On the dynamics of CO2 emissions and economic growth: a comparative analysis using symbolic time series

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Abstract: The aim of this paper is to analyze the dynamic relationship between economic growth and CO2 emissions for a set of 98 countries over the lengthy period from 1951 to 2014. We describe the topology and hierarchy of countries and introduce a different concept of economic performance based on the idea of dynamic regimes. These regimes are defined by the average levels of per capita CO2 emissions and the growth rates of per capita GDP. By presenting a non-

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parametric clustering technique, the paper identifies two main groups. One cluster can be identified as the group of developed countries, which presents a homogeneous structure and tends towards more similar dynamics over time. The other cluster, associated with developing countries, is homogeneous but the dynamics of the countries do not show convergence. The study also finds some, though little, mobility between groups.

Keywords: Regime Dynamics; Cluster Analysis; Economic Growth; CO2 Emissions**.**

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1. Introduction

Greenhouse gas emissions (GHGs) are major contributors to global climate change and the greenhouse effect, and consequently to global warming. The fifth International Panel on Climate Change (IPCC) report stated that over half of the observed increase in global average surface temperature from 1951 to 2010 was caused by an anthropogenic increase in greenhouse gas concentrations and other anthropogenic activities with a 95% confidence interval. It maintains that the key factors leading to increased GHG emissions are, among others, economic activity and energy use. A more recent summary for policymakers by the IPCC (IPCC, 2018) stated that "human activities are estimated to have caused approximately 1.0°C of global warming above pre-industrial levels, with a likely range of 0.8°C to 1.2°C." At the same time, the world economy has multiplied more than fourfold since 1970, while in per capita terms this ratio is 2.2 (using data from the United Nations Conference on Trade and Development, UNCTAD[2]). In this fashion, the aim of decoupling economic growth from environmental pressures and its impact is a key issue in international political agendas (OECD 2019, IRP 2019).

The nexus between energy consumption, emissions, and economic growth has received considerable attention over the years by both policymakers and researchers as achieving long-term sustainable economic growth has gradually become a major global concern. Consequently, a vast number of studies have

[2] Data available online at: https://unctadstat.unctad.org/EN/

been conducted to examine relationships between rising carbon emissions[3], energy consumption, economic growth, and other variables. Most of these studies have confirmed the idea that economic growth and energy use have a significant effect on CO2 emissions (e.g., Atta Mills et al., 2020; Gardiner and Hajek, 2020; Antonakakis et al., 2017, among others). Referenced studies have employed different countries, time periods, proxy variables, and diverse methodologies. For instance, Amin et al. (2020) explored the dynamic relationship between CO2 emissions, urbanization, trade openness, and technological innovation for 13 Asian countries over the period 1985–2019. The authors employed panel cointegration and causal models and found bidirectional causality between these variables and CO2 emissions. Munir et al. (2020) examined the relationship between emissions, energy use, and economic growth in the five initial countries of the Association of Southeast Asian Nations (ASEAN) over the 1980–2016 period. By considering cross-sectional dependence, they found considerable heterogeneity among the countries and brought to light previous misleading results about the Environmental Kuznets Curve (EKC) and causality in those countries. Among other conclusions, they reported causality running from income to emissions for all five countries with the exception of Indonesia. Gardiner and Hajek (2020) used variance decomposition and cointegration models to assess the causal relationship between energy consumption, CO2 emissions, and economic development in European Union countries. They found long-run equilibrium relationships among their variables

[3] CO2 emissions accounted for 76% of global emissions of greenhouse gases (GHGs) in 2015, by far the most significant contributor to climate change (EPA, 2017).

and some heterogeneity in short-term causal relationships. Vujović et al. (2018) applied neuro-fuzzy methods to research CO2 emission intensity based on alternative, fossil, and renewable energy and the connections between economic growth and CO2 emission intensity. Among other results, they found that CO2 emissions intensity from solid fuel has the highest influence on economic growth. Narayan et al. (2016) studied the dynamic relationship between economic growth and CO2 emissions for 181 countries by employing an approach based on cross-correlation estimates. They found that only 21 out of 181 countries (12%) support the idea of the Kuznets Curve hypothesis. However, they showed that increases in income reduced future emissions for 49 countries (27%). Chang et al. (2019) employed the LMDI decomposition method to investigate the time- and spatial-dynamics of drivers such as population, affluence, energy intensity, and carbon intensity governing global CO2 emissions. Among other results, they showed that economic development, among other drivers, serves as a factor in accelerating carbon emissions. They also reported significant heterogeneities in the spatial dynamics of the contribution of different drivers. Lean and Smyth (2010) found a non-linear relationship between emissions and real output for five ASEAN countries in the period 1980–2006, consistent with the EKC hypothesis. However, they did not report consistent long-run causality between the two variables.

The specific literature about the nexus between CO2 emissions and economic growth mostly concerns the EKC framework (Kuznets, 1855). The EKC hypothesis postulates an inverted U-shaped relationship between different pollutants and per capita income. As such, environmental degradation increases up to a certain level as income rises until, at a certain threshold, it starts to decrease. Since the study by Grossman and Krueger (1991), the EKC hypothesis has been widely tested, however the empirical results, as expected, are not categorical. For instance, Galeotti et al. (2009), Saboori et al. (2012), Shahbaz et al. (2013), He et al. (2017), Acheampong (2018), and Munir et al. (2020) provided evidence on the validity of the EKC hypothesis. On the contrary, Azam (2016) and Antonakakis et al. (2017) found a monotonic rising curve, while other researchers found mixed results for the countries under study, as was the case for Narayan et al. (2016), Muhammad (2019), and Liu et al. (2020), among others.

The clear policy implications regarding the EKC hypothesis are that environmental degradation will switch to a downward trend once economic development reaches a certain threshold, which implies that development is following a green path. This would be the ideal situation, as it implies that economic growth is decoupled from environmental degradation as Wu et al. (2018) showed for OECD countries, Cohen et al. (2018) for the top 20 country emitters and, to a certain extent, Xiao-Wei et al. (2016) and Liu et al. (2019) for China, among other studies. On the contrary, if economic growth increases CO2 emissions, then economic development still occurs at the expense of the environment, meaning the economy needs to make growth more environmentally friendly as economic growth and emissions are still coupled (e.g., as Andreoni and Galmarini, 2012, found for the Italian economy or Aye and Edoja, 2017, for 31 developing countries).

