	TGO	191
54	Cyprus	CYP	49	144	Lithuania	LTU	116	234	Thailand	THA	192
55	Czechia	CZE	50	145	Luxembourg	LUX	117	235	Tajikistan	TJK	193
56	Germany	DEU	51	146	Latvia	LVA	118	236	Turkmenistan	TKM	194
57	Djibouti	DJI	52	147	Macao SAR, China	MAC	119	237	Latin America & the Caribbean (IDA & IBRD countries)	TLA	43
58	Dominica	DMA	53	148	St. Martin (French part)	MAF	120	238	Timor-Leste	TLS	195
59	Denmark	DNK	54	149	Morocco	MAR	121	239	Middle East & North Africa (IDA & IBRD countries)	TMN	44
60	Dominican Republic	DOM	55	150	Monaco	MCO	122	240	Tonga	TON	196
61	Algeria	DZA	56	151	Moldova	MDA	123	241	South Asia (IDA & IBRD)	TSA	45
62	East Asia & Pacific (excluding high income)	EAP	6	152	Madagascar	MDG	124	242	Sub-Saharan Africa (IDA & IBRD countries)	TSS	46
63	Early-demographic dividend	EAR	7	153	Maldives	MDV	125	243	Trinidad and Tobago	TTO	197
64	East Asia & Pacific	EAS	8	154	Middle East & North Africa	MEA	29	244	Tunisia	TUN	198
65	Europe & Central Asia (excluding high income)	ECA	9	155	Mexico	MEX	126	245	Turkiye	TUR	199
66	Europe & Central Asia	ECS	10	156	Marshall Islands	MHL	127	246	Tuvalu	TUV	200
67	Ecuador	ECU	57	157	Middle income	MIC	30	247	Tanzania	TZA	201
68	Egypt, Arab Rep.	EGY	58	158	North Macedonia	MKD	128	248	Uganda	UGA	202
69	Euro area	EMU	11	159	Mali	MLI	129	249	Ukraine	UKR	203
70	Eritrea	ERI	59	160	Malta	MLT	130	250	Upper middle income	UMC	47
71	Spain	ESP	60	161	Myanmar	MMR	131	251	Uruguay	URY	204
72	Estonia	EST	61	162	Middle East & North Africa (excluding high income)	MNA	31	252	United States	USA	205
73	Ethiopia	ETH	62	163	Montenegro	MNE	132	253	Uzbekistan	UZB	206
74	European Union	EUU	12	164	Mongolia	MNG	133	254	St. Vincent and the Grenadines	VCT	207
75	Fragile and conflict affected situations	FCS	13	165	Northern Mariana Islands	MNP	134	255	Venezuela, RB	VEN	208
76	Finland	FIN	63	166	Mozambique	MOZ	135	256	British Virgin Islands	VGB	209
77	Fiji	FJI	64	167	Mauritania	MRT	136	257	Virgin Islands (U.S.)	VIR	210
78	France	FRA	65	168	Mauritius	MUS	137	258	Vietnam	VNM	211
79	Faroe Islands	FRO	66	169	Malawi	MWI	138	259	Vanuatu	VUT	212
80	Micronesia, Fed. Sts.	FSM	67	170	Malaysia	MYS	139	260	World	WLD	48
81	Gabon	GAB	68	171	North America	NAC	32	261	Samoa	WSM	213
82	United Kingdom	GBR	69	172	Namibia	NAM	140	262	Kosovo	XKX	214
83	Georgia	GEO	70	173	New Caledonia	NCL	141	263	Yemen, Rep.	YEM	215
84	Ghana	GHA	71	174	Niger	NER	142	264	South Africa	ZAF	216
85	Gibraltar	GIB	72	175	Nigeria	NGA	143	265	Zambia	ZMB	217
86	Guinea	GIN	73	176	Nicaragua	NIC	144	266	Zimbabwe	ZWE	218
87	Gambia, The	GMB	74	177	Netherlands	NLD	145				
88	Guinea-Bissau	GNB	75	178	Norway	NOR	146				
89	Equatorial Guinea	GNQ	76	179	Nepal	NPL	147				
90	Greece	GRC	77	180	Nauru	NRU	148				

Note: Abs(olute) No. (number) denotes the order of each country or group in the databank, whereas the Rel(ative) No. its order in either countires or groups. Country/group Code is as in source: World Bank (online).

Table 1: Greening Prosperity Stripes – Descriptive Statistics Summary

	World	High-Inc Cs	Upper Mid-Inc Cs	Lower Mid-Inc Cs	Low-Inc Cs
GDP pc at PPP in intl USD of 2017					
min	9665.89	31817.69	5712.87	3012.71	1183.15
max	16864.89	50002.95	16738.56	6845.04	1966.98
range	7199.00	18185.26	11025.70	3832.33	783.83
stripe = range/16	449.94	1136.58	689.11	239.52	48.99
mean	12684.74	41141.41	9964.45	4469.28	1535.74
median	12470.71	42620.28	8891.28	4185.14	1486.23
CO2 emissions pc in metric tons					
min	3.84	8.75	3.02	1.03	0.25
max	4.72	11.69	6.01	1.68	0.63
range	0.88	2.94	2.99	0.66	0.38
stripe = range/16	0.05	0.18	0.19	0.04	0.02
mean	4.26	10.91	4.36	1.28	0.39
median	4.29	11.06	4.25	1.19	0.40
GPRs pc in ‘discounted’ USD of 2017					
min	2413.90	2859.95	1862.32	2731.52	2133.65
max	3775.56	5445.74	2784.88	4232.68	7573.84
range	1361.66	2585.78	922.56	1501.16	5440.20
stripe = range/16	85.10	161.61	57.66	93.82	340.01
mean	2954.68	3808.76	2227.60	3422.38	4261.70
median	2880.21	3655.34	2190.06	3514.42	3473.73

Note: The table reports descriptive statistics for our three key variables, as averages over 1990-2020 for the world as a whole and the four major groups of countries it is divided and classified into by the World Bank: namely, high-income countries, upper middle-income countries, lower middle-income countries and low-income countries. The row ‘stripe’ defines the nuance in the colormap visualization that is unique by country (or country group), as per equation (6) with $N = 16$.

Turning to the four major country groups comprising the world, one first sees their significant differences in mean or median GDP pc, going from an average of 41'000-42'000 USD of 2017 pc for the high-income countries to more than 4 times less for the upper middle-income countries, to nearly 10 times less for the lower middle-income countries and to almost 30 times less for the low-income countries. We observe, therefore, a wide disparity of GDP pc that will affect the numerator of our greening prosperity ratio across these groups of countries.

In terms of CO2 emissions pc, the averaged data in Table 1 do not support the environmental Kuznets curve we introduced earlier: namely, the levels of CO2 emissions do not imply an inverted U-shaped relationship between income pc (or GDP pc, here) and the level of economic development, captured by the four major groups of countries in the World Bank classification we use. It is clear that the low-income countries are the lowest CO2 emitters pc, with 0.4 metric tons on average for 1990-2020 (mean and median are almost identical). Lower middle-income countries come next, with CO2 emisssions pc of the order of 1.25 metric tons (with close mean and median, but less so), while the upper middle-income countries emit CO2 pc that is nearly four times higher than the emissions of the lower middle-income group and more than 10 times higher than the emissions of the low-income group. Finally, the high-income countries emit the highest level of CO2 pc, with some 11 metric tons (close mean and median, again), i.e., about 2 times and a half more than the mean or median emissions of the upper middle-income group and almost 30 times more than the emissions of the low-income countries. Again, now in the denominator of the greening prosperity ratio we propose here, one observes a huge diversity in the average volume of CO2 emissions pc over the 1990-2020 period across the four major groups of countries that the World Bank defines and examines in typical comparisons.

However, because the two lower-income groups of countries emit CO2 pc much less than the two higher-income groups, we observe a corresponding 'correction' in the greening prosperity indicators that are measured in USD of 2017 'discounted' by the level of CO2 emissions. This leads to some unsurprising pattern of clustering – but definitely not complete equalization – of the average greening prosperity ratios of the four group of countries, in the range of 2'200 USD of 2017 (lowest, for the upper middle-income countries) to some 3'700 USD of 2107 (highest, for the high-income countries), and with both the lower middle-income countries and the low-income countries coming very close to the high-income countries (indeed, according to the mean value, and not the median, the low-income countries even somewhat overtake the high-income countries).

4 Colormap Stripes Visualization

We, now, present the most original and colorful (literally) visualization of our greening prosperity stripes and their two components, GDP pc in the numerator and CO2 emissions pc in the denominator. In line with the tradition of the Reading warming stripes, we first discuss colormaps that are unique for each country (similarly to the barcodes for each product sold in a supermarket), but not directly comparable across countries. We, then, complement these with colormaps that are dominated by a single or few nuances only, but which allow direct country comparisons by color, at the scale of the global minimum and maximum for a given indicator.[4]

4.1 Stripes Unique by Country across Time: GDP pc

Following the well-known example of the Reading climate stripes, we begin our colormap visualizations applying the same methodology as the one applied by meteorologists, e.g., as implemented in Figure 2 (except that we do not work with deviation from some long-period mean normalized at 0 because our comparable panel sample is only available for 31 years). Figures 4 and 5 collect this kind of stripe visualization that is unique, by construction – as in equations (5), (6), and (11), for each country and grouping in our sample across time. Note, however, e.g., by checking the vertical scales, that these colormaps are not directly comparable across countries.

Beginning with the numerator in the greening prosperity ratio, figures 4 and 5 plot the 24 countries and groupings in our sample in terms of the same popular 16 blue-to-red nuances in the colormap that are now popular across the globe due to the work of our Reading colleague Ed Hawkins. By analogy with the typical terminology in (macro)economics of '(over)heating' versus 'cooling (down)' of the economy and, thus, assigning red versus blue color nuances to higher versus lower real GDP pc values, we have decided to keep these same nuances of colors as in the climate warming stripes to represent GDP pc at PPP in international USD of 2017.[5]

This is a first colormap visualization which sticks to the tradition established with the climate stripes; i.e., the pattern of nuances is unique for each country and depicts its data but is not directly comparable across countries since the scales on the vertical axis are, by construction, different. Indeed, the 16 colors are defined between the minimum and maximum value of the respective indicator, here GDP pc, for each country, and so they split the spread between these minimum and maximum in 16 equal regions, or

[4]The parallel conventional visualization of the same data in terms of time-series and cross-section comparative plots is relegated to the online appendix.

[5]See, again, equations (5) and (6) with $N = 16$ plus definition (11) as well as the note to Table 1, which clarify the computation of each stripe as a 1/16th of the range between the max and min for a given country, or country group.

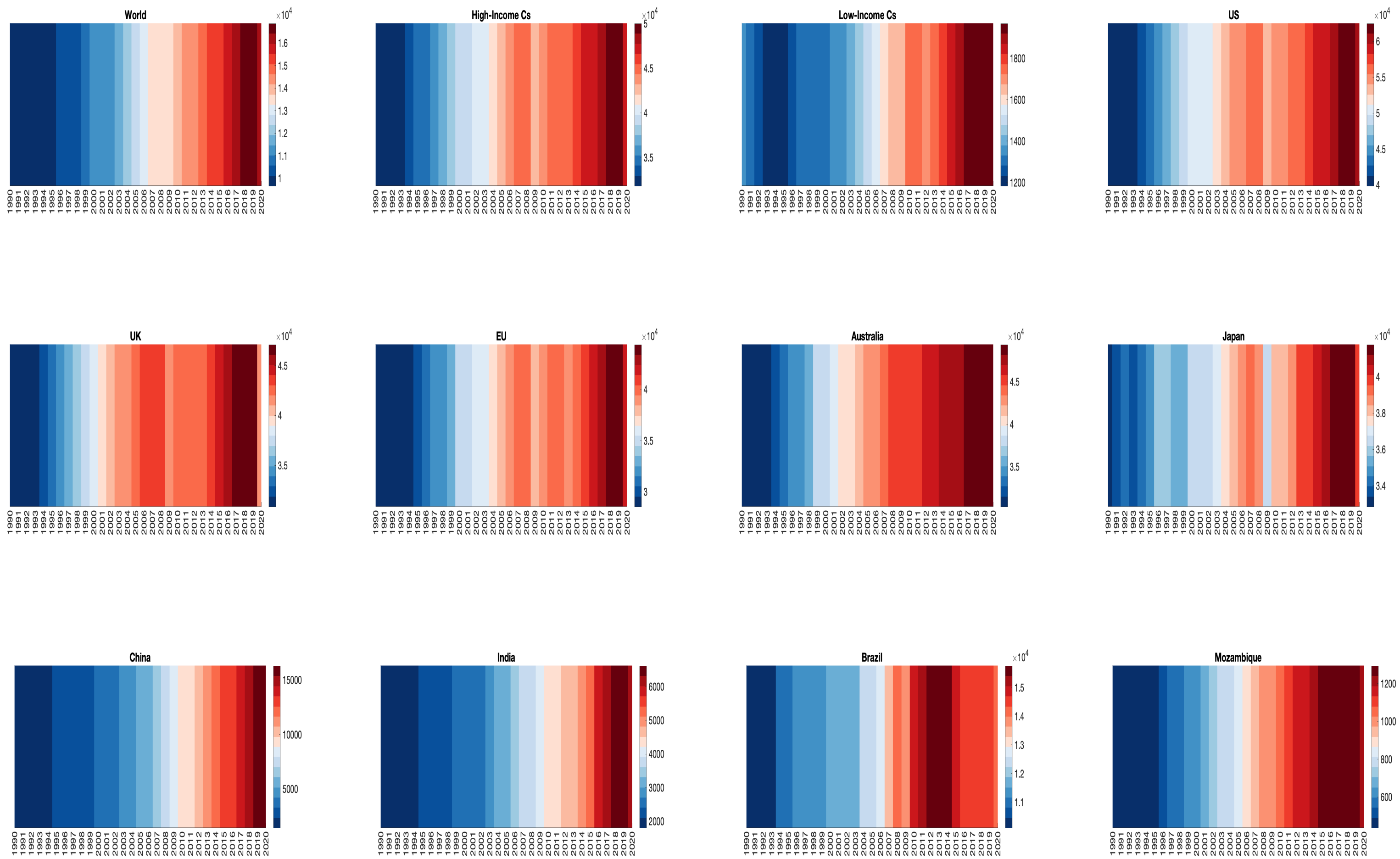
stripes, each accounting for 6.25% of the total spread. In this sense, and by definition, the color stripes are standardized and represent a unique pattern by country – similar to the barcode symbology of the Universal Product Code (UPC).

What do we learn from these color stripe images, in addition to the corresponding conventional visualization presented – to save space – in the online appendix? First of all – and similarly to troughs after peaks in the time-series plots – stripes that tend to move from the blue into the red but reverse for some time capture recessions and crises in GDP pc: one can notice the GFC of 2007-2009 and the start of the pandemic in 2020 in most of the graphs in Figure 4.

Second, relatively narrow (compared to broad) stripes with color going from blue to red nuances capture relatively strong (compared to weak) trend growth in the level of GDP pc. In fact, these GDP pc stripes visualization does not contain any new information relative to the conventional time-series representation, but constitutes just another – and let us say colorful, or artistic, or aesthetic – way of viewing or explaining or analyzing it. Yet, because of the emotional and, hence, stronger sensitivity human psychology displays to colors and images, the vivid awareness that our stripe representations are likely to impinge into people's mind worldwide could help mobilize climate change mitigation action. A rich literature in psychology and color design, e.g., Gao and Xin (2006) and Wilms and Oberfeld (2018) mentioned earlier, has been examining these psychological effects of color on perception and emotion.

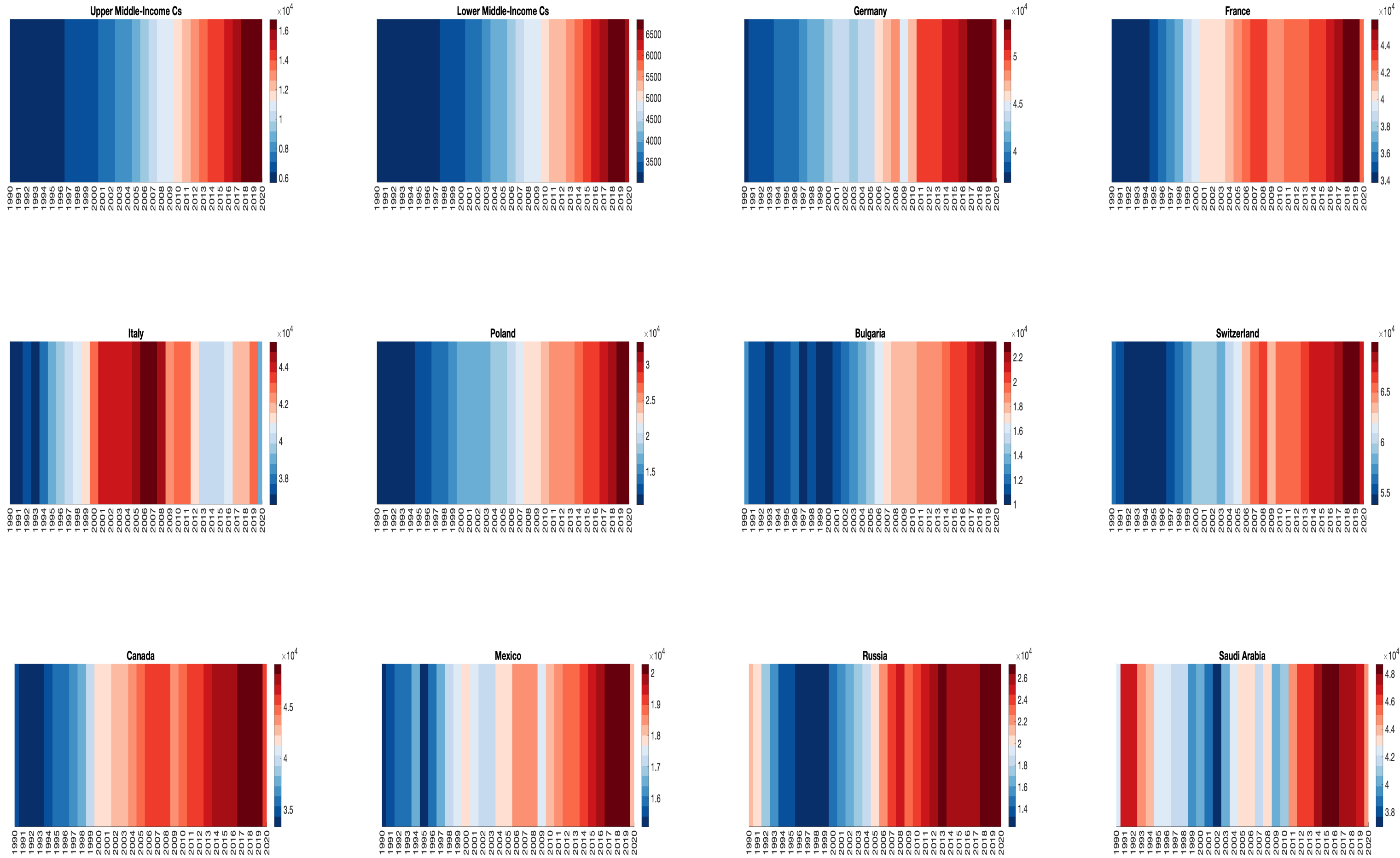
This latter added value will become more evident later on, when we switch the colors to go from green to brown when measuring CO2 emissions pc and from brown to green when measuring our greening prosperity indicators. In this later application lies the originality and usefulness of our current visualization focusing on illustrating how green a country is and what its trajectory to net zero could be, in terms of unique stripe patterns, for any period of time. This usefulness relates mostly to the fact that even a nonspecialsit can recognize the trend in the colors from brown to green (or vice versa), which hopefully makes the issue of environmental pollution and climate change mitigation salient, thus raising awareness and, ultimately, coordinated action across the globe.