As previously mentioned, the literature on this hot topic is diverse, extremely rich, and vast. As a result, quite a few surveys on different aspects of the issue have appeared. For instance, Wiedenhofer et al. (2020) and Haberl et al. (2020) systematically identified and screened more than 11,500 scientific papers (they ultimately conducted an in-depth review of 825 studies) to obtain a broad view of the relationship between economic growth, resource use, and greenhouse gas emissions. Mardani et al. (2019) presented a systematic review of empirical studies on this issue over the past 20 years, carefully analyzing 175 empirical papers. Waheed et al. (2019) presented a survey of the empirical literature on the direction of causality between economic growth and carbon emissions, economic growth and energy consumption, and energy consumption and carbon emissions. Dinda (2004) and Purcel (2020) created extensive and in-depth surveys on the specific issue of the EKC hypothesis.

Considering the topic of this study, the most relevant results emerging from such extensive literature can be summarized in two main ideas. The first idea is that the results are inconclusive and strongly depend on the methodologies, time periods, countries or regions selected, and the variables employed. Results undoubtedly differ from one country to another according to the economic characteristics of each one. Second, connections and causality between economic growth and CO2 emissions are relevant and have important policy implications. At the same time, it seems to be clear that some countries—especially, though not only, developed ones—have achieved a certain degree of progress in decoupling their economic growth path from their pollutant emissions.

Recently, some studies have used hierarchical structure methods to explore connections between economic growth, carbon emissions, and other variables (Kantar and Keskin, 2013; Deviren and Deviren, 2016; Kantar et al., 2016; Kantar et al., 2019; and de Souza Mendonça et al., 2020). In general, these studies describe the topology and hierarchy of different groups of countries, periods, and variables. For instance, Kantar and Keskin (2013) studied the connections between energy consumption and economic growth in a sample of 30 Asian countries across the period 1971–2008. Deviren and Deviren (2016) analyzed the relationship between economic growth and emissions in 33 developed and developing countries over the period 1970–2010. Kantar et al. (2016) conducted research on electricity consumption and economic growth to detect the topological properties of 64 countries from 1971 to 2008. Kantar et al. (2019) examined the hierarchical structures of carbon dioxide emissions and three main sectors, namely electricity/heat, manufacturing/construction, and transportation, in 84 countries over the period 1971–2012. These three papers employed the concepts of minimum spanning trees (MST) and hierarchical trees (HT) as we did in our study. Lastly, de Souza Mendonça et al. (2020) used hierarchical regression modeling to ascertain the impact of economic activity, population growth, and renewable energy generation on CO2 emissions in the 50 largest world economies over the period 1990–2015. However, this study does not employ clustering networks such as MST or HT.

These studies found that countries are grouped into geographical clusters or in terms of their level of development. Additionally, developed countries are at the center of the networks and are, consequently, more important nodes within said networks, particularly in terms of carbon emissions. The approximation we employ in this study is closely related to the abovementioned network studies.

Our study relies on an approximation similar to the aforementioned studies. Specifically, this study contributes to the empirical literature on the topic by focusing on the intense diversity across countries and regions. The aim of this paper is to analyze the dynamic relationship between economic growth and CO2 emissions for a set of 98 countries during the lengthy period spanning from 1951 to 2014. The paper introduces the economic regime concept, whose two-dimensional form extends the reading of economic performance. In so doing, it analyzes the behavior of two variables for a group of countries using a non-traditional (non-parametric) statistical model: the minimum spanning tree and the hierarchical tree. Our study contributes to comparing the dynamic behaviors of different countries without bearing in mind any one specific model. This approach allows us to identify groups of countries with similar dynamic behaviors for which models of the same type could be employed. In this sense, the study is directly interested in the heterogeneity present in the connections between the two variables and the consequences for the empirical analysis and policy implications.

To the best of our knowledge, this is the first study to use the concept of economic regimes applied to economic growth and carbon emissions and to describe the topology and hierarchy of the dynamics presented in our sample of 98 developed and developing countries for the lengthy 1951–2014 period.

The rest of the study is organized as follows: The next section presents the data and numerical methods we employed. Section 3 introduces the minimum spanning tree and the hierarchical tree concepts and presents the results of this network approach for two sub-periods from our sample: 1951–1999 and 2000–2014. In Section 4 we introduce a time-windows analysis to study the cluster dynamics of the cluster we found in the previous section and, finally, Section 5 presents our conclusions and indicates directions for further research.

2. Data and methodology

Economic growth (*x*) is represented by the growth rate of per capita GDP measured at constant 2011 US$. We obtained these data from the Maddison Project Database available online at https://www.rug.nl/ggdc/. In the same manner, global CO2 emissions (*y*) are expressed in per capita terms and were retrieved from the Carbon Dioxide Information Analysis Center (CDIAC), available online at http://cdiac.esd.ornl.gov (Boden, Marland and Andres, 2017). Global CO2 emission data comes from gaseous, liquid, and solid fuel consumption and are expressed in metric tons of carbon per person. The data set includes 98 countries over the period 1951–2014. Countries were selected so as to represent all the geographical regions over this extended period. Armed with these two variables, we transformed them into symbolic series in order to focus on the trajectories that countries follow over time. We describe the dynamics of a country as a sequence of economic regimes (see Brida, Puchet and Punzo, 2003; Brida and Punzo, 2003). The partition of the state space is defined by the annual average of rate of growth of per capita GDP (μ_x), and the annual average of the level of metric tons of CO2 emissions per person (μ_y). In this case, we split the state space into 4 different regimes or regions determined by μ_x and μ_y.

Figure 1 shows the partition of state space defined by the average values of μ_x and μ_y. Each data point represents the position of a country in a single year while the green lines represent the mean of emissions and growth for the whole period. As expected, most of the data points are close to the average emissions and economic growth. In the same manner, we can see that the data points are evenly spread around the average growth rate. For example, the lower part of Figure 1 shows the same information, but only for 2014. When we look at a single year, it is clear that greater heterogeneity can be found and the data points are not evenly distributed along the partitions we previously defined.

INSERT FIGURE 1 BY HERE

Next we describe the qualitative behavior of any country by using the notion of regime. Broadly speaking, an economic regime characterizes a particular qualitative behavior that is different from the others. Therefore, any change of regime represents a signal of some qualitative transformation. In the present study, the selection of the average values as thresholds is exogenous and consequently our results are contingent upon these exogenous cut-offs.

To explore these qualitative changes we substitute our bi-dimensional time series $\{(x_1, y_1),\ (x_2, y_2), \dots, (x_{\mathrm{T}}, y_{\mathrm{T}})\}$ for a sequence of symbols: $s = \{s_1, s_2, \dots, s_T\}$ such that $s_t = j$ if and only if (x_t, y_t) belongs to a selected state space region, R_j. As previously mentioned, we defined four regions in the following way:[4]

$$R_1 = \left\{(x_t, y_t) : x_t \leq \mu_{x_t}\ ,\ y_t \geq \mu_{y_t}\right\}$$

$$R_2 = \left\{(x_t, y_t): x_t \geq \mu_{x_t}\ , y_t \geq \mu_{y_t}\right\}$$

$$R_3 = \left\{(x_t, y_t) : x_t \geq \mu_{x_t}\ , y_t \leq \mu_{y_t}\right\}$$

[4] The boundaries of the different regimes are defined by means of ≥ or ≤ because the probability of being in two regimes at the same time is 0.

$$R_4 = \{(x_t, y_t) : x_t \leq \mu_{x_t}, y_t \leq \mu_{y_t}\}$$

where, for example, R_1 is the regime of low GDP growth and high per capita CO2 emissions, so a country occupying that period would be slow-growing and a polluter. The other regimes can be interpreted similarly. At this point, we can ignore the precise values for GDP growth rates and per capita CO2 emission levels and describe an economy's evolution based on the regime changes that have occurred throughout its history. This gives us a rough description of the dynamic, telling us only what regime an economy was in at a given point in time.

Focusing on the environmental side, we can see regimes 3 and 4 are those wherein a country is emitting lower-than-average per capita metric tons of CO2. Regime 3 represents the best possible behavior: lower emissions and higher growth than the average. On the other hand, regimes 1 and 2 show worse-than-average environmental performance, with regime 1 representing the worst situation: higher emissions and lower growth than the average. Table 1 shows the percent of the year that each country is in each regime and the acronyms we use in the figures throughout the paper.

INSERT TABLE 1 AROUND HERE

Figure 2 shows different trajectories across regimes for selected countries[5]. We can observe intense heterogeneity in the behavior that countries experience over the time period.

[5] This figure includes globally relevant countries (United States, China, Japan, Germany,etc.); countries that change groups between periods—see final part of Section 3—such as Sweden, Spain, Portugal, or Venezuela, and some other countries (Libya, Equatorial Guinea, or Saudi Arabia).

INSERT FIGURE 2 BY HERE

For instance, some countries never reside in regimes 3 and 4 (e.g., Germany, Denmark, U.S.A., United Kingdom, Australia, South Africa, or Poland). On the other hand, other countries never reside in regimes 1 and 2 (e.g., India, Albania, Argentina, Bolivia, Egypt, Gambia, Iraq, Philippines, or Thailand). Lastly, a smaller group of countries move across the most regimes over the time period (e.g., Bulgaria, Cyprus, South Korea, Finland, Hong Kong, Hungary, Portugal, or Sweden).

3. Regimes and clustering dynamics

After verifying the heterogeneity present in country dynamics when it comes to the different regimes they occupy over time, we created a topology and hierarchy according to their dynamic economic-environmental behavior. We employed a non-parametric methodology based on the non-loop networks of MST and HT. These methods were pioneered in economics and finance by Mantegna (1999) and Mantegna and Stanley (2000). To build these networks, we defined a metric distance between the dynamical performances of each pair of countries. This "distance'' measures how close two countries are in their respective regime dynamics. Several distances can be postulated (see Piccardi, 2004; Molgedey and Ebeling, 2000; Tang et al., 1994; Tang et al., 1995 and Tang et al., 1997). We have chosen the most used notion of distance for symbolic time series: the discrete metric distance. Given the symbolic sequences $\{s_{it}\}_{t=1}^{t=T}$ and $\{s_{jt}\}_{t=1}^{t=T}$ the distance between two countries i and j is given by:

$$d(s_i, s_j) = \sum_{t=1}^{64} f(s_{it}, s_{jt}); \quad f(s_i, s_j) = \begin{cases} 0 & si\ s_{it} = s_{jt} \\ 1 & si\ s_{it} \neq s_{jt} \end{cases}; \ t = 1, \dots, 64; \ i = 1, \dots, 98$$

That is, each of the 64 adding terms is 0 if countries *i* and *j* are in the same regime at that time, or 1 if are not in the same regime. Thus, we obtained a distance that takes on a value of 0 if the two countries coincide in the same regime throughout the entire period and takes on a maximum value of 64 if the two have not coincided at any point in the same regime during the period under consideration.

To build the hierarchical tree, we employed the nearest-neighbor single-linkage cluster algorithm as described in Mantegna and Stanley (2000). This technique uses an aggregative process that directly uses the distance matrix. We began by connecting the closest countries, meaning those with the shortest distance between them (in our case, France and Austria had the shortest distance which was equal to 10). We then proceeded by linking the remaining countries according to their distances to the previously connected countries. For instance, the shortest distance after France and Austria is the same for Canada and the US, with a distance of 11. The next shortest distance belongs to Belgium. In this case, Belgium joins the group initially formed by France and Austria (distance equal to 12). Proceeding in this manner, we constructed a tree with the 98 countries and 97 links among them. As clearly observed, the distance between clusters is given by the minimum distance between each pair of countries. This is how the minimum spanning tree (Kruskal, 1956) was gradually constructed. This construction is represented in a graph of *n* vertices corresponding to each country and n-1 links where the most relevant links for each particular country are selected.