Figure 4: GDP pc at PPP in International USD of 2017 – Colormap Stripes for Our 1st Subsample



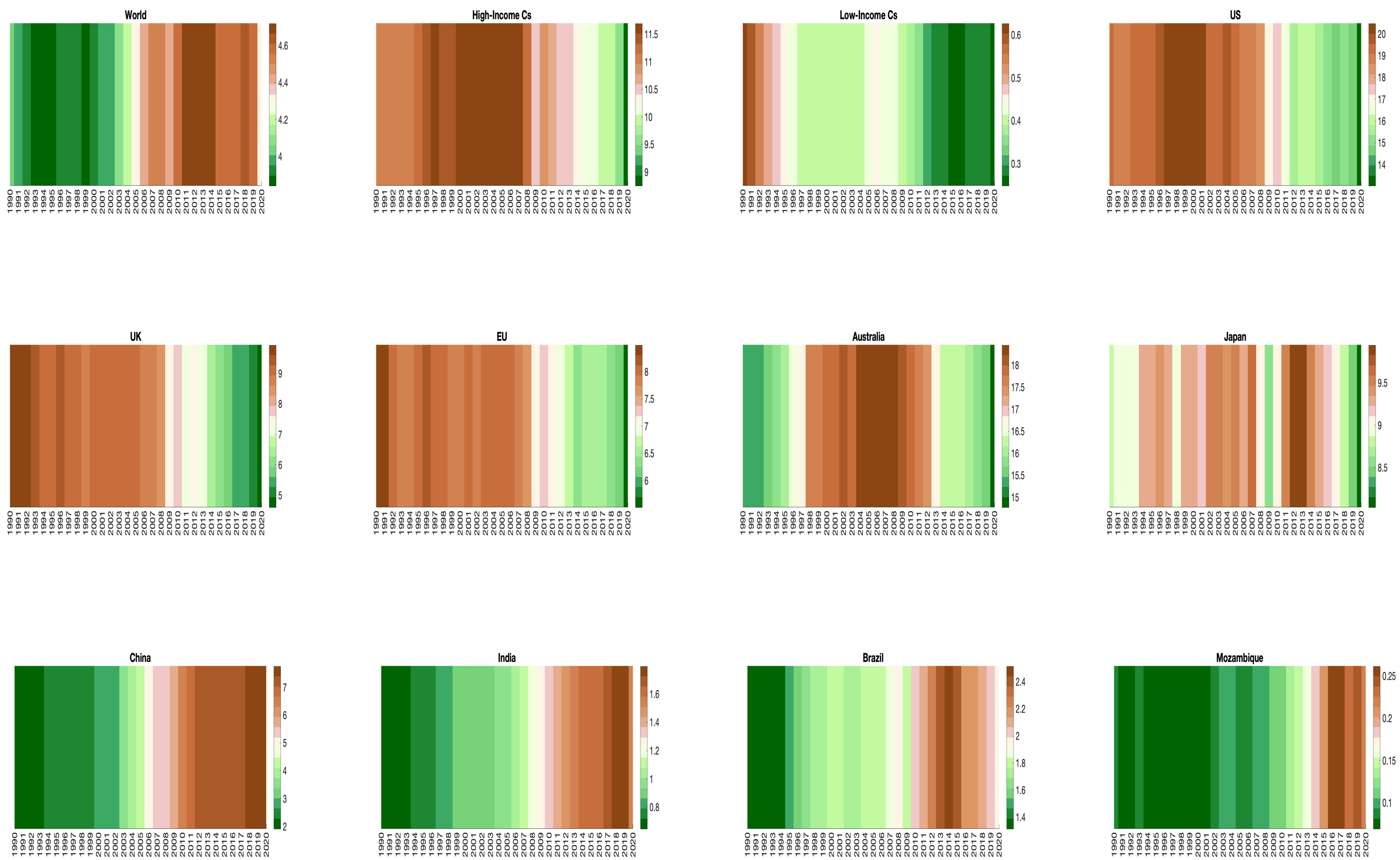
Note: 12 groups or countries: the horizontal scales are still identical but not the vertical scales. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

Figure 5: GDP pc at PPP in International USD of 2017 – Colormap Stripes for Our 2nd Subsample



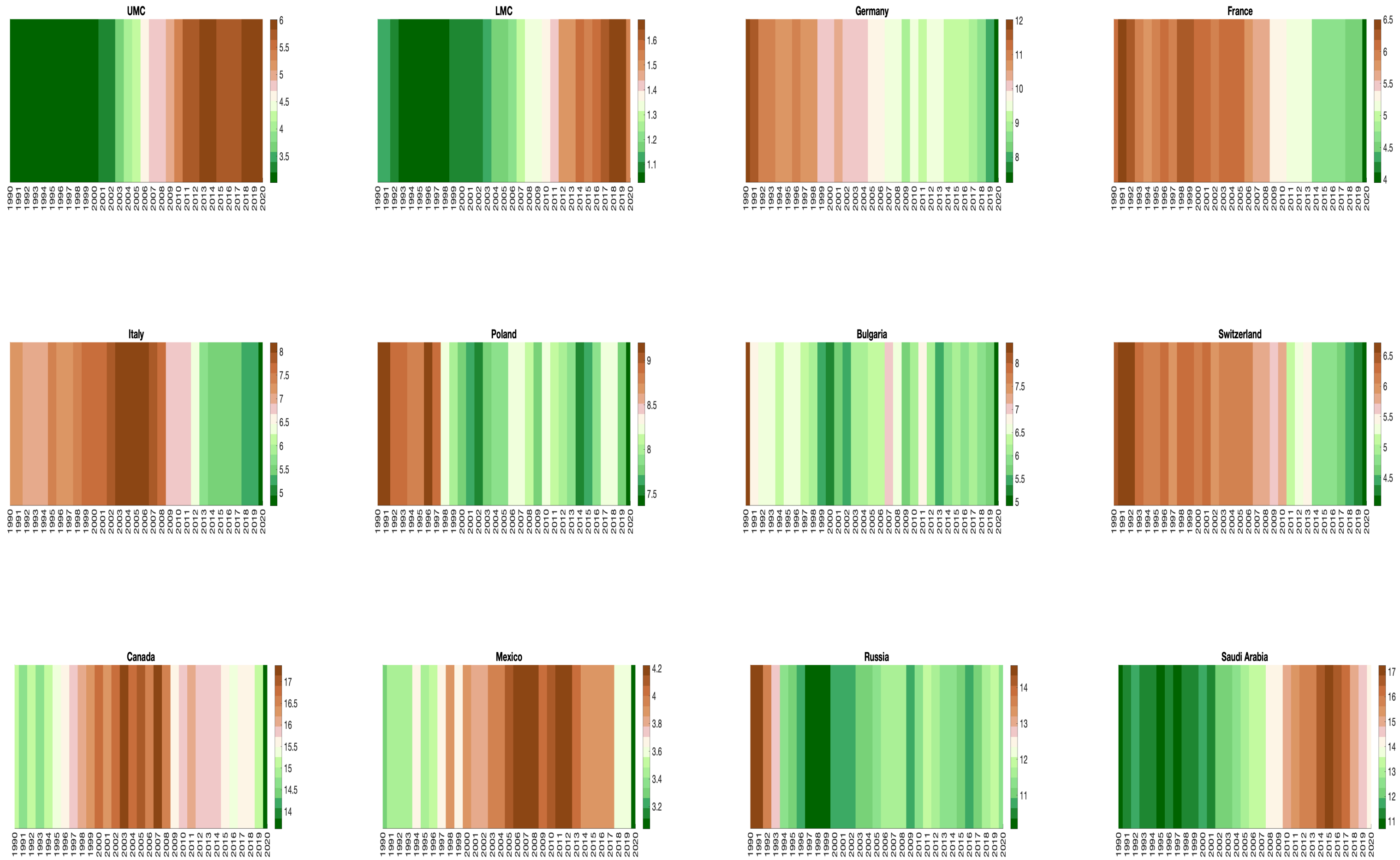
Note: 12 groups or countries: the horizontal scales are still identical but not the vertical scales. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

Figure 6: CO2 pc in Metric Tons – Colormap Stripes for Our 1st Subsample



Note: 12 groups or countries: the horizontal scales are still identical but not the vertical scales. *Source*: World Bank,`https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

Figure 7: CO2 pc in Metric Tons – Colormap Stripes for Our 2nd Subsample



Note: 12 groups or countries: the horizontal scales are still identical but not the vertical scales. *Source*: World Bank, `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

4.2 Stripes Unique by Country across Time: Emissions of CO2 pc

Now moving to the denominator in our greening prosperity ratio, CO2 pc emissions, we change the definition of the color map to better suit our purpose. We apply a new color and nuance scale that moves from green to brown as a country emits a higher volume of CO2 pc in metric tons.

What is insightful in the collection of color stripes in figures 6 and 7 is that we can observe countries that become greener when going along time from 1990 to 2020, as they have reduced gradually their CO2 emissions: this visual impression applies (in our sample) to the world as a whole, both the high- and low-income countries, the US, the UK, the EU, Japan (quite hesitantly), Germany, France, Italy, Switzerland, Poland, Bulgaria and Russia (these three latter post-communist economies with some hesitation, captured in the temporary stripe pattern reversals). We, however, observe as well the opposite trend in the stripe pattern, as some economies are not becoming greener, but browner instead, i.e., increasing their emissions of CO2 pc: these are (in our sample) China, India, Brazil, Mozambique, the upper middle-income countries, the lower middle-income countries, Mexico, Saudi Arabia and – to a lesser extent – Australia and Canada. Here the usefulness of the colormap stripe visualization is really more direct, evident and, therefore, worthwhile.

4.3 Stripes Unique by Country across Time: Greening Prosperity pc

In this most important aspect of our study, when we are now presenting the greening prosperity stripes visualization pc, the logic of color meanings and conventions implies another redefinition: indeed, we use again the same color and nuance definitions in 16 ranges as in the preceding figure, mapping CO2 emissions pc, but we now reverse the direction, showing brown in the bottom of the scale and green in the top of the scale.

Accordingly with this redefinition, we observe most countries going greener, that is, achieving greening prosperity stripes that are dominated by the nuances of green as we move from 1990 to 2020. There are, however, a few exceptions where the brown color stripes dominate in the right-hand side of the panels, rather than in the left-hand side, thus exhibiting a worsening of the greening prosperity indicator: such are the cases (in our sample) of Saudi Arabia and the upper middle-income country group, as well as, less so – and with some reversals in the stripe patterns – China, India, Brazil, Mozambique, Canada, Mexico (and to a minor extent, the post-communist economies of Poland, Bulgaria and Russia).

The colormap stripes visualization here again appears insightful, and adds value to the presentation of the analysis by getting it across to a wider and unspecialized audience.

4.4 Country Colors Comparably Defined Using a Common Scale: GDP pc

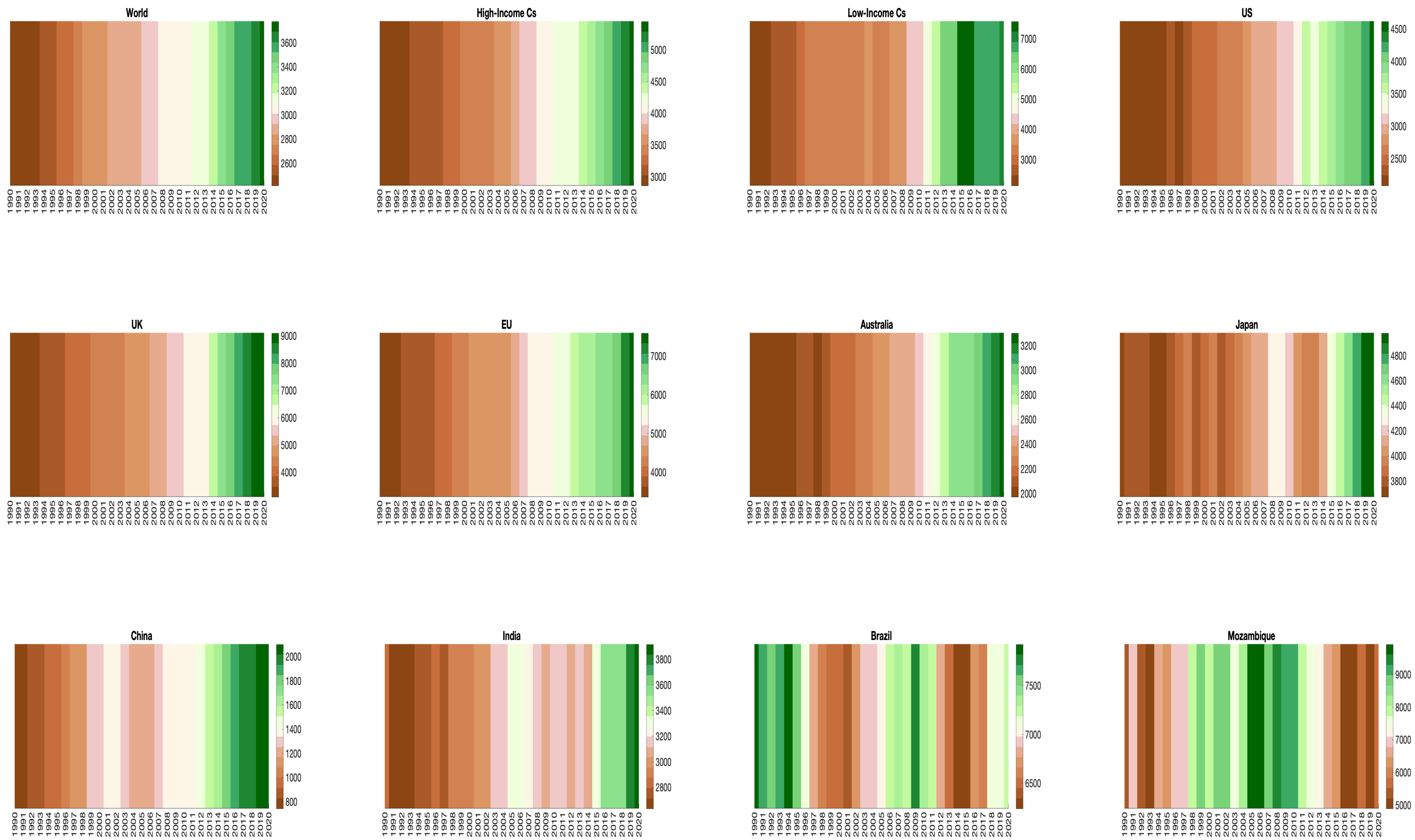
We, now, proceed to a redefinition of the displayed colors by country that makes comparisons clear and easy across all of them. For that purpose, we scale our color definitions not by the min and max spread within a country for the period 1990-2020, but instead by the min and max spread for all countries across the globe for the same period of time as in equations (3), (4), and (11). That is, we now redefine the colormap globally, i.e., with respect to the global min and max for a given indicator, not locally, i.e., with respect to the national (or group-of-countries average) min and max (as was earlier).

This redefinition generates colormaps that are not as rich and beautiful in terms of colors and nuances, but allows straightforward visual comparisons. Usually, as will be seen, a single color, or just a few nuances dominate per country, spanning the scale from the global min to the global max per respective indicator: GDP pc at PPP in international USD of 2017, CO2 emissions pc in metric tons, and – finally – their ratio that we interpret as a measure of greening prosperity pc.

As before, we begin with GDP pc, the numerator of our greening prosperity ratio. GDP pc is, again, defined in the colormap to increase from dark blue (lowest) to dark red (highest). Looking across the subsamples of graphs in figures 10 and 11, we can see that the blue nuances dominate the red ones, even for advanced and rich economies such as Switzerland or the US. This is because, as we illustrate and argue in more detail in the online appendix, the GDP pc of the dozen or so extremely rich small countries just 'dwarfs' the GDP pc of the high-income or advanced market economies in our sample.

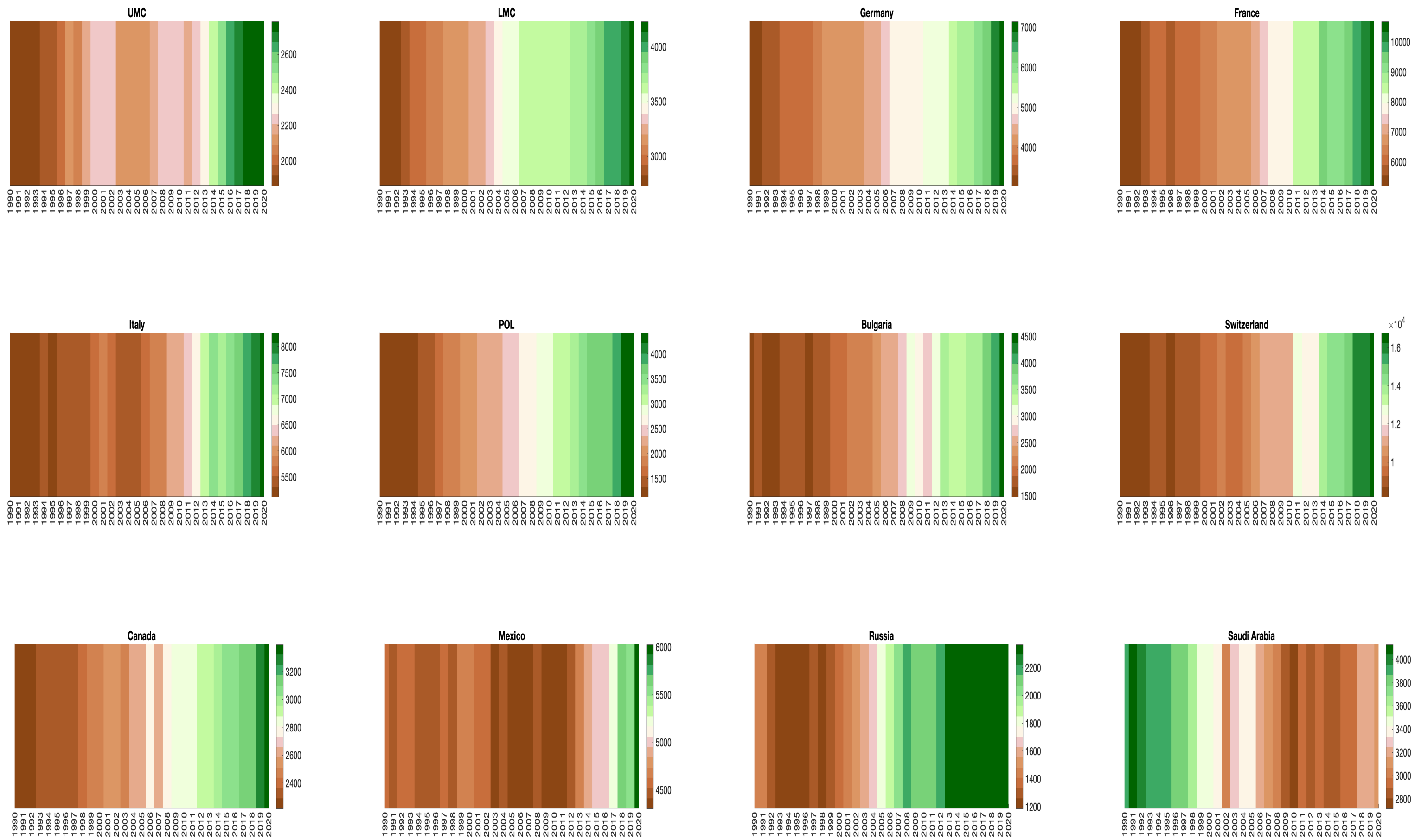
In the particular case of GDP pc at PPP in international USD of 2017, the global minimum in our sample is 436.4 (for Mozambique in 1992) and the global maximum is 157'602.5 (for Macao, SAR, China, in 2013). At such a globally defined scale, with the purpose to arrive at a visual comparison by color across all countries in the world, only a handful of countries – and they are not illustrated in our sample, being less central to the global economy – will attain the red nuances in the colormap.