It is also possible to construct a hierarchical organization, or hierarchical tree, using the single-linkage clustering algorithm (Johnson, 1967) in which “similar” objects (i.e., single commodities or groups of commodities) are clustered in each step according to their characteristics. This classical agglomerative single-linkage algorithm enables the construction of a hierarchical dendrogram to illustrate the clustering characteristics of the data organization.

By means of the MST and the HT, we extracted country clusters that showed similar dynamic performance over the state space partitions.

Figures 2 and 3 show the HT and the MST for the entire period for our group of 98 countries.

INSERT FIGURES 3 and 4 BY HERE

A set of indicators were considered in order to determine the optimal number of clusters using the Pseudo-F (Calinski and Harabasz, 1974) and the Pseudo-t^2 (Duda and Hart, 1973) methodologies. In this study, both tests indicated that the optimal number of groups is 5 (2 main groups and 3 outliers).

Two large groups were detected and only three isolated countries forming their own single-country cluster[6] were detected (Iran, Equatorial Guinea, and North Korea). The two clusters are composed of the following countries:

[6] If we consider the maximum number of possible clusters, which is eight, the results do not change much. In this latter case, we found that only Barbados is left out of the green group, forming a single-country cluster, and Romania and Bulgaria formed their own clusters and, consequently, are separated from the

1. Cluster one is formed by countries that are mostly located in regimes 3 and 4 (regimes with lower-than-average per capita CO2 emissions). We colored and labeled this as the *green* group. Geographically, countries in this group are mostly located in Asia, Africa, and Latin America and the Caribbean. Specifically, the countries in this cluster are: Afghanistan, Albania, Argentina, Barbados, Bolivia, Brazil, Cameroon, Chile, China, Colombia, Costa Rica, Cuba, Democratic Republic of the Congo, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Gambia, Ghana, Guatemala, Guinea-Bissau, Haiti, Honduras, India, Indonesia, Iraq, Jamaica, Jordan, Kenya, Lebanon, Liberia, Madagascar, Mauritius, Mexico, Mongolia, Morocco, Mozambique, Myanmar, Nepal, Nicaragua, Nigeria, Panama, Paraguay, Peru, Philippines, Saint Lucia, Sierra Leone, Sri Lanka, Syria, Thailand, Togo, Tunisia, Turkey, Uganda, and Uruguay.

2. Cluster two on the other hand is formed by countries with dynamic performance that are mostly located in regimes 1 and 2 (regimes with higher-than-average per capita CO2 emissions). We colored and labeled this as the *pink* group. In this case, the countries in this group are mostly located in North America, Europe, and Oceania and some other petrol abundant countries such as Venezuela, Saudi Arabia, and others. The countries in this cluster are: Australia, Austria, Belgium, Bulgaria, Canada, Cyprus, Denmark, Ethiopia, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Israel, Italy, Japan, South Korea, Libya, Luxembourg, Malta, Netherlands, New Zealand, Norway, Poland,

pink group. Therefore, essentially, there are no relevant changes in the topology and hierarchy of the dataset.

Portugal, Romania, Saudi Arabia, South Africa, Spain, Sweden, Switzerland, Taiwan, Trinidad and Tobago, United Kingdom, United States, and Venezuela.

Map 1 shows the geographical distribution of the clusters we obtained.

INSERT MAP 1 BY HERE

In fact, it is readily apparent that we can split our dataset into developed (pink group) and developing countries (green group) with a few outliers as we previously pointed out. This configuration is easily explained: Figure 4 shows per capita GDP rate of growth (upper part) and per capita metric tons of CO2 emissions (lower part) for clusters one and two.

INSERT FIGURE 5 BY HERE

We clearly observed three relevant features. Firstly, per capita emissions are much higher in the pink group than the green group over the whole period (despite the pink group having reduced its growth trend during the eighties, nineties, and particularly in the new century). Secondly, per capita economic growth is significantly higher for the pink group during the second half of the past century, but since then the green group took the advantage in terms of rates of growth. This situation is especially clear after the 2008-2009 global financial crisis. Thirdly, we intuitively observed a correlation between the two variables, though this was not the subject of this study.

It seems that per capita emissions somehow dominate the dynamics in this structural view of the whole period. However, changes in the dynamics of the variables around the end of the past century inside the two clusters highlight the interest of analyzing what happened during the past century. Therefore, we repeated the analysis for both sub-periods: 1951–1999 and 2000–2014. Map 2 shows a world map wherein the countries have been colored according to their clustering group.

INSERT MAP 2 BY HERE

This map presents our analysis for the 2000–2014 period in comparison to the previous period from 1951 to 1999. The green and pink colors represent the countries that, over the 2000–2014 period, remain in the same group as during the previous period from 1951 to 1999. Countries not included in our analysis are shown in gray. Lastly, those countries that switch clusters between the two periods are marked in red. The lower part of Map 2 presents a table detailing the group that each of the countries that switch belonged to in the previous period. Only Romania and North Korea move to the group of lower pollutant countries. However, only Romania leaves the pink group for the green as North Korea forms a single-country group in the previous period. On the contrary, countries such as South Korea, Hong Kong, Spain, or Venezuela, among others, switch to the more pollutant group (as most of them became developed countries during the lengthy period from the fifties to the end of the century). Portugal, on the other hand, abandons the green group in the second period and forms a greener self-group. Sweden and Switzerland create their own group in 2000–2014 when they were previously in the pink cluster, or the pollutant group. This new group seems to be less pollutant than the average of the pink group and, therefore, represents a successful green change between the two periods (see Figure 2 to see the countries' trajectories over the whole period).

Note that most of the countries in our dataset (80 out of 98) remain in the cluster in which they were located during the lengthy previous period 1951–1999, this being the most relevant, and somewhat surprising, feature in the dynamics of our group of countries.

To check the results of this part of the study, we extended our analysis by including an exercise using GDP per capita levels instead of its variations. Aside from this difference, we ran the analysis in the same manner. In doing so, we looked more directly at the role of developed and developing countries in relation to global CO2 emissions. Figures and tables with the results from this new approach are included as an annex.

From this exercise, we show that, essentially, the two groups we previously found still hold. Only 15 countries of the 98 switch from their original group while the rest stay in their same previous group when using per capita GDP variations (see dendrogram, Figure S2). Switching countries are marked in italics and underlined in Table S1. Out of those, only South Korea, Malta, and Taiwan switch from the pink to the green group while the remaining 12 countries move and become outliers or move from being outliers to join the green or pink groups. Details of these movements are presented in Table S2.

As mentioned, we still obtain the “green” group, formed by the less pollutant and low GDP per capita level countries, and the “pink group” which includes high income and high CO2 emitter countries. Therefore, the picture does not change much in comparison to the choice of variations with GDP as the income variable.

We also see that 55 countries remain in the same regime throughout the time sample (see Table S1, light gray cells). This is due to the economic inequality observed in the world. In our period of analysis, most developed countries had much higher than average income and their CO_2 emissions per capita were much higher than the average as well. The opposite applies to less developed countries as well. In this sense, by using GDP per capita variations, we focused on the economic dynamic rather than looking at the evolution of level positions.

4. Global distance and convergence

This section presents an analysis of the evolution inside and between the groups we found in the previous section. To do so, we defined the evolution of the global distance inside the MST as the sum of their 97 links (corresponding to the 98 countries included in our dataset). The global distance therefore is a kind of diameter of the sample whose dimensions are measured in terms of the size of the MST. Consequently, the evolution of the global distance reflects the expansion or contraction of this diameter over time. This is interesting for analyzing whether countries are converging towards or diverging (on average) from the same type of regime dynamics. Divergence is understood as the spread of the size of the branches in the MST. On the other hand, a convergence path is observed when the tree is diminishing in size.

Figure 5 shows the evolution of the global distance for an overlapping window of ten years.

INSERT FIGURE 6 BY HERE

As is easily observed in the evolution of the MST diameter for all countries, the observed trend shows a clear converging path. Considering that we identified two clear groups with different dynamics, we extend this analysis to our two different groups. When we look at our two groups, it is clear that the size of the pink cluster experienced fairly significant changes in its configuration while the green cluster shows no major changes. The figure shows that the pink group tends to be more compact, while the trend of the green group remains relatively constant.

5. Conclusion

This paper presents a non-parametric clustering technique based on the dynamic regime concept and symbolic time series. This methodology is applied to a set of 98 countries over the 1951–2014 period to analyze the relationship between per capita economic growth and carbon emissions. Our study contributes to the literature on this topic focused on comparing the dynamic behavior in the relationship between our variables without any specific model in mind. This approach allows us to identify groups of countries with similar dynamic performance and that show clustering results that a traditional analysis of causal relations between carbon emissions and economic growth would not bring to light (see Haberl et al, 2020).

First, two well-differentiated clusters were endogenously marked out. These groups basically correspond to developed and developing countries, which is in line with other studies such as those by Kantar and Keskin (2013), Deviren and Deviren (2016), Kantar et al. (2016), and Kantar et al. (2019). Additionally, homogeneous performances were found within the two clusters.

A second remarkable behavior that can be found in this analysis is the presence of larger disparities in the “developing” country group than in the “developed” one. While “developed” countries have converged among themselves in their dynamics, the “developing” countries have shown a tendency to maintain the dispersion of the group over time. We might think that developed countries as a group are converging in their dynamics to a progressive decoupling of economic growth from carbon emissions and, consequently, confirmation of the existence of an EKC as Narayan et al. (2016) and Chen et al. (2018) pointed out. Developing countries seem to be still far from the peak point of their CO2 emissions and the time to reach said peak differs greatly from one to another, as some studies suggest (IEA, 2020; Jiang et al. 2019; Levin and Rich, 2017)

We found little mobility of countries between groups when we looked at the different periods (specifically, 1951–1999 and 2000–2014). This result is somewhat surprising as international environmental agreements have been implemented over the past decades and, consequently, more friendly environmental policies have been proposed, especially by developed countries. However, today developed countries are still the highest per capita emitters and consequently they should make the largest effort to reduce emissions. The significant differences between per capita CO2 emissions levels in developed and developing groups seem to be behind this result (see Fig. 4). Only Sweden and Switzerland have abandoned the pollutant group to create a new greener group. In a similar manner, Portugal became a developed country at the end of the century, but it did not join the pollutant group as other countries such as Spain, South Korea, or Hong Kong did. In this situation, the average per capita emissions of the two groups we found are very different, which is the most likely explanation for the low mobility between the groups.

Future research should focus on a more in-depth study of these two heterogenous groups. Despite the fact that they behave like a homogeneous performance group, we may find different environmental and economic behaviors within them. Building regimes that consider this question could be a further extension of this study.

By using this methodology, homogenous countries in terms of the long-term growth and CO2 emissions relationship emerge. This is especially useful for governments to find similar countries to learn from. Is important for countries to focus on improving their development policies by looking to countries with similar but better performance trajectories and factor endowments.

The non-parametric methods we used made it possible to integrate other variables into the study (social, institutional, economic, etc.) to analyze the effect of these variables on the conformation of the clusters and their dynamic performance. This could be a topic of future research.