Figure 8: Greening Prosperity pc at PPP in International USD of 2017 ‘Discounted’ by CO2 Emissions pc – Colormap Stripes for Our 1st Subsample



Note: 12 groups or countries: the horizontal scales are still identical but not the vertical scales. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD` and `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`

Figure 9: Greening Prosperity pc at PPP in International USD of 2017 ‘Discounted’ by CO2 Emissions pc – Colormap Stripes for Our 2nd Subsample



Note: 12 groups or countries: the horizontal scales are still identical but not the vertical scales. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD` and `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`

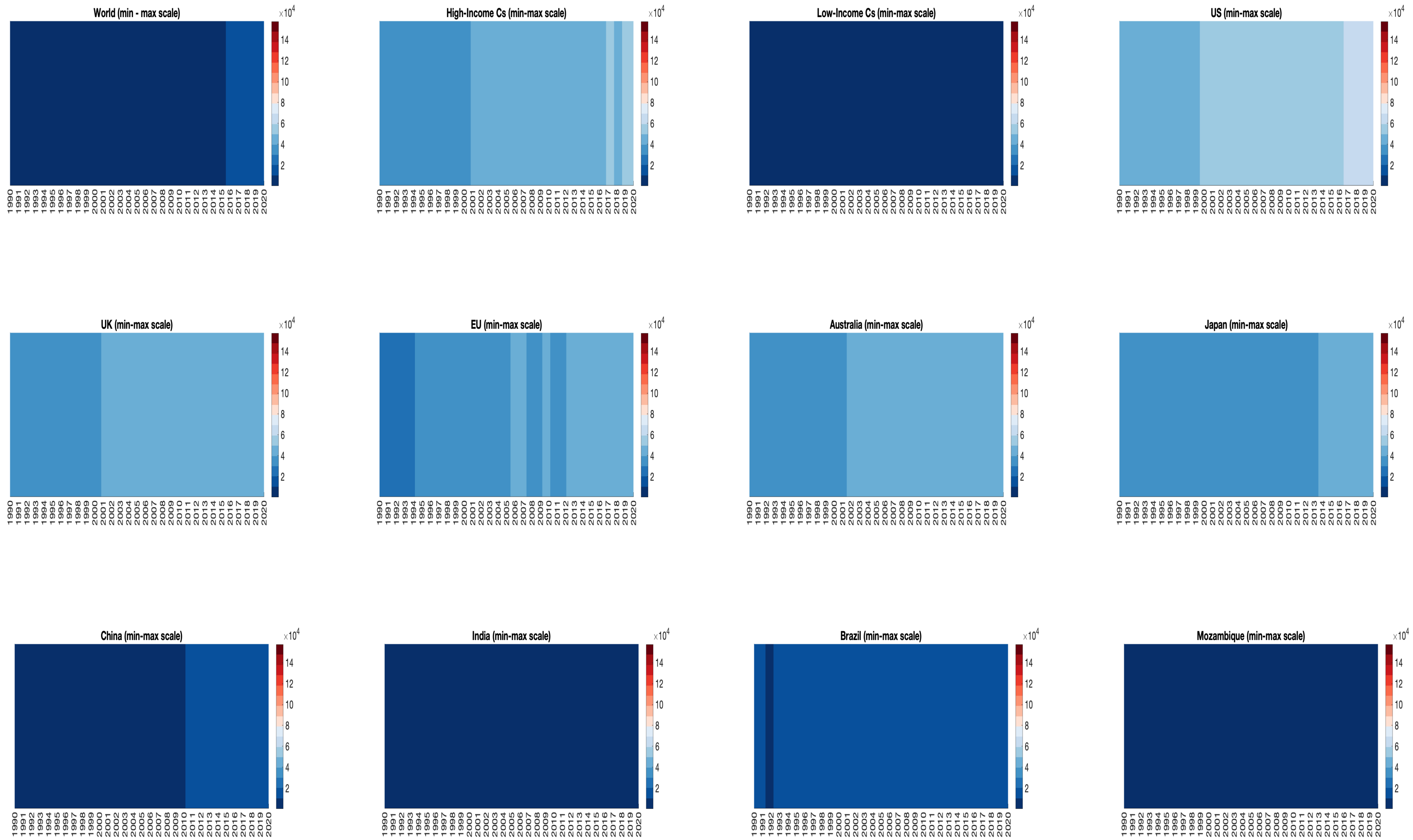
Yet the dominant nuances of the blue in the sample of 24 countries and country groupings we highlight are really very useful in visualizing the comparisons at a global and meaningful scale. Moreover, when there is no single nuance dominating a graph for a country, the change of nuances, often two or three times within the period of 1990-2020 we examine, traces progress in increasing GDP pc.

Note, for example, how clearly the nuances of the blue in our sample of 24 countries and country groups oppose the unchanged darkest blue of Mozambique and the low-income countries, i.e., the country and the country group it belongs to, respectively, with the lowest GDP pc at PPP in international USD of 2017, on one hand; versus, on the other hand, the three nuances of lighter blue that characterize Switzerland, the country with the highest GDP pc at PPP in international USD of 2017 in our sample.

Thus, the nuances of blue in the two subsamples in figures 10 and 11 help the observer to easily spot the poorest economies as well as the richer advanced ones. It is also instructive to see, by any change in the nuances, whether some of these countries have made enough progress over time (on the x-axis) to move them across the now globally defined ranges of the nuances, and a gradual transition to lighter blue nuances depicts in such cases the successful countries and groups having achieved a considerable (to allow them to shift stripes of nuances) increase in their GDP pc, as measured here.

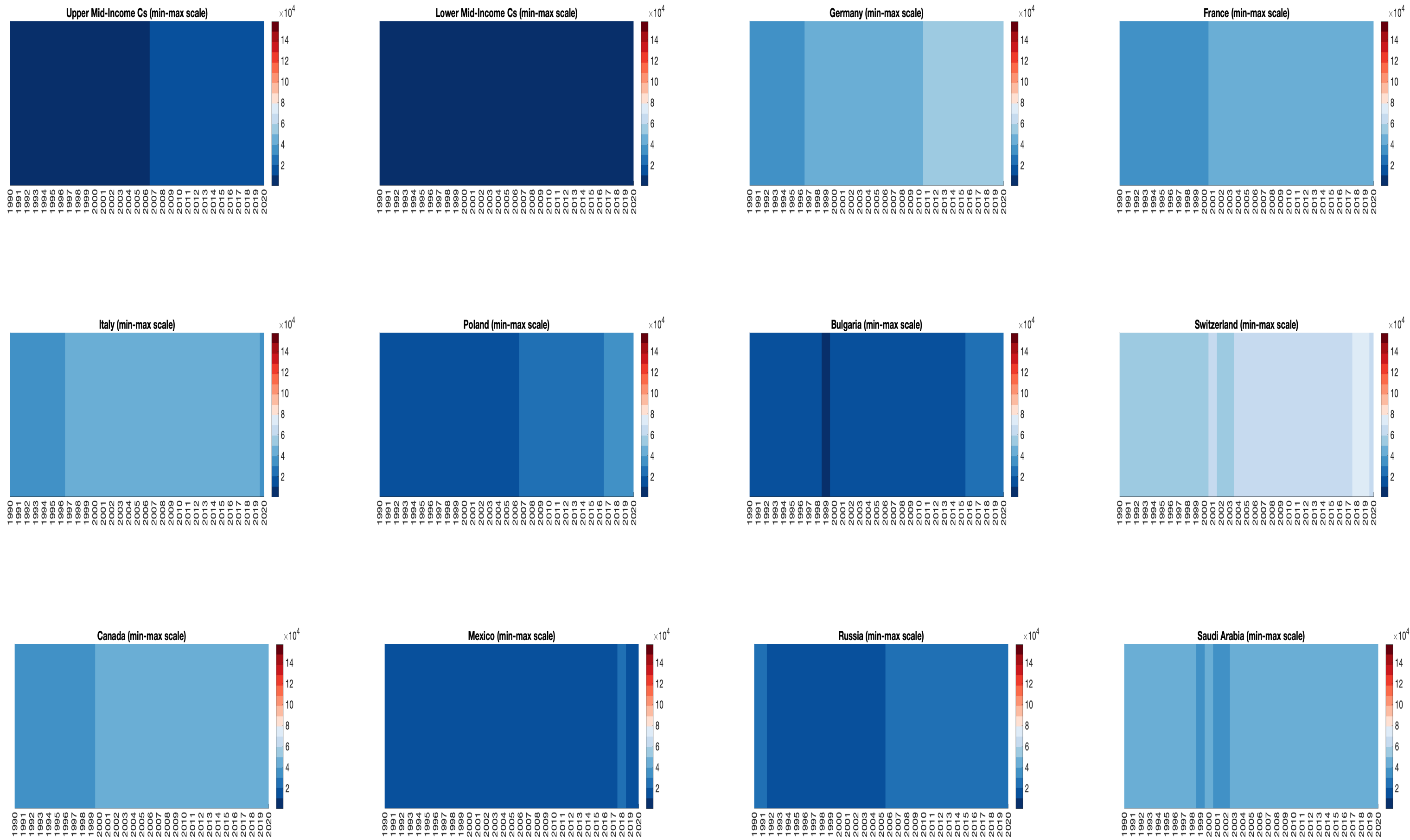
This is typical for Switzerland, transitioning along the lightest blue nuances, and also for the richer countries in our sample, such as the US and Germany, and less so for the group of the high-income countries, to which the mentioned three advanced economies belong. Comparing the nuances of the blue for the remaining countries and groups allows further to clearly see in nuances of the blue their relative standing in a particular year as well as their progress across years. Such a comparison makes the differences between the countries evident, and we can see that in many cases the colormaps allow a stark contrast between any two compared economies, even similar ones, e.g., the UK and France, or China and Brazil, or Australia and Canada, or Poland and Bulgaria.

Figure 10: GDP pc at PPP in International USD of 2017 – Comparable Colors Obtained via a Scale between the Min and the Max across the Globe for Our 1st Subsample



Note: 12 groups or countries: the vertical and horizontal scales are kept identical on all 12 graphs on purpose, for a visible comparability. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

Figure 11: GDP pc at PPP in International USD of 2017 – Comparable Colors Obtained via a Scale between the Min and the Max across the Globe for Our 2nd Subsample



Note: 12 groups or countries: the vertical and horizontal scales are kept identical on all 12 graphs on purpose, for a visible comparability. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

4.5 Country Colors Comparably Defined Using a Common Scale: CO2 pc

We now turn to the graphs of dominant colormap nuances that allow direct comparisons across countries and country groups in terms of their emissions of CO2 pc, that is, the degree to which each of them pollutes the global climate. The scales of the respective global minimum and maximum now range from 0 (for several small nations in several years) to 47.7 (for Qatar in 2004) metric tons pc. Given this excessively high – in relative terms – global maximum, it is not surprising that most countries in our sample come out as dominantly green in their prevailing stripe nuances.

The countries that have the darkest nuance of green as a single color dominating through the whole 1990-2020 period are the countries that pollute the least in our sample in terms of CO2 emissions pc. These are the low-income countries, as well as Mozambique (one of that same group), the lower middle-income countries, as well as India (one of that same group), and Brazil (an upper middle-income country).

The countries that pollute the most in terms of CO2 emissions pc in our sample come out with the lightest nuances of green. These largest (in our sample) CO2 emitters are Canada, US, Australia, Russia, Germany and Saudi Arabia – all (except Russia) belonging to the group of the high-income countries.

In-between fall the countries and country groups in our sample that are 'moderate' polluters, depicted by the nuances of green in-between the darkest and the lightest nuances. Such countries are the UK, France, Switzerland, Italy, Poland, Bulgaria.

Indeed, no country or country group in our sample reaches the brown stripe nuances, which may seem encouraging and may cause some optimism. Yet, the next panel of comparative colormaps for our sample, showing the greening prosperity ratios, reverses the optimistic interpretation here into a rather pessimistic one, so let us see why.

4.6 Country Colors Comparably Defined Using a Common Scale: GPR pc

Considering, next, the comparable greening prosperity ratios by country or group in our sample, we see in figures 14 and 15 that the brown discouragingly dominates. Indeed only a few countries (the UK, France, Switzerland and – with some reversals – Mozambique) manage to come out of the dark brown into a lighter brown near the end of the period 1990-2020.

Again, the absence of green nuances is explained by the dominance of about a dozen economies with excessively high greening prosperity ratios, as we discuss in more detail in the online appendix. Indeed, and as becomes clear in the spikes of the cross-section bar figures for all countries in the world in the appendix (i.e., figures 36 and 37), the min and the max on this indicator range in our comparative scales from a global minimum of about 1000 ‘discounted’ USD of 2017 (for many countries) to a global maximum of nearly 120’000 ‘discounted’ USD of 2017 (for countries such as Macao, for example in 2010 as visible in the mentioned bar plots). Relative to such extremely high levels of the global maximum in our panel data, more generally, the identical scales on the right-hand side of all colormap graphs here clearly justify the brown-nuanced prosperity ratios displayed by our sample.

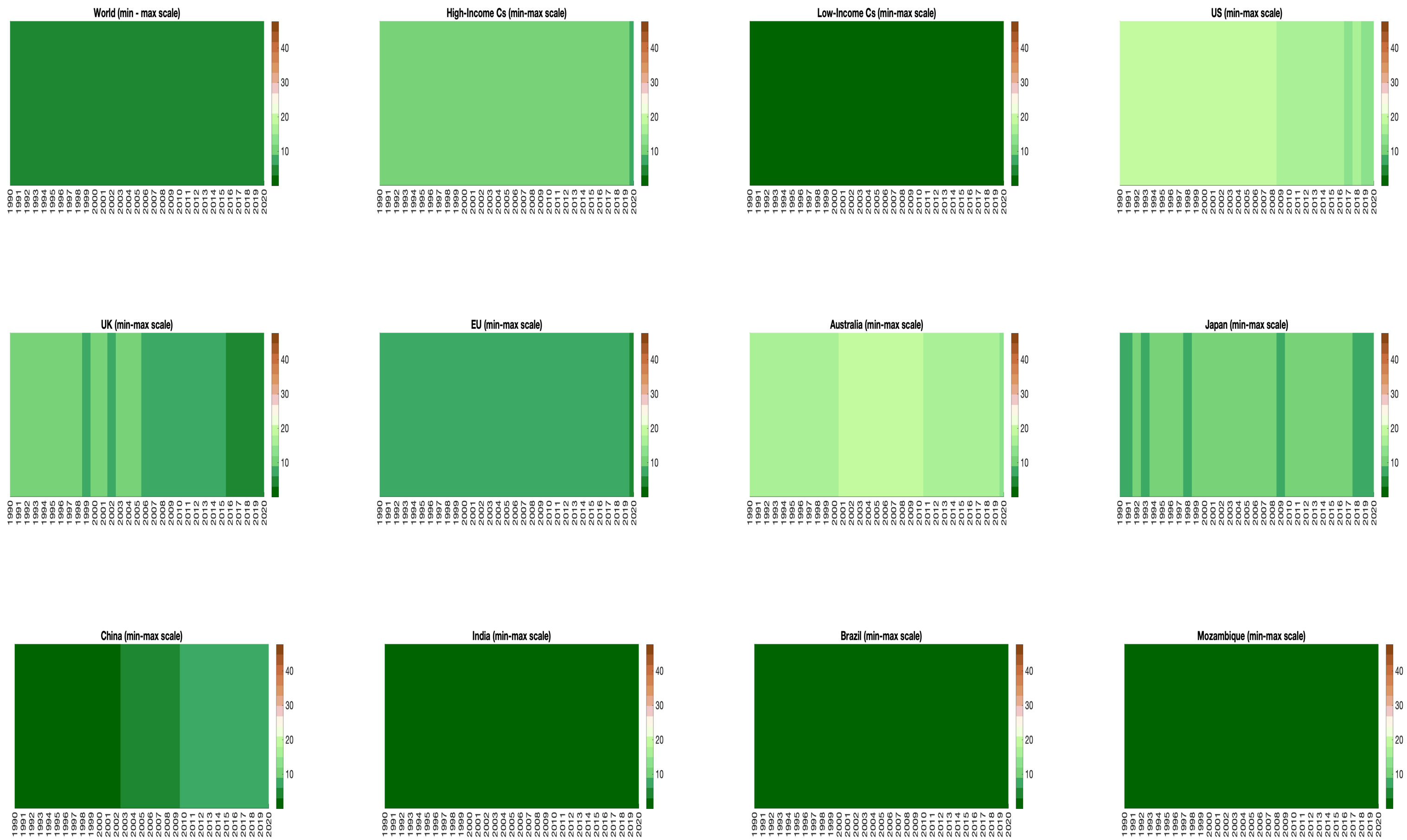
4.7 All Countries in Cross-Sections of Stripes across the Globe

We now present a final aspect of our greening prosperity stripes, visualizing them in colormaps that encompass the whole World Bank database of 218 countries and 48 groupings, and this is done for four cross-section years considered (1990, 2000, 2010 and 2020) and for the three indicators we focus on (GDP pc, CO2 pc and GPR pc).

What this colormap cross-section perspective confirms is the dominance of the nuances we already highlighted and interpreted: blue for the GDP pc indicator, with about a dozen red stripes for the richest countries, in figures 16 and 17; green for the CO2 pc indicator, with about a dozen brown stripes for the most polluting countries, in figures 18 and 19; and brown for the greening prosperity ratio pc indicator, with about a dozen green stripes for the countries that either pollute the least, even if poor, or do not pollute that much, given their excessive GDP pc levels, in figures 20 and 21.

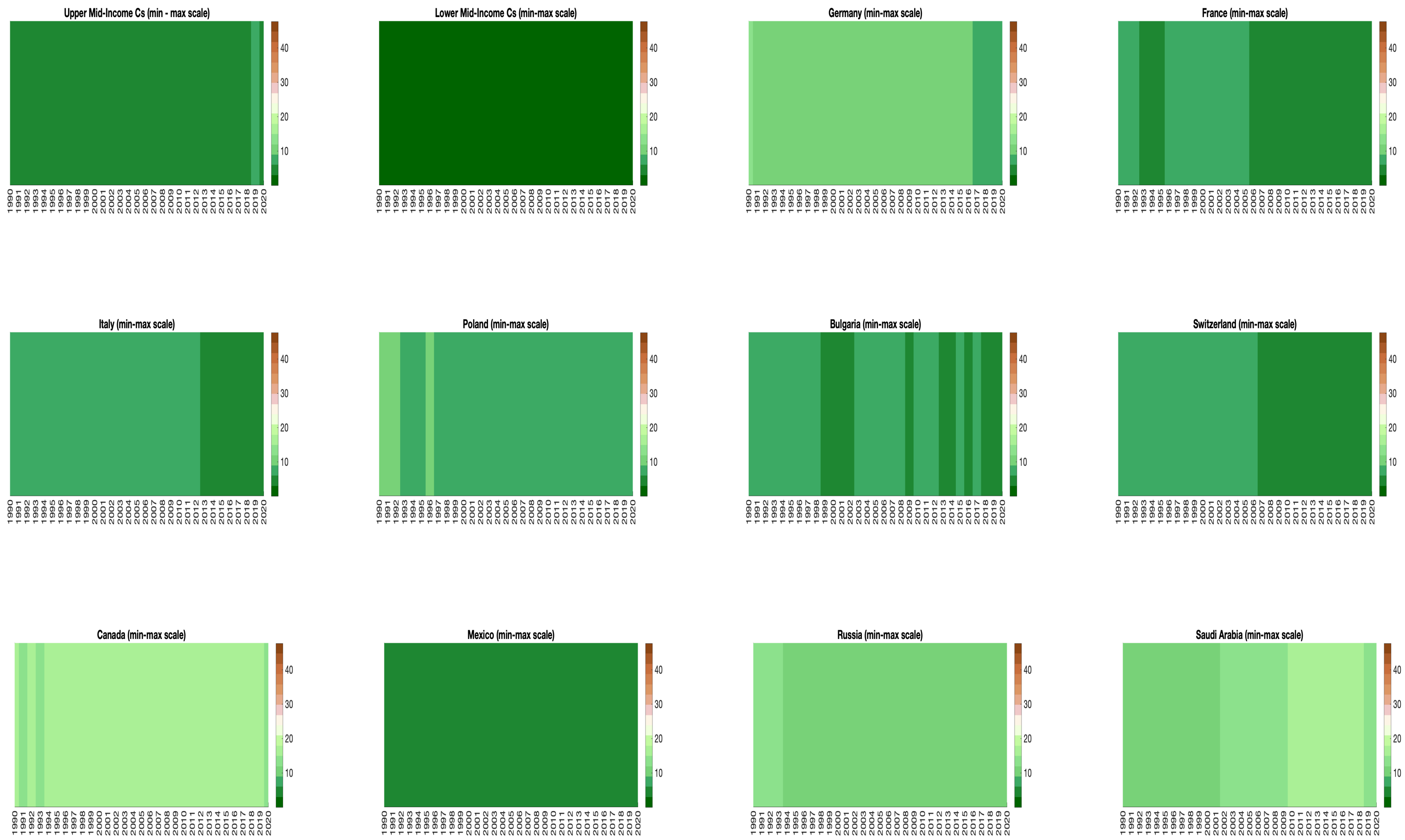
Due to the page limit, we relegate to the online appendix any further discussion on these (colormap) stripe cross-section analogs of the conventional cross-section (bar-graph) visualization of the same data, with country and group names and numbers provided by the World Bank data base we employed, as in Figure 3. Of course, the illustrative, pedagogic and exhaustive value of the cross-section stripe visualization of environmental deterioration and its desirable reversal across the globe has an additional power over the conventional plots in the online appendix that we hope to have demonstrated with this paper.