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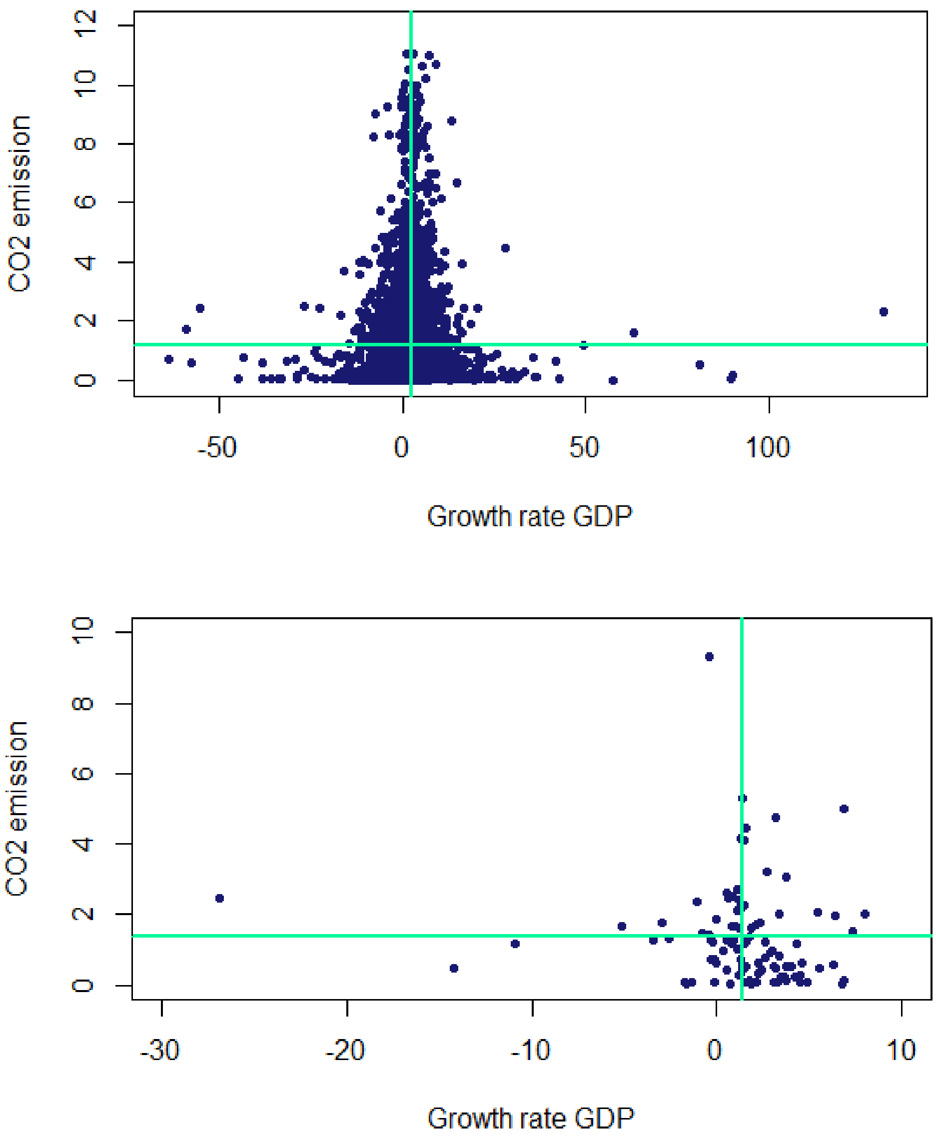
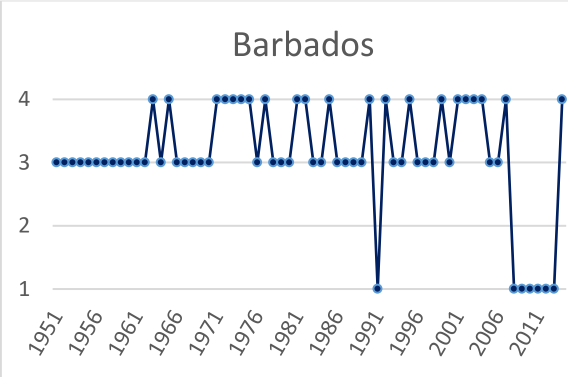