Figure 12: CO2 pc in Metric Tons – Comparable Colors Obtained via a Scale between the Min and the Max across the Globe for Our 1st Subsample



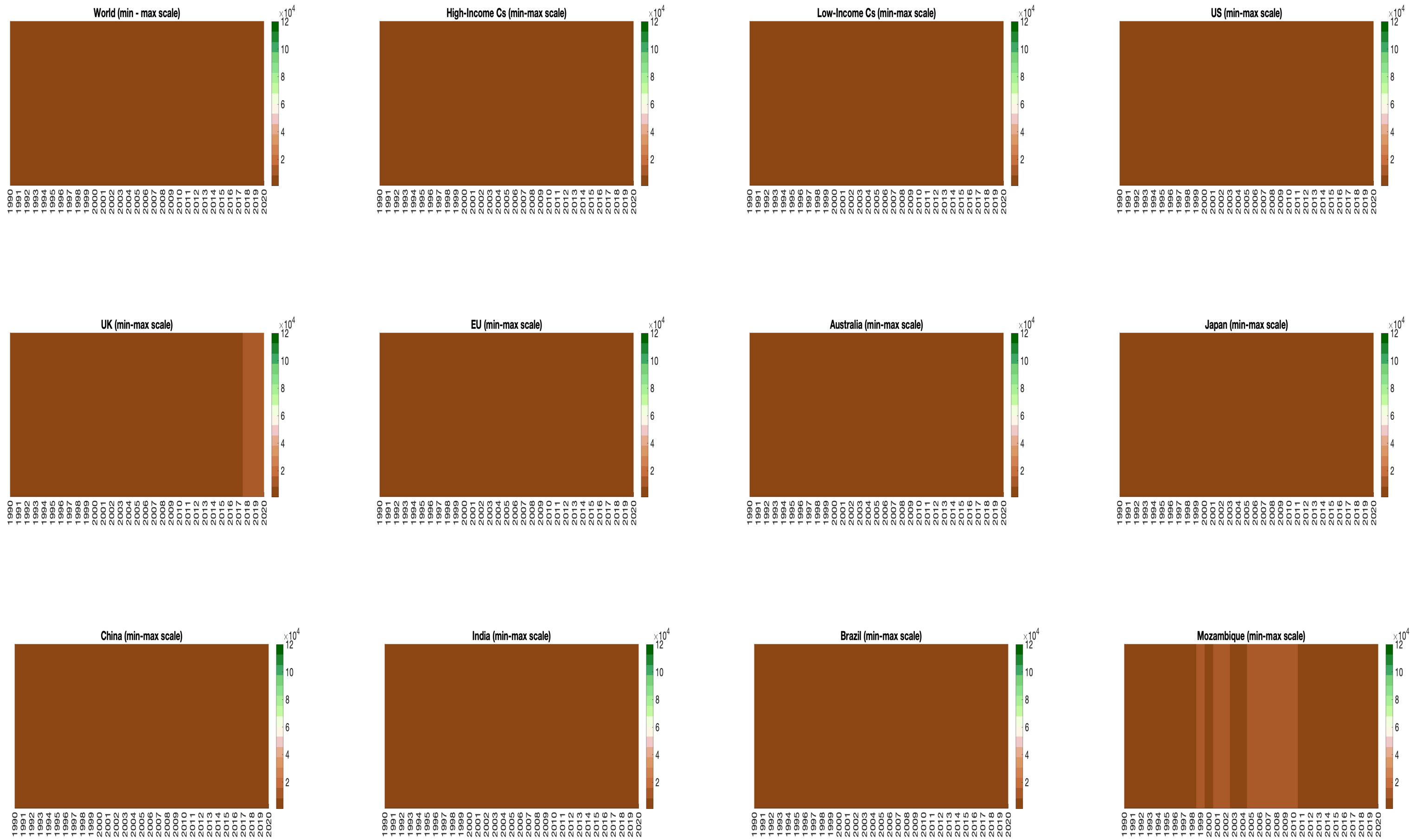
Note: 12 groups or countries: the vertical and horizontal scales are kept identical on all 12 graphs on purpose, for a visible comparability. *Source*: World Bank, `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

Figure 13: CO2 pc in Metric Tons – Comparable Colors Obtained via a Scale between the Min and the Max across the Globe for Our 2nd Subsample



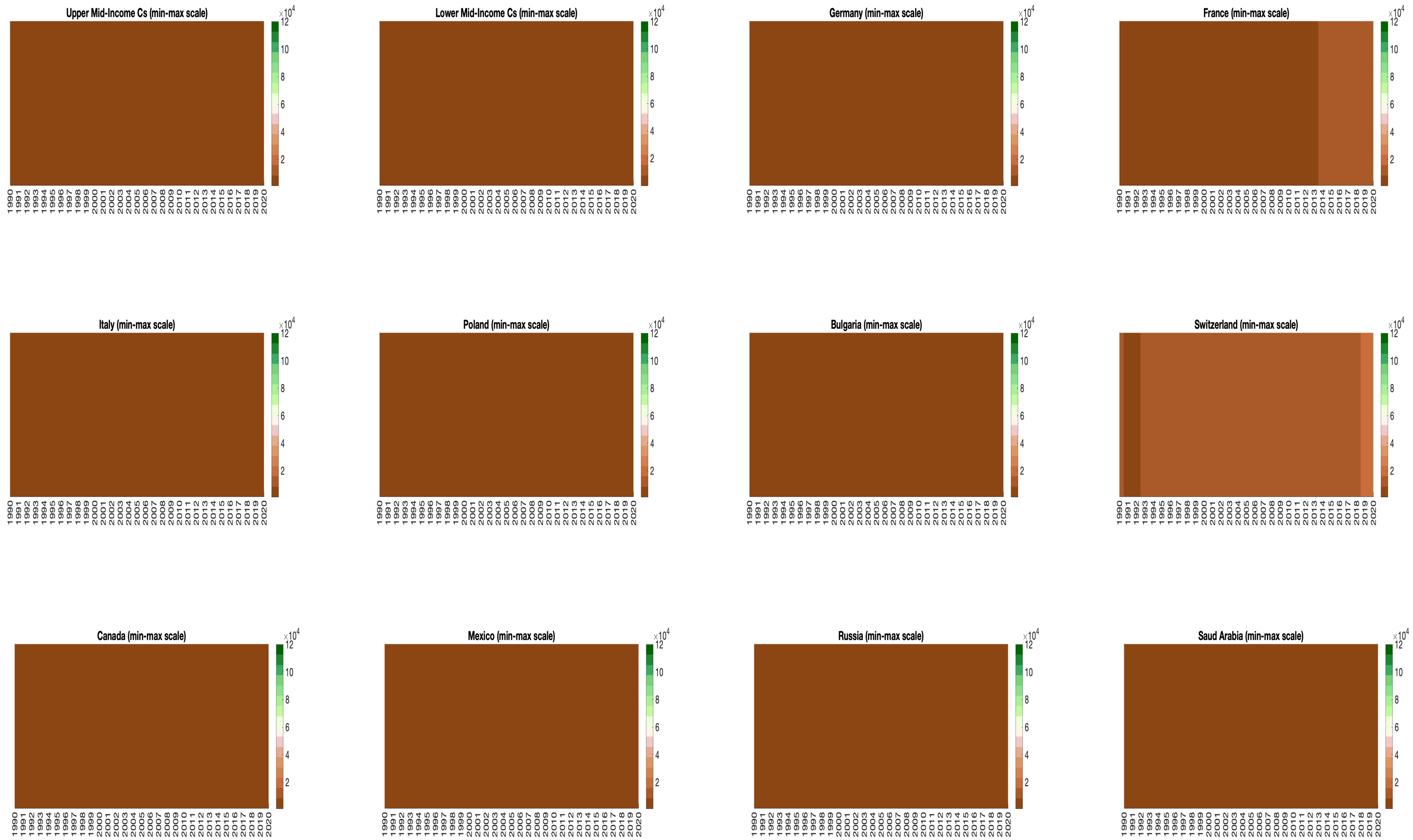
Note: 12 groups or countries: the vertical and horizontal scales are kept identical on all 12 graphs on purpose, for a visible comparability. *Source*: World Bank, `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

Figure 14: Greening Prosperity pc at PPP in International USD of 2017 'Discounted' by CO2 Emissions pc in Metric Tons – Comparable Colors Obtained via a Scale between the Min and the Max across the Globe for Our 1st Subsample



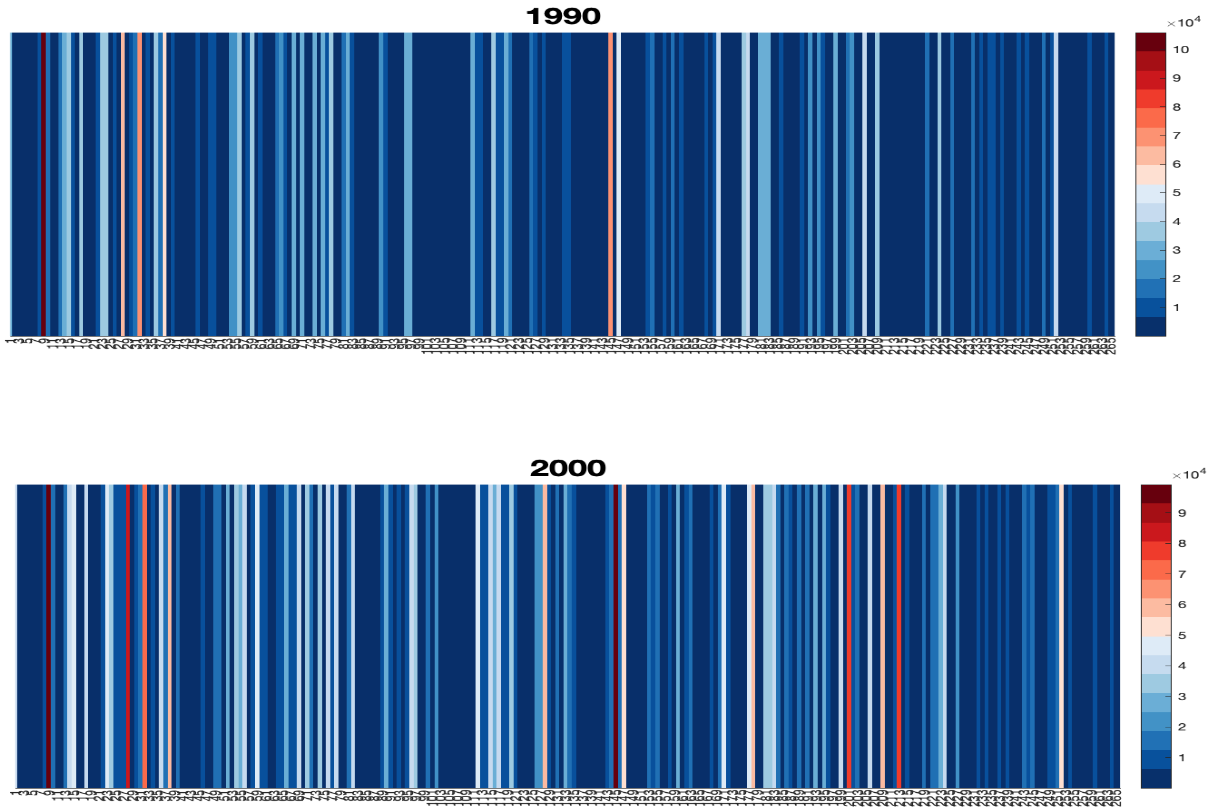
Note: 12 groups or countries: the vertical and horizontal scales are kept identical on all 12 graphs on purpose, for a visible comparability. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD` and `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

Figure 15: Greening Prosperity pc at PPP in International USD of 2017 ‘Discounted’ by CO2 Emissions pc in Metric Tons – Comparable Colors Obtained via a Scale between the Min and the Max across the Globe for Our 2nd Subsample



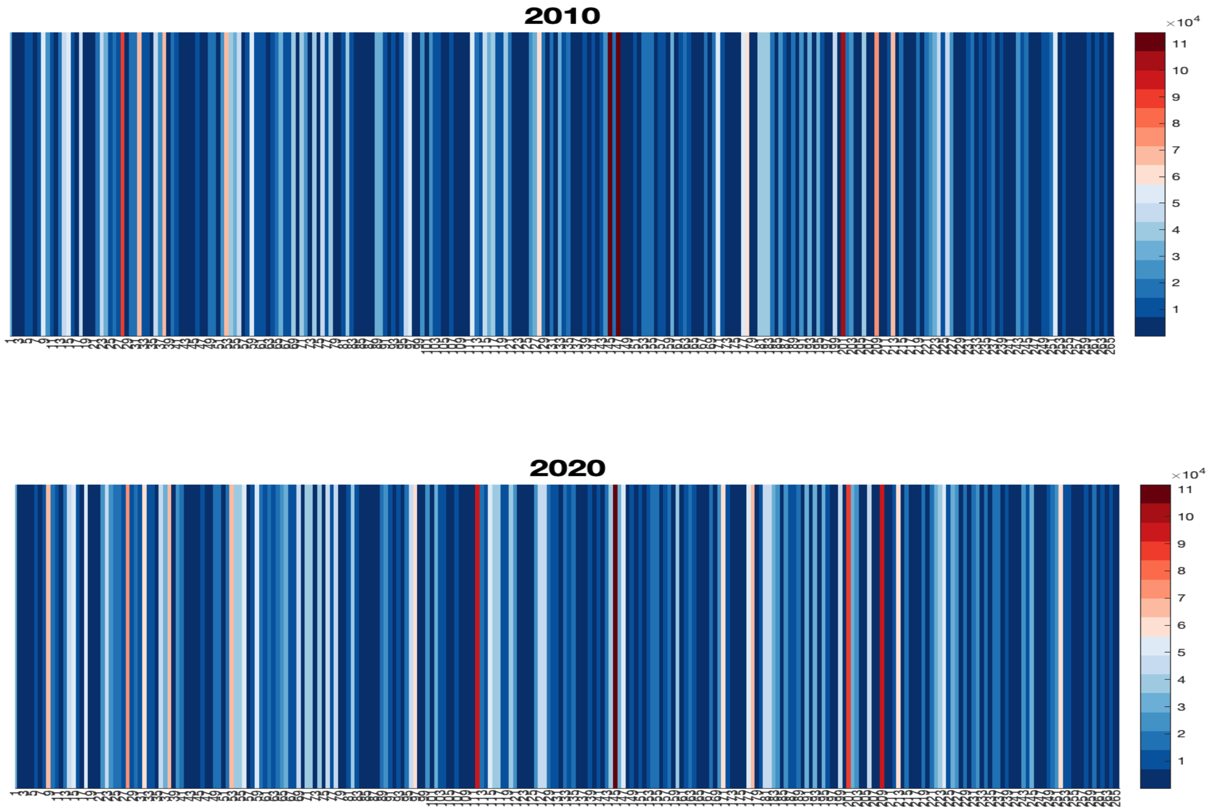
Note: 12 groups or countries: the vertical and horizontal scales are kept identical on all 12 graphs on purpose, for a visible comparability. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD` and `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

Figure 16: GDP pc at PPP in International USD of 2017 – World Cross-Section of 1990 (top panel) and 2000 (bottom panel)



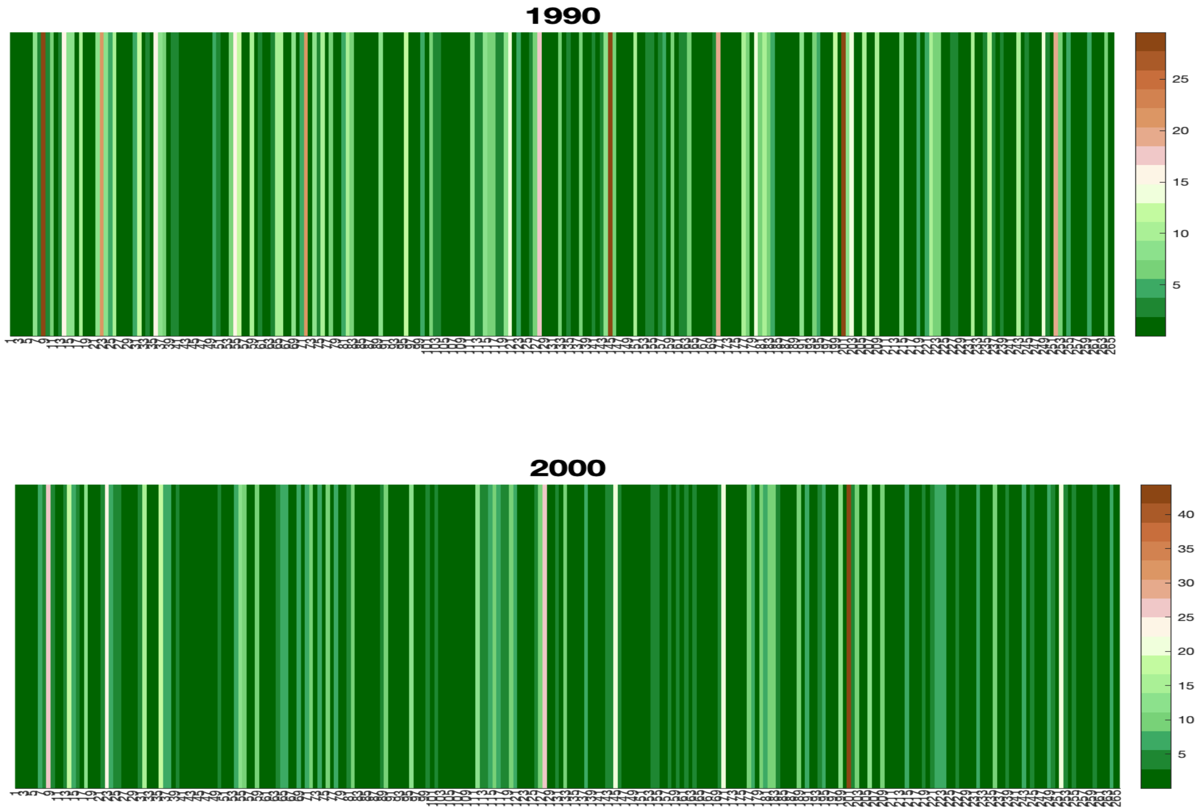
Note: Countries and country groups are listed in the order of Figure 3: please refer to it to identify a particular numbered bar on the plot. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