FIGURE 1: Upper part: Data partition in the state space for the set of 98 countries for the whole period. Lower part: Data partition in the state space for the set of 98 countries during 2014 Sources: Maddison project database (MPD) and Carbon Dioxide Information Analysis Center (CDIAC). Authors' calculations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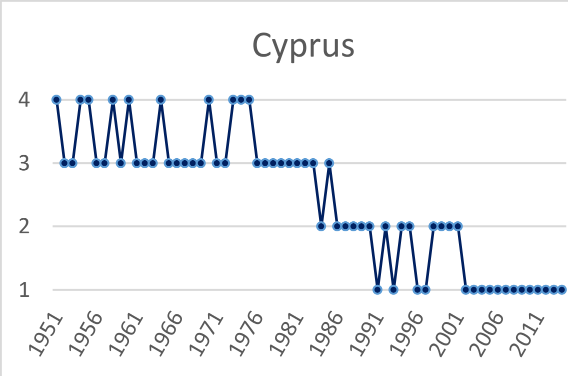
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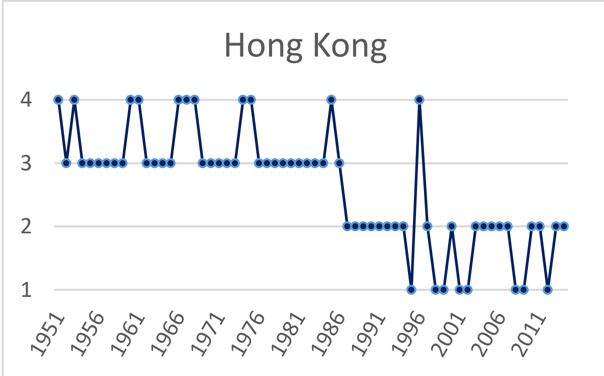
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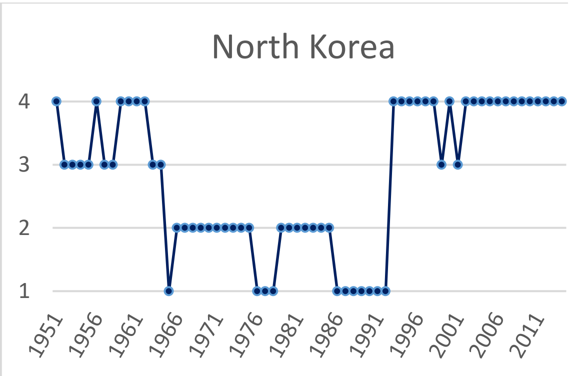
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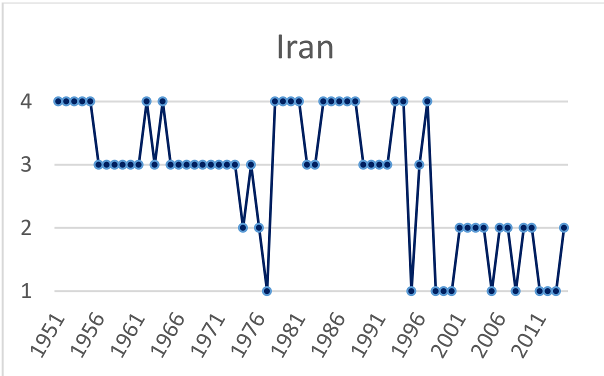
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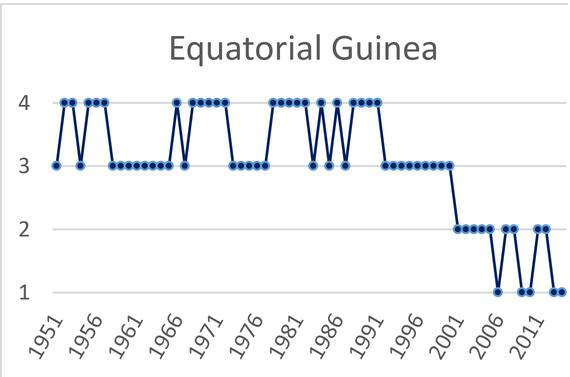
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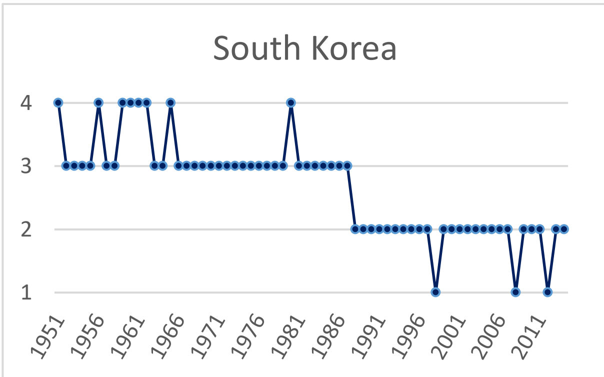