Figure 17: GDP pc at PPP in International USD of 2017 – World Cross-Section of 2010 (top panel) and 2020 (bottom panel)



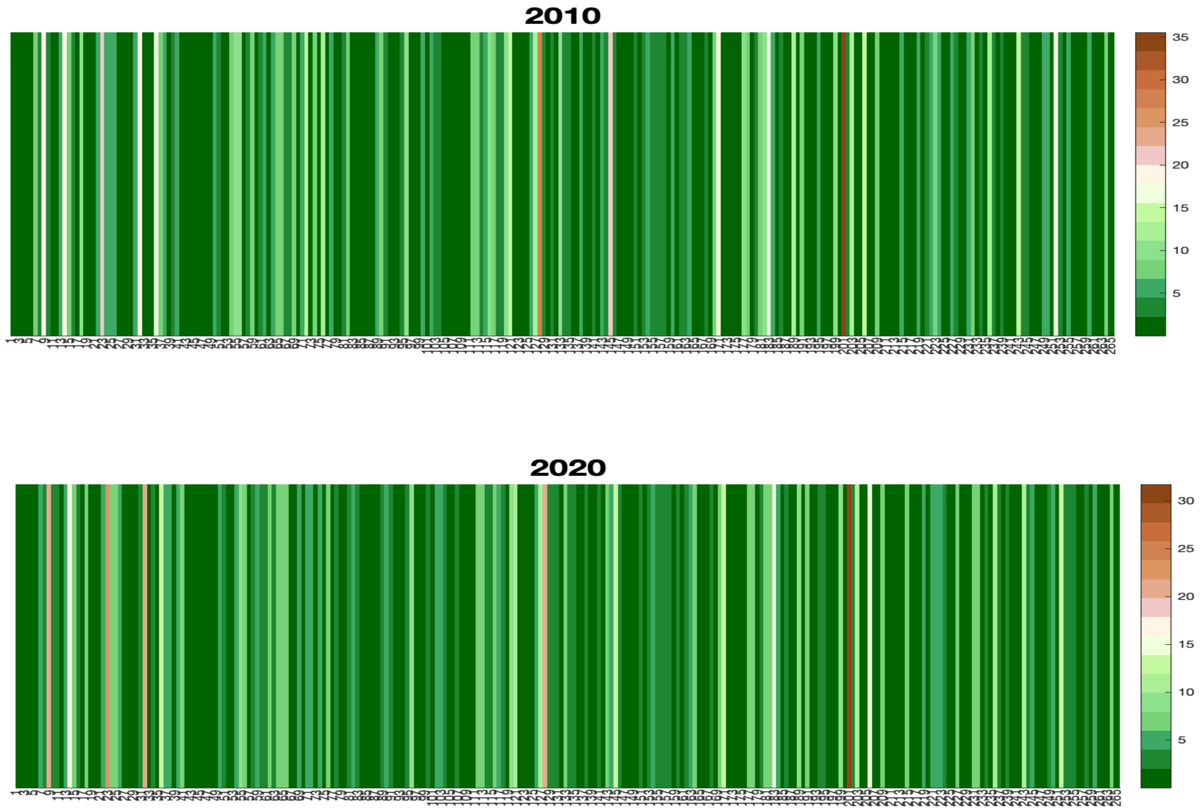
Note: Countries and country groups are listed in the order of Figure 3: please refer to it to identify a particular numbered bar on the plot. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

Figure 18: CO2 Emissions pc in Metric Tons – World Cross-Section of 1990 (top panel) and 2000 (bottom panel)



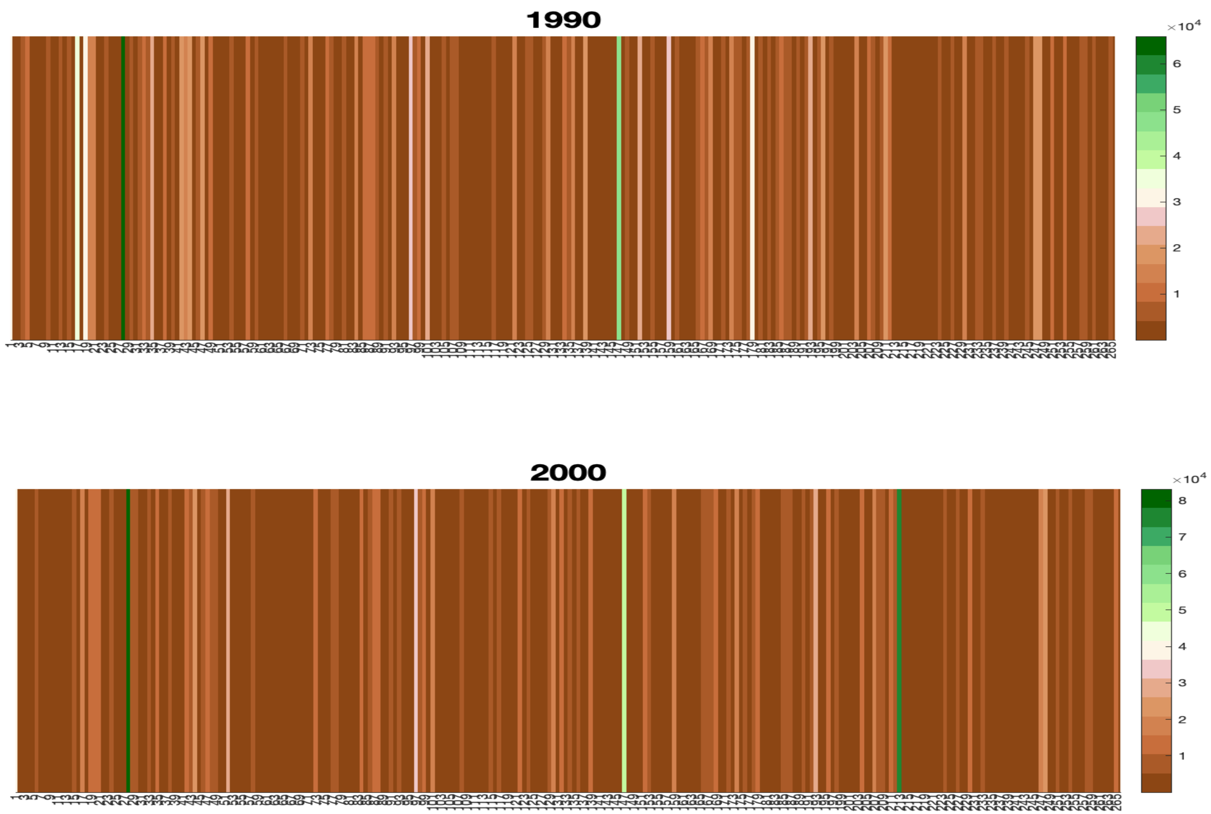
Note: Countries and country groups are listed in the order of Figure 3: please refer to it to identify a particular numbered bar on the plot. *Source*: World Bank, `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

Figure 19: CO2 Emissions pc in Metric Tons – World Cross-Section of 2010 (top panel) and 2020 (bottom panel)



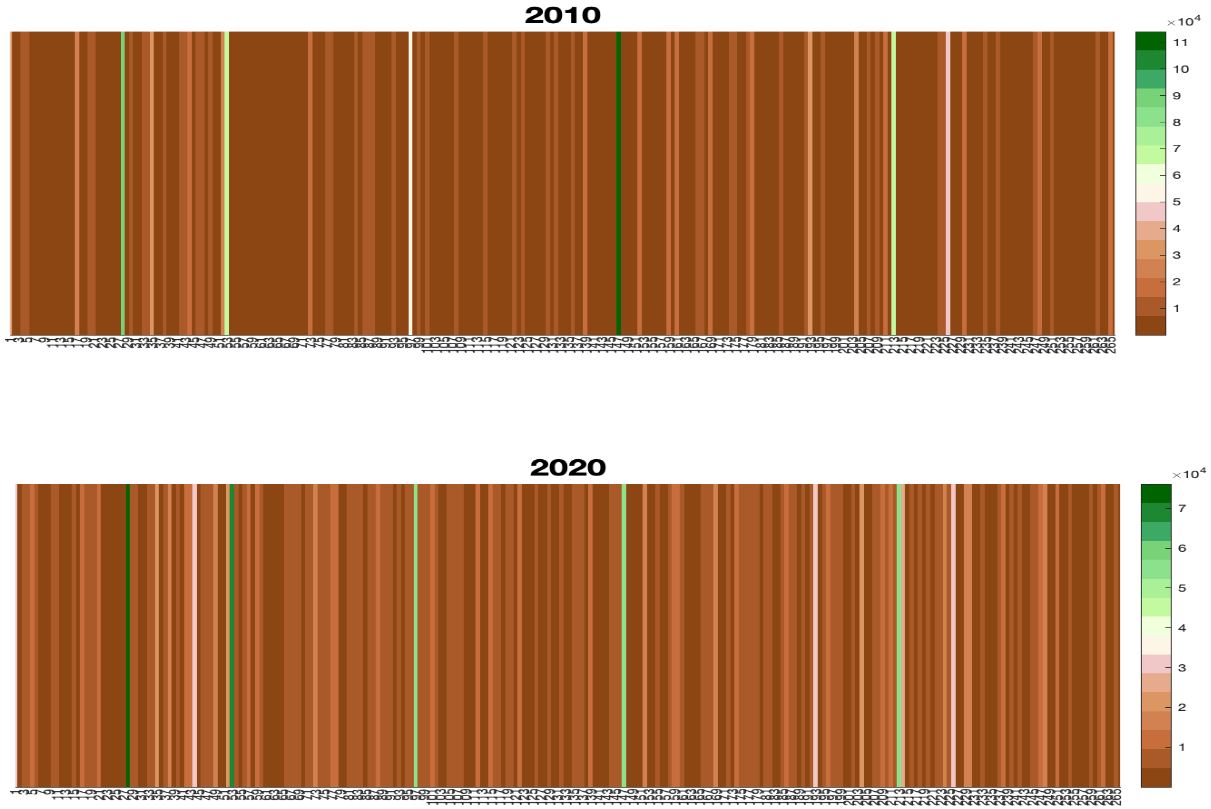
Note: Countries and country groups are listed in the order of Figure 3: please refer to it to identify a particular numbered bar on the plot. *Source*: World Bank,`https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

Figure 20: Greening Prosperity Stripes pc in PPP-USD of 2017 pc 'Discounted' by CO2 Emissions pc in Metric Tons – World Cross-Section of 1990 (top panel) and 2000 (bottom panel)



Note: Countries and country groups are listed in the order of Figure 3: please refer to it to identify a particular numbered bar on the plot. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD` and `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

Figure 21: Greening Prosperity Stripes pc in PPP-USD of 2017 pc ‘Discounted’ by CO2 Emissions pc in Metric Tons – World Cross-Section of 2010 (top panel) and 2020 (bottom panel)



Note: Countries and country groups are listed in the order of Figure 3: please refer to it to identify a particular numbered bar on the plot. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD` and`https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

5 Policy Implications

Our present work was intended mainly to propose a comprehensive and systematic visualization of the comparative degree of GDP pc, of CO2 emissions pc and of the resulting ratio of greening prosperity pc with regard to all countries and major four World Bank country groups across the globe. The purpose of the visualizations was to raise widespread awareness of the urgency of climate change mitigation, an issue of the highest order of magnitude that our world has to solve today. Hence, the policy implications of the proposed visualization are immediate and immense. In addition to raising awareness and alarm, possibly coordinating action too, our greening prosperity indicator could be directly used to track progress for each country along the goal of net zero emissions in the years and decades to come, as we argued.

A key policy implication is that academic research needs to disseminate its most important results to a mass audience, and in such a nonspecialist dissemination what matters is that 'pictures (or images) speak louder than words'. The import of the current work also lies in the effectiveness of such colormap stripes visualization, popular recently in scientific articles as well as on social media, and in addition to conventional time-series and cross-section line or bar or histogram plots. Without doubt, the use of color nuances along the naturally perceived brown-to-green scale, given the task of environmental greening at hand, constitutes the main visualization contribution in our paper. As we stressed, colors evoke emotional responses: recall Gao and Xin (2006) and Wilms and Oberfeld (2018) cited earlier.

To link once again the proposed work here with the immediate policy implications it attempts to address, by visualization and hence raising awareness and possibly coordinated action worldwide, we could restate the huge concern in science and media recently that 2023 has become the warmest year on record. Indeed, the summer of 2023 was already the hottest on record too. Data from, e.g., the European Union Climate Change Service cited by Reuters[6] have stressed that the three-month period from June through August 2023 surpassed previous records by a large margin, with an average temperature of 16.8 degrees Celsius (62.2 Fahrenheit), i.e., 0.66 C above average in August 2023. At the same time, the global ocean saw the warmest daily surface temperature on record. Furthermore, July 2023 remains the hottest month ever recorded, while August's record makes the northern hemisphere's summer the hottest since records began in 1940 (by this particular data source).

What is really worrisome is that August 2023 is estimated to have been around 1.5 degrees Celsius hotter than the pre-industrial average for the 1850-1900 period. Whereas

[6]https://www.reuters.com/business/environment/august-was-hottest-ever-recorded-third-straight-month-set-record-2023-09-06/

– as widely known – pursuing efforts to limit the global temperature increase to 1.5 degrees Celsius compared to these pre-industrial levels is the goal of an unprecedented effort in international cooperation, namely, the Paris Agreement on climate change signed by 196 countries in 2015 (and ratified by 2020).

A related aspect of the policy implications of this ‘positive’ (awareness and visualization) paper is our conviction that the world should immediately act to save the planet, from a normative point of view too. In Ferret Mas and Mihailov (2021)[7], we have already addressed the issue of climate change mitigation from the perspective of moral philosophy and the politics and economics of intergenerational climate justice. Our 2021 DP proposes a rich menu of policy options, in particular some novel and unconventional ones, to resolve the climate mitigation urgency immediately but flexibly. We incorporate growth, nominal interest, expected inflation and an option for partial repayment of public debt in the overlapping-generations model of Sachs (2015) and discuss how the global network of central banks could implement a *2nd-best* climate mitigation policy (the *1st-best* is a uniform carbon tax in all countries in the world that has proved hard to agree and enforce). Similarly, but even without full repayment, we find such kind of policy, which we label ‘green quantitative easing, or green QE’, to be Pareto-efficient across generations.

6 Concluding Remarks

The Reading climate, or warming, stripes are now world-famous. They are everywhere, including on local trams and buses all over the world, raising awareness of environmental pollution and reminding us that we need to act immediately to reverse climate change. The University of Reading now complements the above stripes with its greening prosperity stripes, and these may serve well the purpose of measuring and visualizing clearly, in colormap nuances, progress along the net zero goal by country. Similarly to what Professor Hawkins has achieved with regard to his climate stripes, a website hosted by the University or, perhaps, the World Bank, could raise awareness and track the greening prosperity stripes for all countries across the globe in a straightforward (indeed, ‘colorful’) and informative way.

In this initial work, and paper, a basic concept, its measurement and visualization was proposed, but much more remains to be done. In essence, we have attempted to show the visualization power of the colormap approach, depicting intuitively and comparing in a visual way that is easy to convey and understand even by nonspecialists similarities and differences in all countries around the world in terms of GDP pc, CO2 emissions pc and the proposed here greening prosperity stripes pc.

[7] `https://www.reading.ac.uk/web/FILES/economics/emdp202116.pdf`

Possible avenues for further work remain, e.g.: (i) prosperity may be measured along several dimensions, two of which were illustrated here (GDP pc, exhaustively, and life expectancy, minimally) – and a composite index could be constructed out of such multiple ingredients; (ii) the same applies to climate change and environmental pollution that capture the degree of ‘greening’ of the global and national economies; (iii) extensions are welcome into the direction of a more refined comparative empirical analysis and as to what we learn from it about understanding and modeling, forecasting and influencing via policy and regulation, the key forces and interrelationships at play; (iv) similar graphs could be prepared, more generally, for the global emissions of greenhouse gases (GHG), and the analysis could be extended to greening prosperity requirements and scenarios for the future.

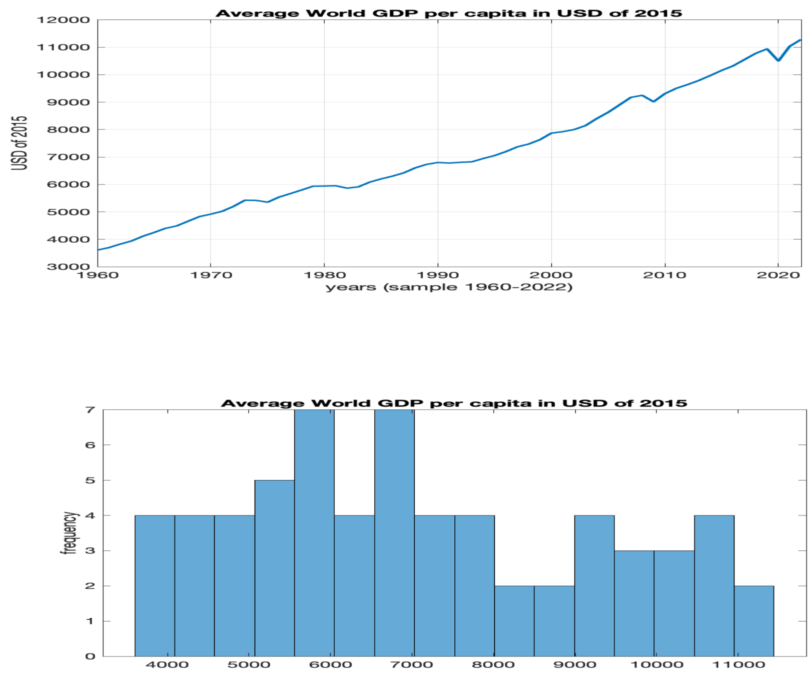
A Supplementary Online Material

A.1 Data

A.1.1 Sources of the Longest Available Data on Real GDP

The longest available comparable data on real GDP per capita, to our knowledge, are publicly available online from the World Bank.[8] We begin by first taking a look at the world as a whole.

Figure 22: Average GDP pc for the World in USD of 2015 since 1960, Level



Note: The top panel provides a time-series view, while the bottom panel complements it by a frequency dimension for the same data. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

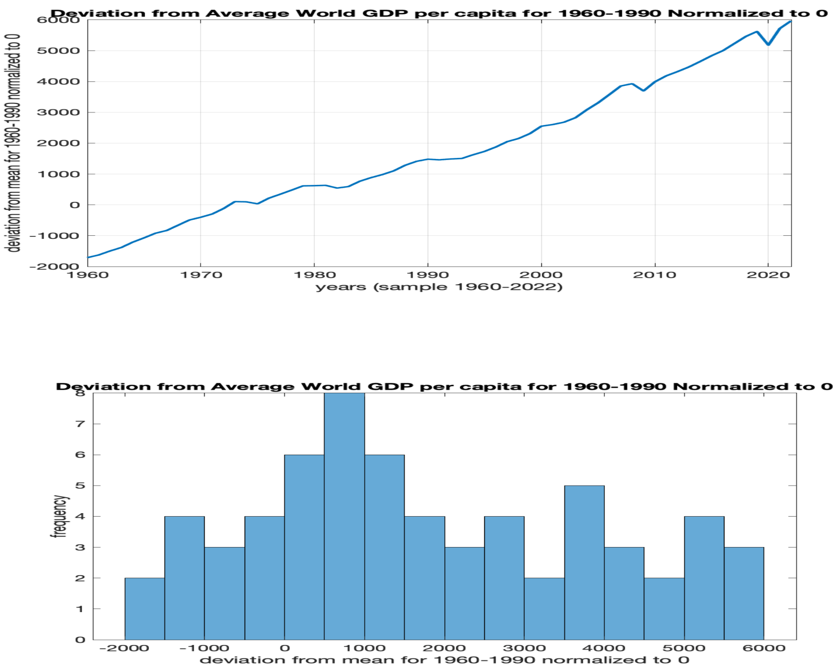
Figure 22 plots our preferred indicator (or measure, or proxy) for prosperity: namely, average world GDP per capita in constant USD of 2015, since 1960 – as this is the longest possible period with recorded comparable internationally numbers for real GDP available from the mentioned World Bank data base.

The top-panel graph presents the time-series (TS) dimension, whereas the bottom-panel graph complements it by the statistical dimension, as we will continue doing in several subsequent figures, for the sake of uniformity as well as comparability. One can clearly see the two deepest world recessions since 1960, namely, the Global Financial Crisis (GFC) in 2007-2009 and the COVID-19 pandemic in 2020. The histogram representation

[8] `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`

is less readable, even if it shows that the world has roughly uniformly achieved higher GDP pc.

Figure 23: Average GDP pc for the World in USD of 2015 since 1960, Deviation from the Mean for 1960-1990 Normalized at 0



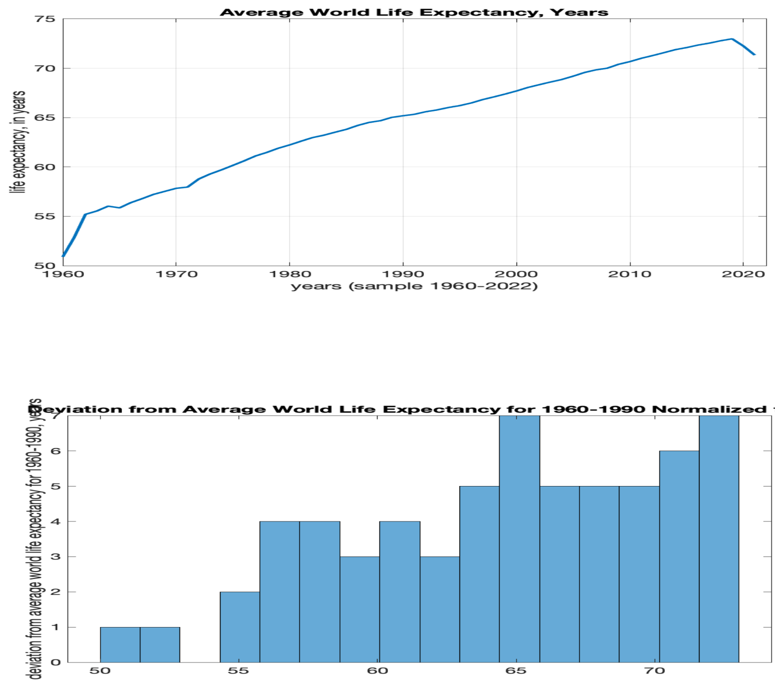
Note: The top panel provides a time-series view, while the bottom panel complements it by a frequency dimension for the same data. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

Figure 23 plots the same data as in Figure 22, but now – as meteorologists tend to represent similar data – in terms of 'anomalies', or deviations from the average world GDP pc for 1960-1990 when the latter 'steady state' is normalized at 0. This view of the same underlying information in the top/TS panel highlights how after the first oil crisis in 1973 the world has surpassed the average, or 0, line and has permanently headed up and away from it, even if with occasional recessions, typical for the business cycle. The asymmetric distribution with a long upper/right tail testifies to the same conclusion in the bottom/histogram panel.

A.1.2 Sources of the Longest Available Data on Life Expectancy

It is well-known that, while generally accepted as the most common and usually precisely measured indicator of prosperity or well-being, GDP pc has a number of potential weaknesses. Therefore, the literature has concluded in favor of using several indicators – not just to quantify and compare internationally well-being or prosperity as in our context here, but also other aspects of socio-economic comparisons of achievement or failure – e.g., as in Boyce et al. (2016) we cited. Hence, to complement our preferred prosperity measure, we next provide similar information, in Figure 24, on average world life expectancy in years, since 1960 and again according to the same World Bank data base accessible online.

Figure 24: Average Life Expectancy for the World in Years since 1960, Level



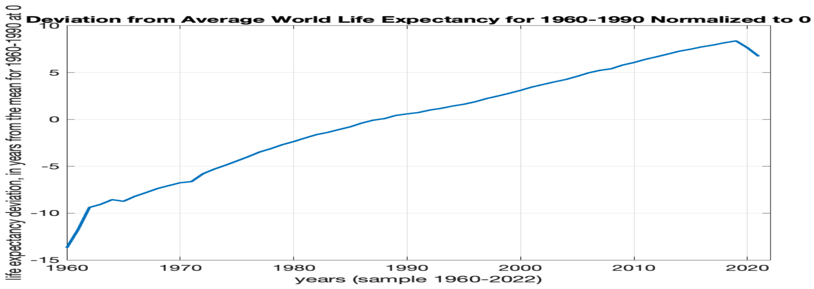
Note: The top panel provides a time-series view, while the bottom panel complements it by a frequency dimension for the same data. *Source*: World Bank, `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

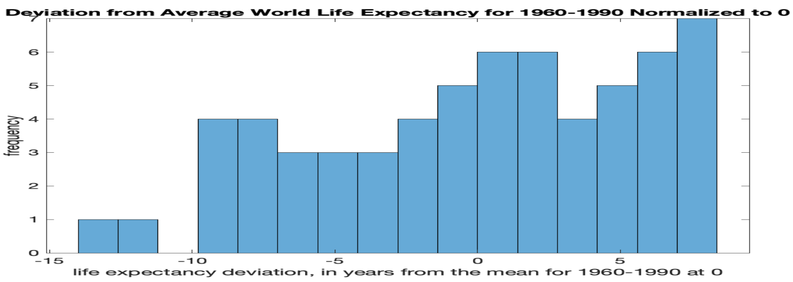
What may not be widely understood and appreciated is that during 62 years of time, between 1960 and 2021, life expectancy on the Earth has increased, on average, by 20 years, from about 51 to about 71, that is, about 1 year of life has been added with every 3 years of progress of time. This looks like a considerable achievement, and has certainly been due to improved public health service and other socio-economic advancement across the globe. Of course, the average trend hides heterogeneities by country, and this pace of improvement has not been available to some of the population on the planet. The other curious fact to note is that, differently from GDP pc, as plotted earlier, average life expectancy for the world has witnessed its most impressive drop in two consecutive years, 2020 and 2021, at the very end of our sample. This has certainly to do with the COVID-19 pandemic.

Figure 25 plots the same data as in Figure 24 but – to represent this statistical information by analogy with the approach in meteorology regarding the data on temperatures – in deviation from the average world life expectancy for 1960-1990, when the latter has been normalized at 0. This view of the same data highlights the fact that since the late

1980s the average life expectancy in the world has headed above the 0 normalization and steadily upward.

Figure 25: Average Life Expectancy for the World in Years since 1960, Deviation from the Mean for 1960-1990 Normalized at 0



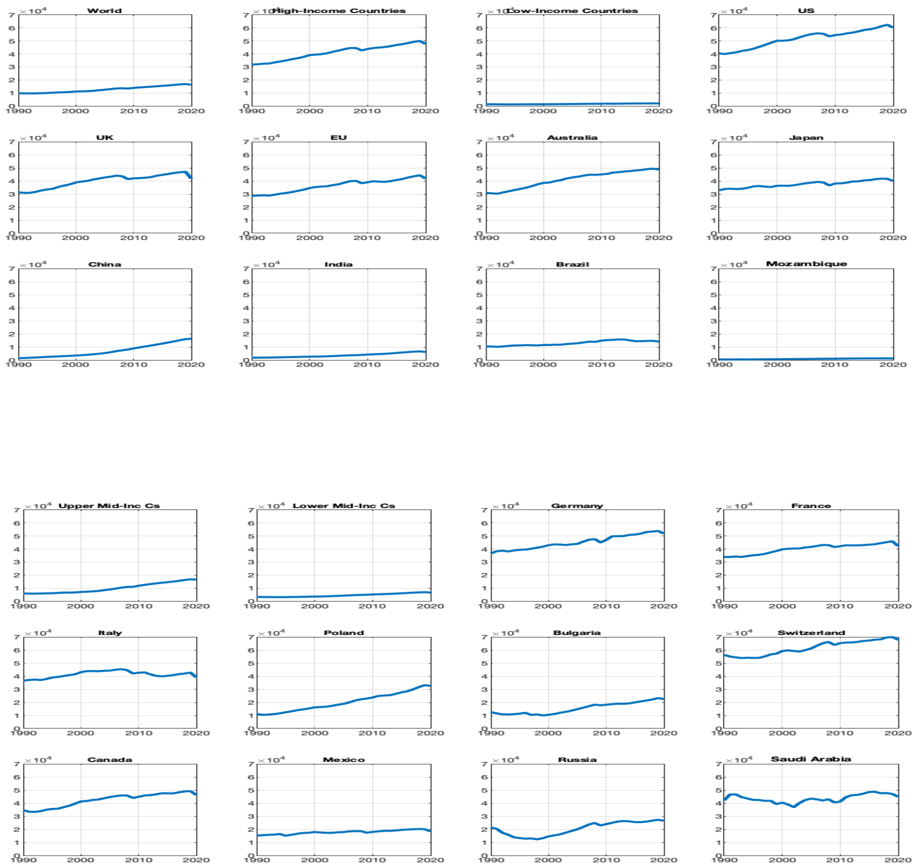


Note: The top panel provides a time-series view, while the bottom panel complements it by a frequency dimension for the same data. *Source*: World Bank, `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

A.2 Conventional Visualization

A.2.1 Comparative Time-Series Plots: GDP pc and Its Growth Rates

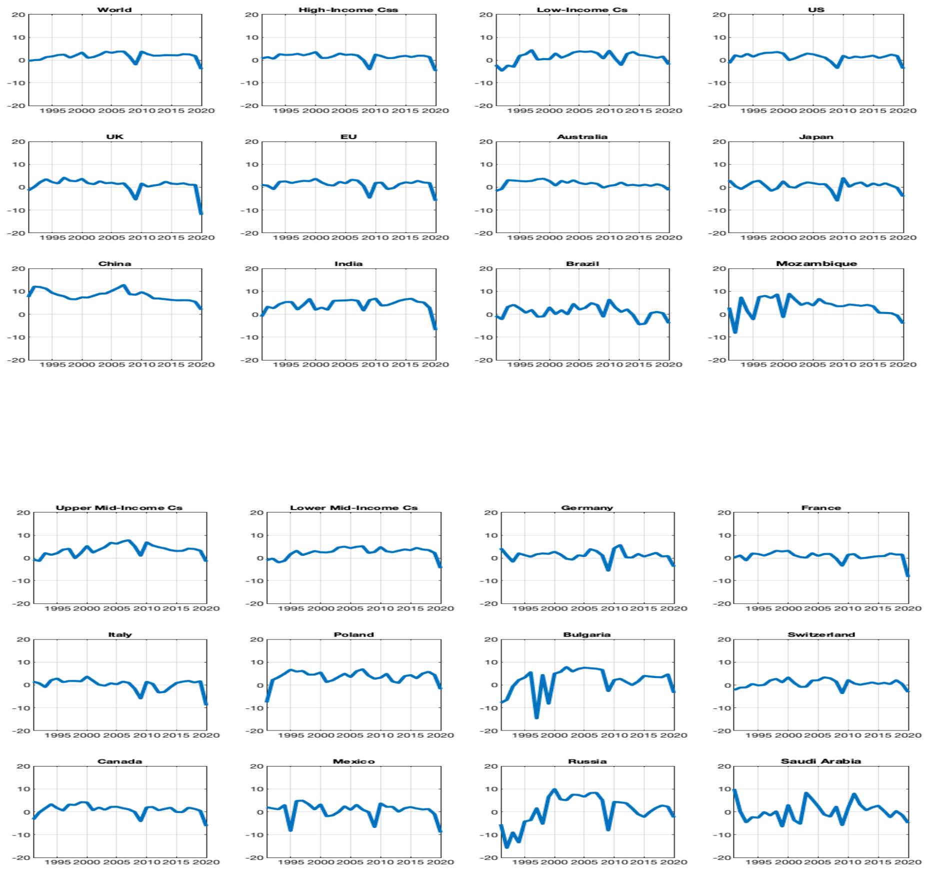
Figure 26: GDP pc at PPP in International USD of 2017 since 1990, Level



Note: The vertical and horizontal scales are kept identical on all graphs on purpose, for a visible comparability. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

Figure 26 keeps on purpose all x-axes between 1990 and 2020 and all y-axes between 0 and 70'000, to facilitate visual comparisons. Comparing the 24 graphs, each showing a time-series plot of GDP pc at PPP in international USD of 2017 drawn on the same scale vertically as well as horizontally, one can easily see the richest country (in this sample) by the end of the time-span, Switzerland, as well as the poorest one, Mozambique. One can also compare the dynamics of the same variable from the beginning of the period, in 1990. What is worth noting is the huge diversity among the countries in the sample, where Switzerland (67'766 PPP-USD of 2017) has 55 times more real GDP pc in 2020 than Mozambique (1'233 PPP-USD of 2017). However, Switzerland is much poorer in GDP pc when compared to the richest countries in the world such as Luxembourg (111'751 PPP-USD of 2017 in 2020) and Qatar (89'019 PPP-USD of 2017 in 2020) – as we saw in colormap illustrations earlier in the main text. In terms of dynamics, most national and group curves trend upward, but those for Mozambique and the low-income countries hardly make any progress over the period and remain close to flat.

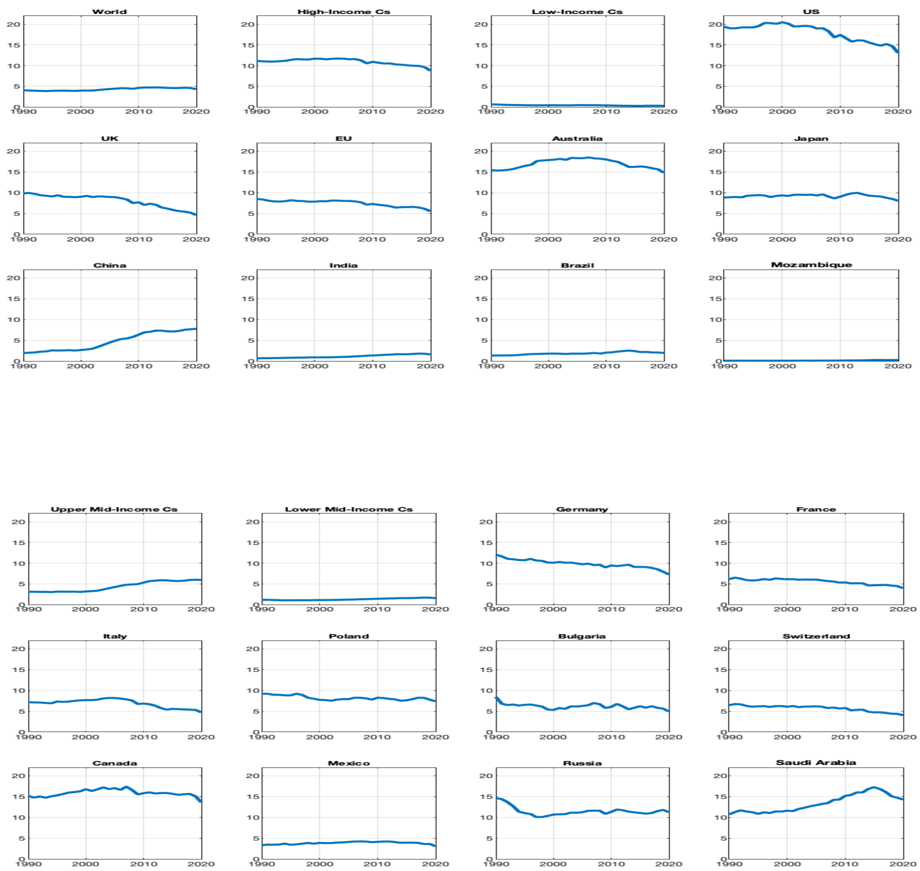
Figure 27: GDP pc at PPP in International USD of 2017 since 1990, Annual % Change



Note: The vertical and horizontal scales are kept identical on all graphs on purpose, for a visible comparability. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

Figure 27 presents the same data as Figure 26, but now in terms of annual % growth of GDP pc at PPP in international USD of 2017 (hence, losing one observation at the start of the sample in the log-differencing), and employing again the same scales on the x-axes (now, 1991-2020) and on the y-axes (now, –20% to +20%), for clear comparisons. The main pattern that one clearly sees in these 24 plots is the higher volatility (from lower levels) of GDP pc growth in less developed economies, such as Mozambique, as well as during the turbulent transition period of post-communist economies, such as Bulgaria and Russia, in the 1990s.

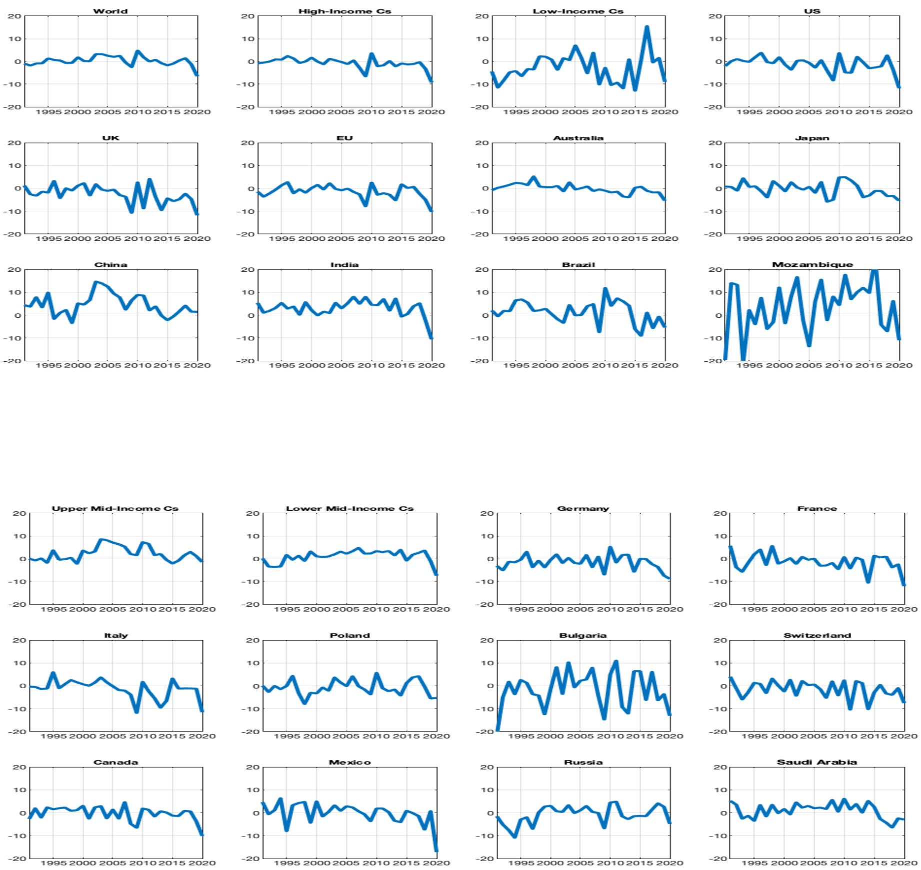
Figure 28: CO2 pc Emissions in Metric Tons since 1990, Level



Note: The vertical and horizontal scales are kept identical on all graphs on purpose, for a visible comparability. *Source*: World Bank, `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

On the other hand, comparing the groups representing the four levels of development in the World Bank classification into high-income, upper middle-income, lower middle-income and low-income countries does not seem to make a big difference in terms of growth volatility. Another common feature is the huge drop in GDP pc caused by the pandemic in all plots (except in Australia, and especially in the UK, India, Italy and Mexico) and less so during the GFC (except Australia, again). Beyond these general patterns, there is a sufficient diversity in the plotted growth curves across the countries in the sample.

Figure 29: CO2 pc Emissions in Metric Tons since 1990, Annual % Change

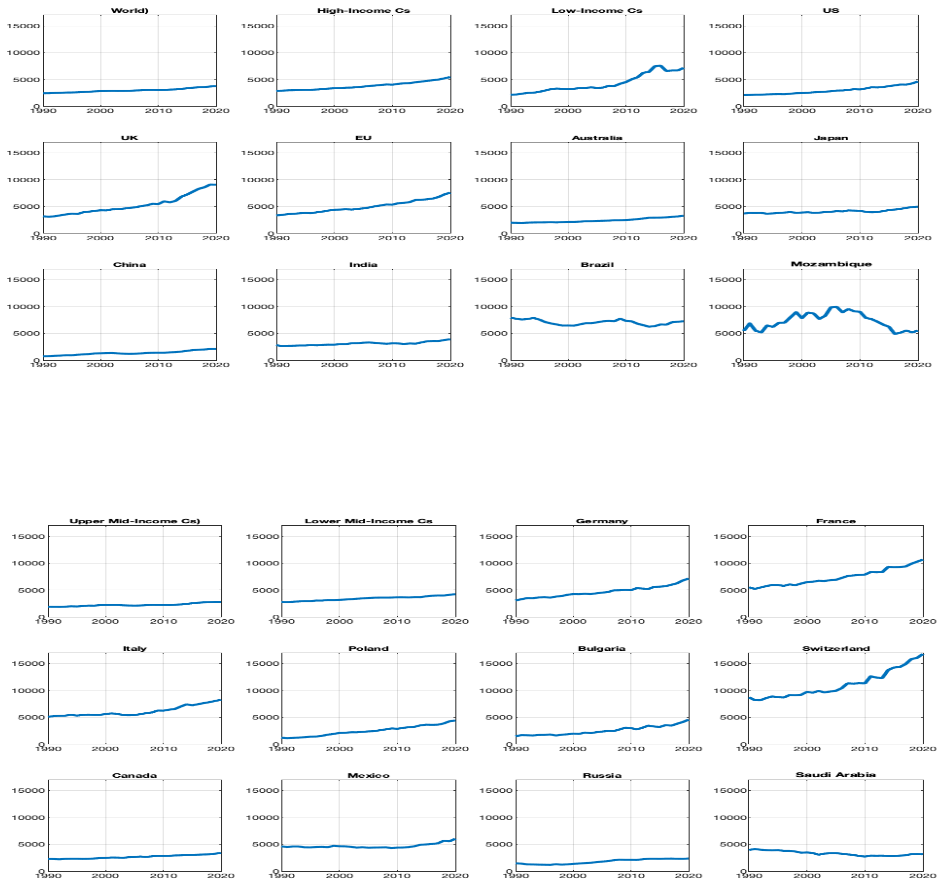


Note: The vertical and horizontal scales are kept identical on all graphs on purpose, for a visible comparability. *Source*: World Bank, `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

A.2.2 Comparative Time-Series Plots: CO2 Emissions pc and Their Growth Rates

Figure 28 depicts, in turn, CO2 pc emissions in metric tons, along the same sample in the plots and keeping the x-axes (1990-2020) and the y-axes (from 0 to 22) identical to allow for direct visual comparisons. The US has been the biggest polluter in the sample back in 1990, emitting 19.4 metric tons of CO2 pc, but has reduced this amount by nearly a third, to 13.0 metric tons in 2020. Hence, in 2020 Australia (14.8 metric tons pc), Saudi Arabia (14.3) and Canada (13.6) pollute a bit more than the US.

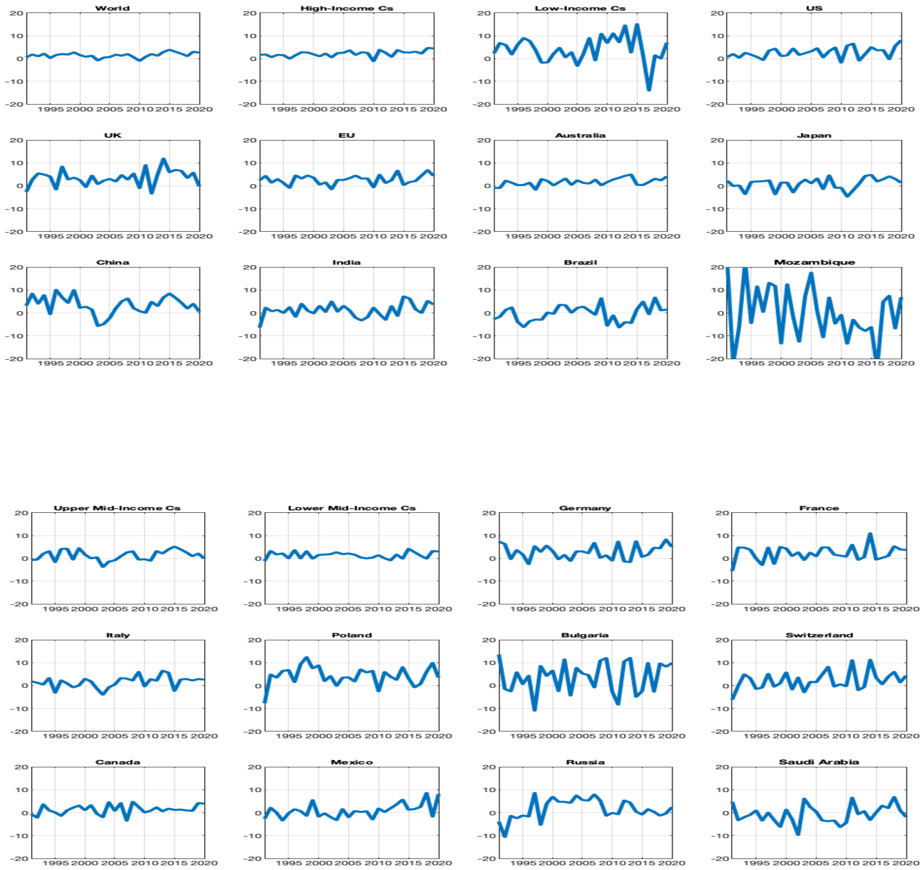
Figure 30: Greening Prosperity Ratios pc since 1990, Level



Note: The vertical and horizontal scales are kept identical on all graphs on purpose, for a visible comparability. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD` and `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`

We see that while some countries have decreased CO2 emissions pc, most obviously the UK (recall the explanation by Ritchie (2021) we cited in the literature review section of the main text), Germany and Switzerland, many countries and groups have increased them, especially China, Saudi Arabia and the upper middle-income group and – less so – India and Brazil, whereas a third subset of countries have roughly kept the same levels of CO2 emissions throughout the examined period, notably Australia, Japan, Canada, Mexico and the high-income group.

Figure 31: Greening Prosperity Ratios pc since 1990, Annual % Change



Note: The vertical and horizontal scales are kept identical on all graphs on purpose, for a visible comparability. *Source*: World Bank,`https://data.worldbank.org/indicator/NY.GDP.PCAP.KD` and `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`

The data trends illustrated here could also be interpreted from the perspective of the environmental Kuznets curve. Consistent with most studies we cited in the literature review section, we do not see a clear EKC pattern in our World Bank group classification capturing various stages of development. Namely, low-income countries have maintained, on average, and even somewhat decreased over the period of analysis, their CO2 emissions pc at a level below 1 metric ton, whereas the lower middle-income group has, on average, somewhat increased the same indicator at levels that are 2-3 times higher. Then, the upper middle-income countries have, on average, sharply increased their CO2 emissions pc since the early 2000s, reaching by 2020 levels that are of the order of 6 metric tons pc, i.e., double the size of the same measure of emissions by the lower middle-income countries. Finally, the high-income countries have, on average, somewhat reduced their CO2 emissions pc since the GFC, to about 9 metric tons pc in 2020, an amount that still remains by almost 50% higher than the corresponding indicator for the upper middle-income countries.

Figure 29 employs the same data as Figure 28, but presents them in terms of annual % growth of C02 pc emissions in metric tons, with the scales on the x-axes (1991–2020) and on the y-axes (from –20% to +20%) kept identical again to facilitate comparisons. The variety of patterns one sees in the plots spans a whole spectrum. On one end, the volatility of CO2 emissions pc is moderate, e.g., in Australia and Canada, while on the other end this volatility is huge, especially in Mozambique (but from a very low level) and – less so – Bulgaria (from an average level for our sample). The volatility of CO2 emissions pc has marked a notable increase in the last decade for the group of the low-income countries.

A.2.3 Comparative Time-Series Plots: GPR pc and Its Growth Rates

Combining the information in the preceding plots, Figure 30 now compares the greening prosperity ratios (GPR) pc of the respective groups and countries in the sample, as per our definition in equation (11) keeping the x-axes from 1990 to 2020 and the y-axes from 0 to 17'000 in all graphs for clear comparability. What we learn from this figure is that Switzerland, with 'CO2-emissions pc discounted' GDP pc in 2020 of some 17'000 USD of 2017, is the country in our sample that performs best in terms of greening its prosperity. In the Swiss case, both the growing numerator of GDP pc and the falling denominator of CO2 emissions pc – an obvious and considerable 'decoupling' since the early 1990s (see, again, Ritchie (2021) for the case of the UK) – contribute to achieving this positive trend over the analyzed period. The second-best greening prosperity indicator in the sample in 2020 belongs to France, of some 11'000 USD of 2017, and it is similarly explained by contributing 'decoupling' trends in both the numerator and denominator of the ratio.

On the other end, we find China, with the lowest greening prosperity indicator pc in our sample, of some 2'000 USD of 2017. Russia comes second-worst, with the same indicator in 2020 reaching some 2'500 USD of 2017. Perhaps surprisingly, advanced economies such as Australia and Canada are not that far from these ranges of our greening prosperity indicator in 2020. From the country groupings, only the upper middle-income countries, on average, end up with indicator of greening prosperity in the range a bit higher than that for Russia and a bit lower than those for Australia and Canada. For the countries with poor greening prosperity indicators we mentioned, it is the denominator increase or lack of a considerable improvement – i.e., absence of decoupling – that drags the ratio down, even if for some of them the numerator growth has not been impressive either (as we saw in the earlier comparative plots).

Figure 31 now visualizes in a comparative perspective the annual % growth of our greening prosperity ratios, with x-axes on all panels identical from 1991 to 2020 and y-axes from –20% to +20%. This representation of the data highlights again the unusual volatility of the greening prosperity ratio in poor countries that, in relative terms, almost do not pollute, e.g., Mozambique, from very low levels of both the numerator and the denominator. Such an excessive volatility of our indicator is also typical for the last decade or so for the group of low-income countries, on average. Excessive volatility of the ratio is also observed in the post-communist economies of Bulgaria, Poland and Russia, as well as in the rapidly growing economies of China and Brazil.

A.2.4 Comparative Cross-Section Plots: GDP pc

Commencing with the cross-section of GDP pc in 1990, plotted in Figure 32, top panel, we would highlight the following salient facts. The countries that have had back then the highest levels of GDP pc are relatively small in land size oil-exporting economies or small-territory financial centers (or tax havens): UAE (the spike at No. 9 in Figure 32) comes top, with above 100'000 USD of 2017 pc, followed by Luxembourg (the spike at No. 145) and Brunei Darussalam (at No. 32), both just above 70'000 USD of 2017 pc, then Bermuda (No. 28), just above 60'000 USD of 2017 pc, and Switzerland (No. 38), just below 60'000 USD of 2017 pc. The US (No. 252) comes 9th in this ranking.

Continuing with the cross-section of GDP pc in 2000, plotted in Figure 32, bottom panel, there is some reshuffling in the five highest pc incomes in the world, with Brunei Darussalam and Switzerland being overtaken by the 'newcomers' in the top-5, Qatar (the spike at No. 201), now 4th, and Singapore (No. 209), now 5th. The US (No. 252) has come closer to the leaders in GDP pc level, but still remains twice lower, with 50'000 USD of 2017, and has dropped out of the top-10 richest countries.

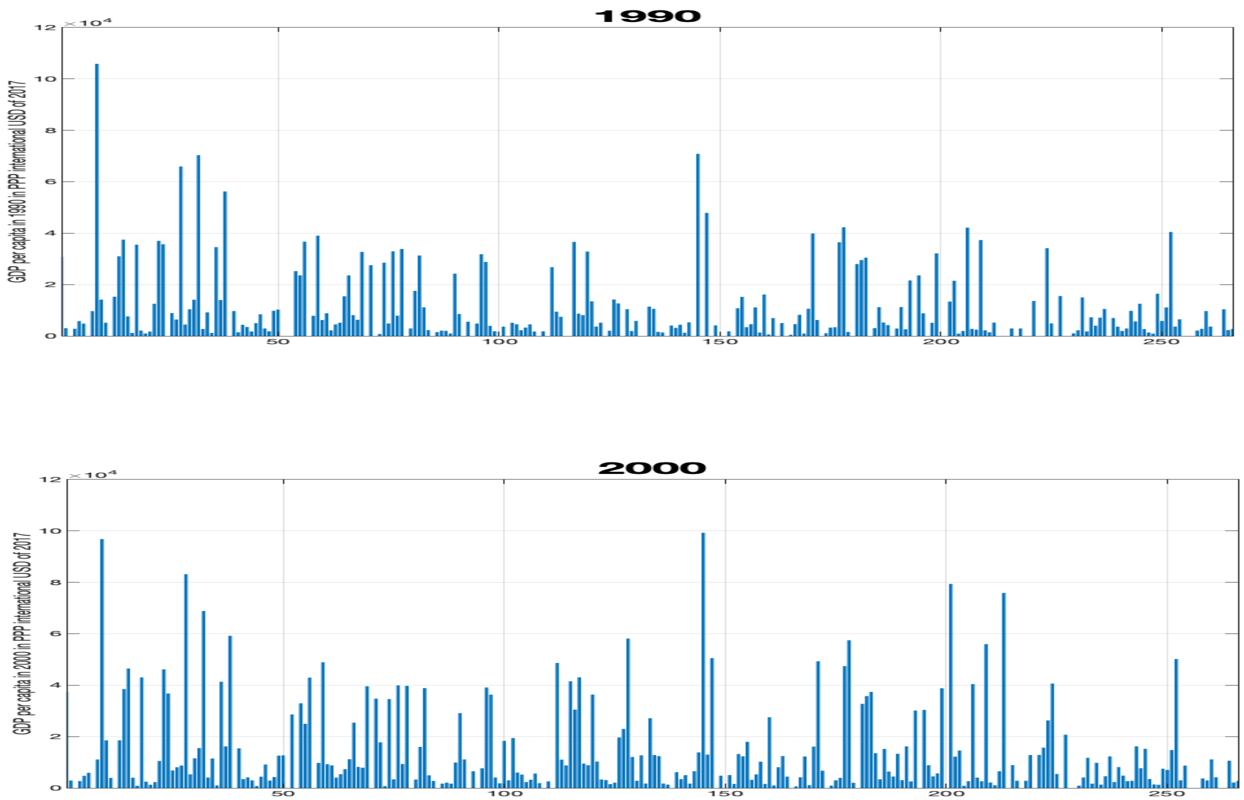
A decade later on, in 2010, Luxembourg (No. 145) and Macao, SAR China (No. 147), both with almost 120'000 USD of 2017 pc, have reached the maximum of this measure for our sample, which has fallen somewhat ever since. Qatar (No. 201), Bermuda (No. 28) and Singapore (No. 209) come next. The US (No. 252) has moved a bit higher in level of GDP pc, at close to 60'000 USD of 2017, but remains just out of the top-10.

Finally, in the last year of our sample, Ireland (No. 112), with just above 90'000 USD of 2017 pc, has jumped up in the third place, following Luxembourg (No. 145), still a bit above 110'000 USD of 2017 pc, and Singapore (No. 209), around 95'000 USD of 2017 pc. Qatar (No. 201) comes 4th, close to Singapore (No. 209), and Bermuda (No. 28) comes 5th, around 75'000 USD pc. Switzerland (No. 38), UAE (No. 9) and the Cayman

Islands (No. 53) come next, with about nearly 70'000 USD of 2017 pc. The US is 11th, with 60'000 USD of 2017.

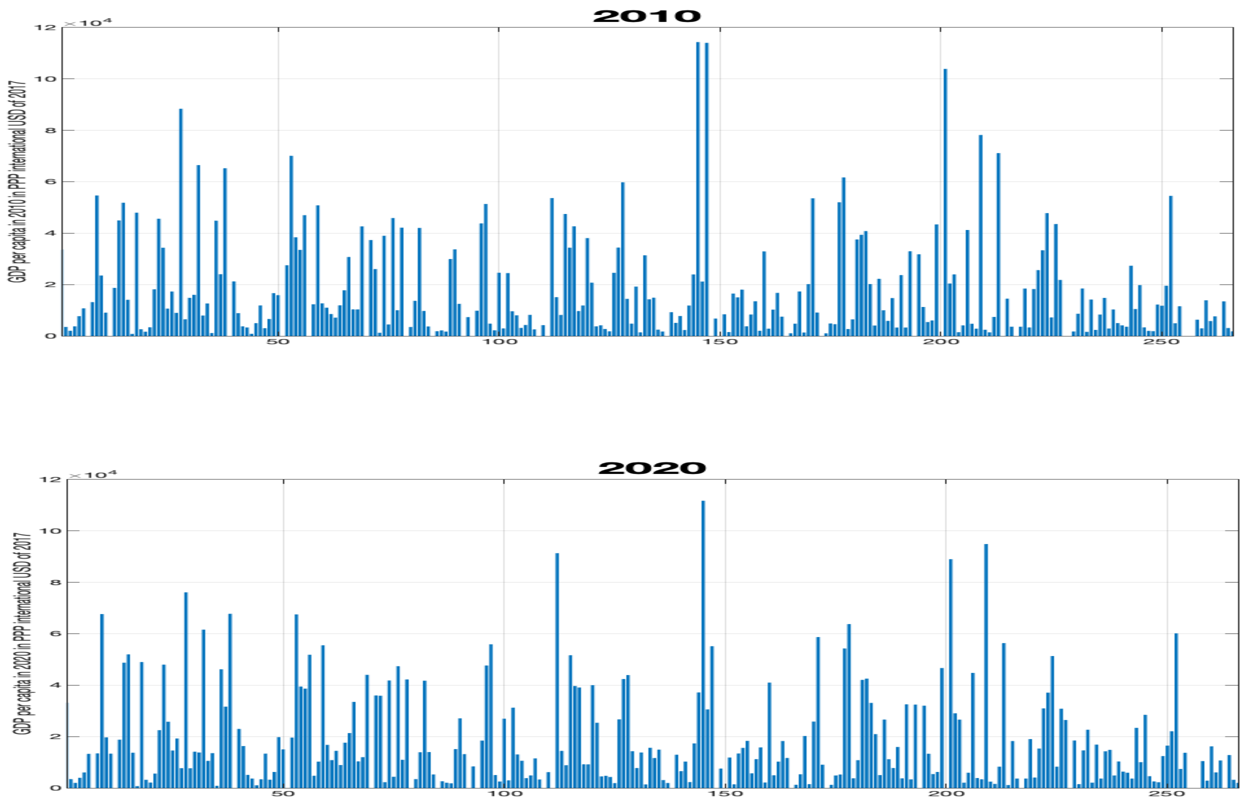
Overall, the preceding four cross-section plots demonstrate a huge diversity across the globe in GDP pc levels. While there are about half a dozen 'super-rich' economies in 1990 and in 2000 and about a dozen in 2010 and 2020, there are plenty that are doing relatively well or not too bad over the years. Of course, one can easily see on these cross-section graphs many among the poor(est) countries clustered very close above 0.

Figure 32: GDP pc – World Cross-Section in 1990 (top panel) and 2000 (bottom panel)



Note: Countries and country groups are listed in the order of Figure 3: please refer to it to identify a particular numbered bar on the plot. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

Figure 33: GDP pc – World Cross-Section in 2010 (top panel) and 2020 (bottom panel)



Note: Countries and country groups are listed in the order of Figure 3: please refer to it to identify a particular numbered bar on the plot. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`.

A.2.5 Comparative Cross-Section Plots: CO2 pc

We, next, view the same cross-section figures in the same 4 years, but now considering CO2 pc emissions in metric tons. Beginning with 1990 in the top panel of Figure 34, we could establish the following facts. The obvious, extreme polluters are not that many, and about half of them are the same small rich countries we already mentioned when considering GDP pc. Luxembourg (the spike at No. 145) was the highest emitter of CO2 pc in 1990, with almost 30 metric tons, followed closely by the UAE (the spike at No. 9) and Qatar (No. 201). Estonia (No. 72), with about 22 tons, and Bahrain (No. 23) with about 21 tons, come 4th and 5th, and the US (No. 252) is 6th, with just below 20 tons.

A decade later, in 2000, Qatar (the spike at No. 201) has jumped first, far ahead of all other countries, attaining the maximum in our sample, nearly 45 metric tons of CO2 emission pc. Kuwait (No. 128) has now moved up, with just above 25 tons pc, a value similar to that attained by the UAE (No. 9), and so these two countries have shared tightly the 2nd and 3rd ranks. Bahrain (No. 23) comes fourth with almost 23 metric tons pc. The US has remained 5th, with just above 20 metric tons pc.

In 2010, the levels of CO2 emissions have fallen 'across the board' even for the mentioned most polluting countries. This considerable improvement may have partly been due to many countries either observing their commitments according to the Kyoto Protocol of 1997 or following the example of such committed countries to reduce CO2 emissions, and partly to the reduced economic activity caused by the Global Financial Crisis of 2007-2009 and the credit crunch that was its consequence almost all over the world. Qatar, Kuwait, Luxembourg, Bahrain, the UAE, now Australia in the 6th position with CO2 emissions of about 18 metric tons pc (at spike No. 14 in the respective cross-section panel), and Brunei Darussalam form the leading 'seven', with the US arriving 8th, at nearly 18 metric tons of CO2 emissions pc.

Finally, the latest situation features the same five leading polluters at the top, excluding Luxembourg (at No. 145) from the 'seven' CO2 emitters just mentioned. Luxembourg has meanwhile managed to reduce significantly its CO2 emissions and has moved out of the 10 most polluting countries in 2020. By contrast, Australia (at No. 14) has meanwhile also achieved a slightly lower level of CO2 emissions, at just below 15 metric tons pc, which has not been sufficient to move it out of the top-10. The US, with some 13 metric tons pc is just after the 10 largest polluting countries.

Overall, one could conclude that only about a dozen countries in the world attained such by-far-excessive levels of CO2 emissions in 1990 and in 2000, and about a dozen in

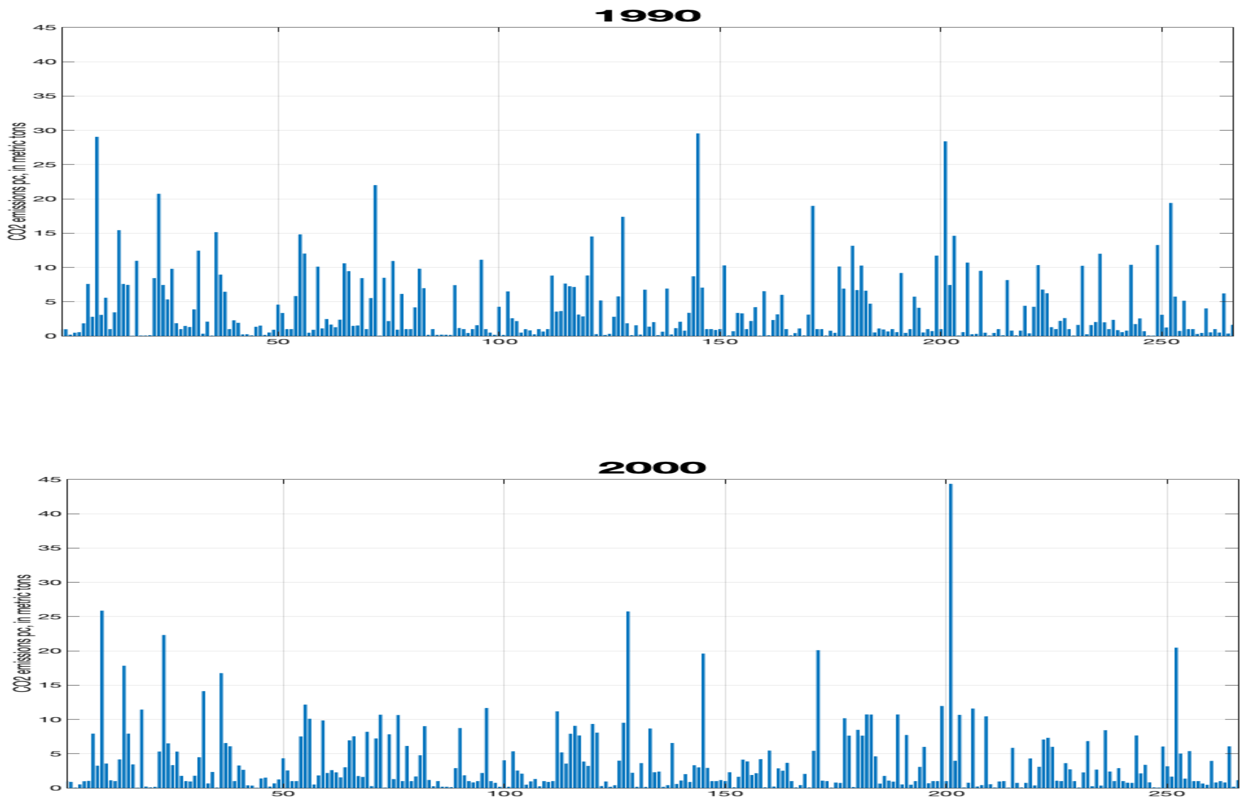
2010 and in 2020, at less 'exorbitant' levels at that. By contrast most of the remaining CO2-polluting economies in the world have remained clustered around the lower but still unsatisfactory levels, given the Paris Agreement commitments, of around 5 metric tons pc or somewhat less.

A.2.6 Comparative Cross-Section Plots: GPR pc

We, finally, turn to the same panels of cross-sections over time across the globe, but now comparing the greening prosperity ratios we defined. Given our observations with regard to the preceding two cross-sections, of GDP pc in the numerator of our ratio and of CO2 emissions pc in its denominator, it is clear that what we discuss briefly next is the result of the salient facts highlighted in the analysis so far.

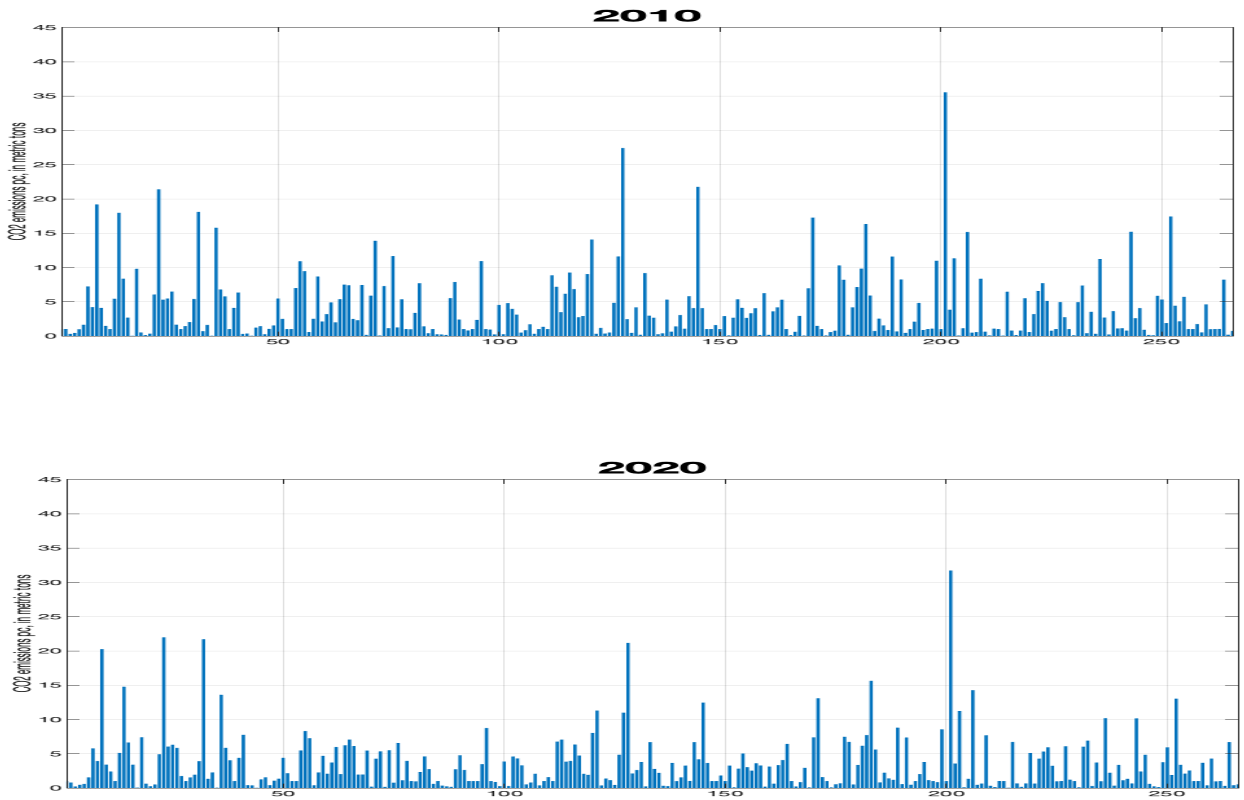
It is not too much surprising, therefore, to verify in Figure 36 that back in 1990 the economies with the highest greening prosperity indicators are either the rich ones we have in part highlighted, provided they do not also pollute a lot, or the poorest ones, for which the denominator of the ratio is extremely low. Bermuda (the spike at No. 28) comes 1st in rank, with a greening prosperity ratio (GPR) of some 60'500 'CO2-emission discounted' USD of 2017 pc, followed by Macao, SAR China (No. 147), at just below 50'000 discounted USD of 2017, Burundi (No. 17), Benin (No. 19), Nepal (No. 179) and Hong Kong, SAR China (No. 97). It is worth noting that Uganda (No. 248), with 20'000 discounted USD of 2017 pc, and Tanzania (No. 247), a bit less, come quite close to the top-10 in this ranking for 1990.

Figure 34: CO2 pc – World Cross-Section in 1990 (top panel) and 2000 (bottom panel)



Note: Countries and country groups are listed in the order of Figure 3: please refer to it to identify a particular numbered bar on the plot. *Source*: World Bank, `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

Figure 35: CO2 pc – World Cross-Section in 2010 (top panel) and 2020 (bottom panel)



Note: Countries and country groups are listed in the order of Figure 3: please refer to it to identify a particular numbered bar on the plot. *Source*: World Bank, `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

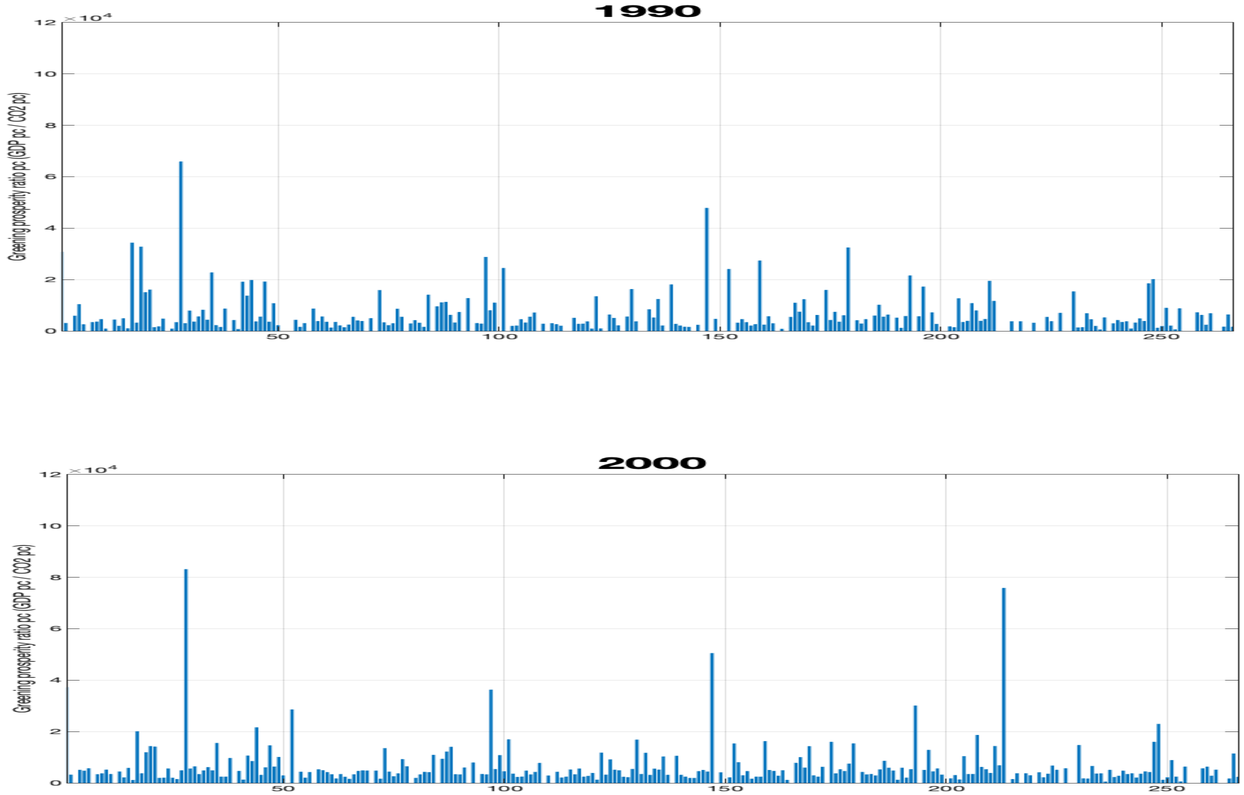
A decade later, we see some countries consolidating their greening prosperity indicator, such as Bermuda, coming on top again, with somewhat above 80’000 discounted USD of 2017 pc, and Macao, remaining 3rd, whereas San Marino (No. 213) jumps 2nd, with a bit below 80’000 discounted USD of 2017 pc. Puerto Rico (No. 193) jumps too in the top-10, coming close to Hong Kong (No. 97) and the Cayman Islands (No. 53), and Uganda (No. 248) moves up 7th, with just above 20’000 discounted USD of 2017.

Further on, in the cross-section for 2010, Macao (the spike at No. 147) marks the maximum greening prosperity ratio in our sample, reaching nearly 120’000 discounted USD of 2017, and Bermuda (No. 28), the Cayman Islands (no 53), San Marino (No. 213) and Hong Kong (No. 97) keep their position in the top-5.

And no much change has, finally, occurred over the period between 2010 and 2020 in the pattern highlighted already: the same top-5 countries in terms of their GPRs remain in the lead, but now in the order of Bermuda, the Cayman Islands, San Marino, Hong Kong and Macao, and the levels of the GPRs have decreased for all countries in this top-5, except for Hong Kong.

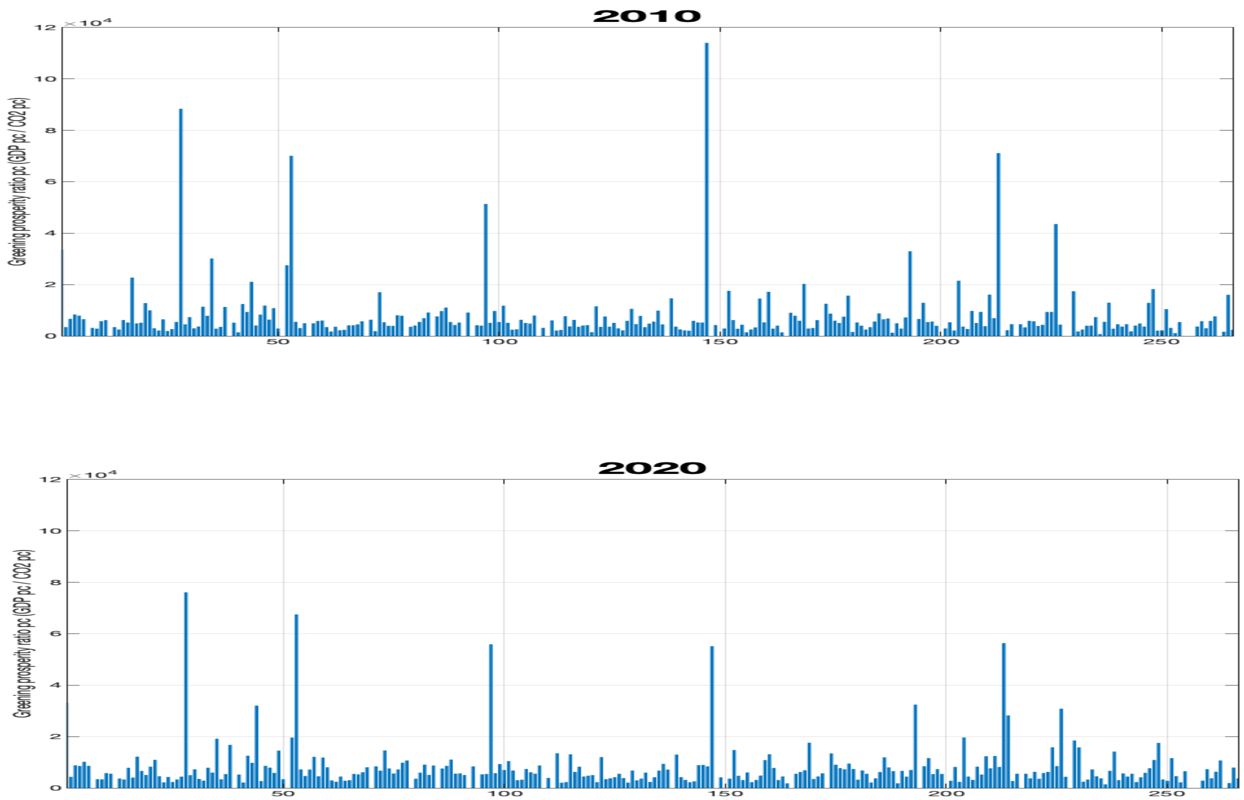
Restating our impressions from comparing the greening prosperity indicator across all countries in the world in the evolving cross-sections of 1990, 2000, 2010 and 2020, we could conclude that for all these years only the mentioned countries, some 10-12 in number, have managed to achieve a GPR that is salient in the spikes in the respective graphs we commented. By contrast, the common finding is that the greening prosperity ratios for all other countries in the world remain too low, below 10’000 discounted USD of 2017. This is either because the huge part of the economies in the world are considerable polluters (and hence their greening prosperity ratios feature a high denominator) or do not have quite an impressive GDP pc (and hence the numerator takes a relatively weak value), or both.

Figure 36: Greening Prosperity Ratios pc – World Cross-Section in 1990 (top panel) and 2000 (bottom panel)



Note: Countries and country groups are listed in the order of Figure 3: please refer to it to identify a particular numbered bar on the plot. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD` and `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

Figure 37: Greening Prosperity Ratios pc – World Cross-Section in 2010 (top panel) and 2020 (bottom panel)



Note: Countries and country groups are listed in the order of Figure 3: please refer to it to identify a particular numbered bar on the plot. *Source*: World Bank, `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD` and `https://data.worldbank.org/indicator/SP.DYN.LE00.IN?name_desc=true`.

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