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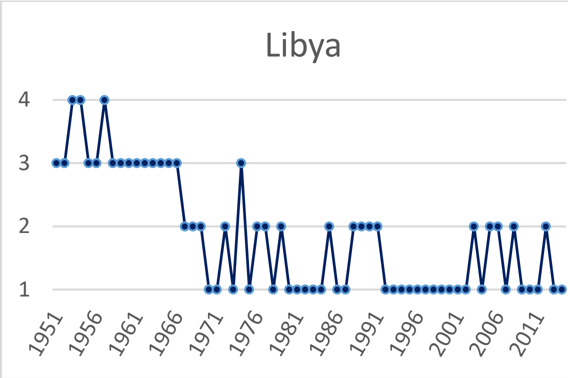
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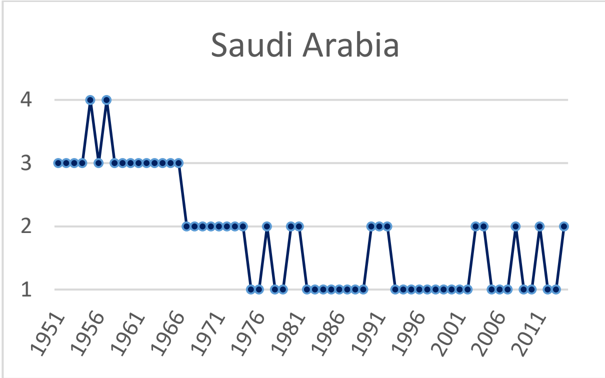
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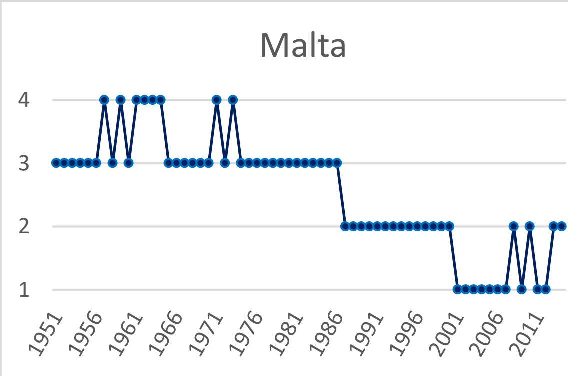
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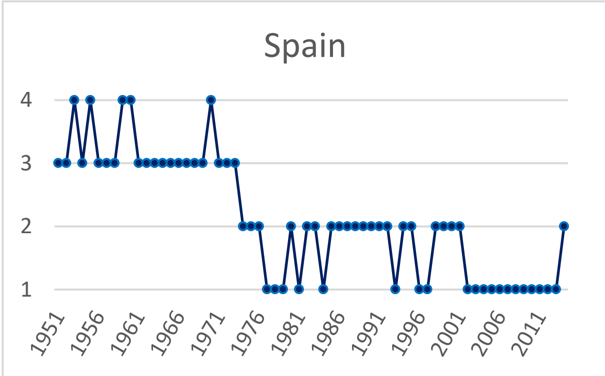
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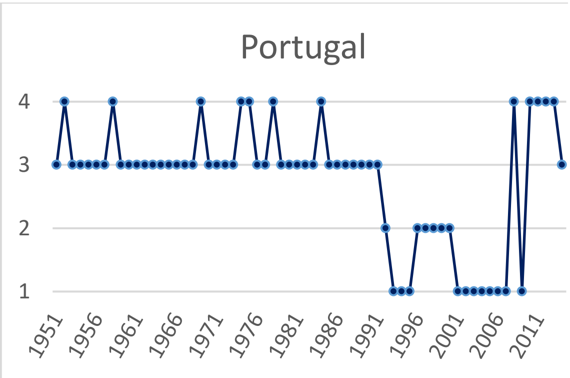
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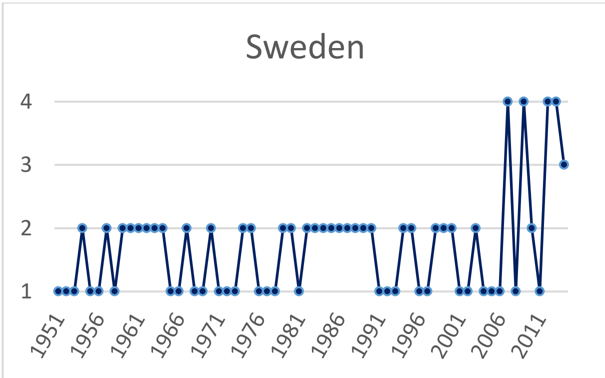
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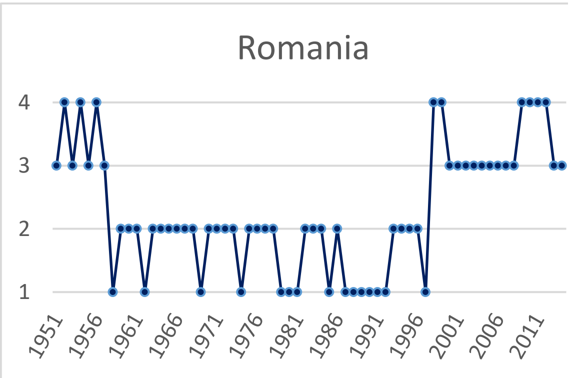
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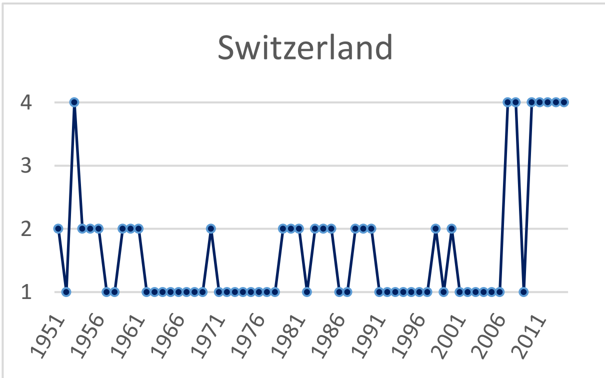
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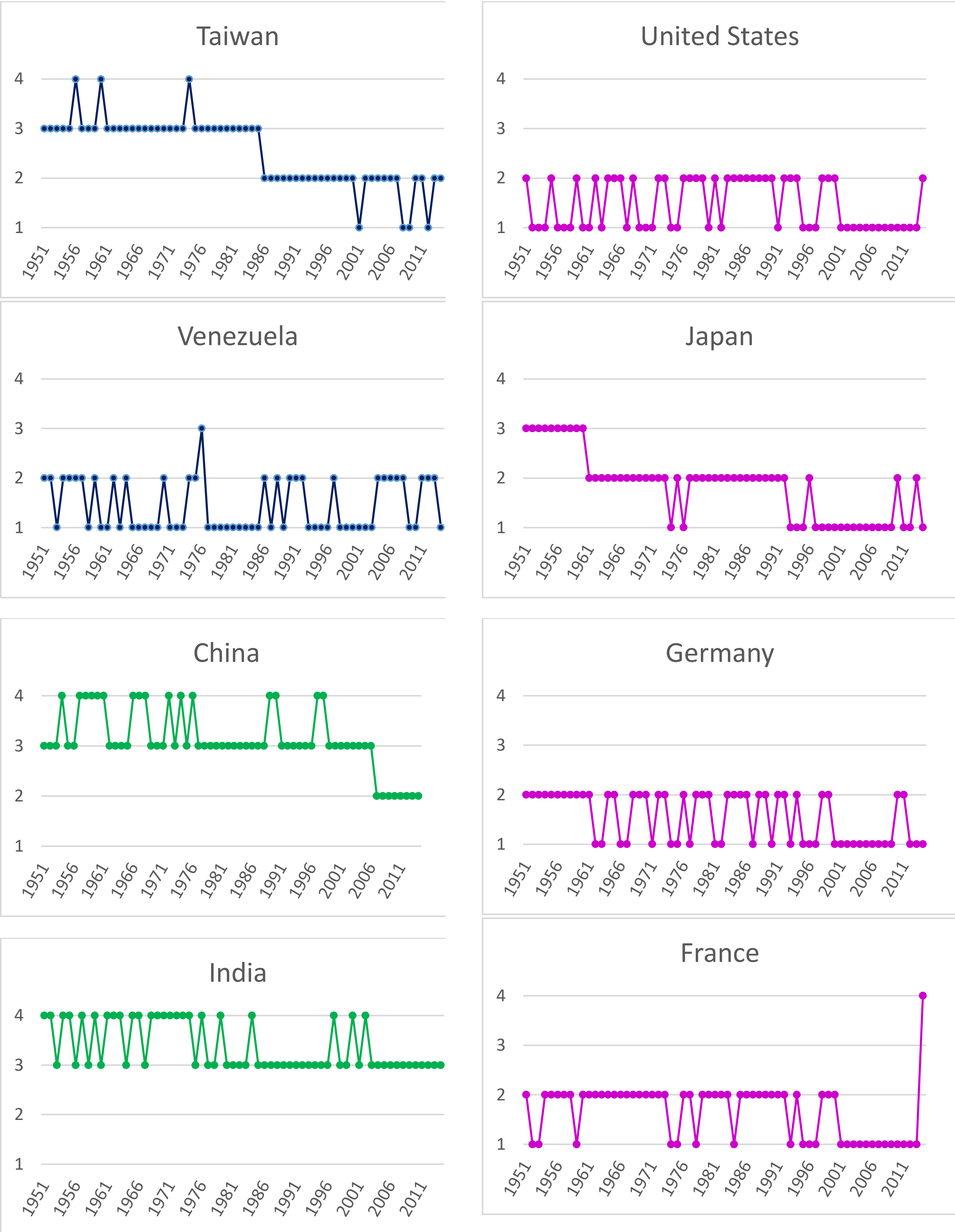


FIGURE 2: Representation of regimes dynamics during the period 1951-2014. Selected countries.

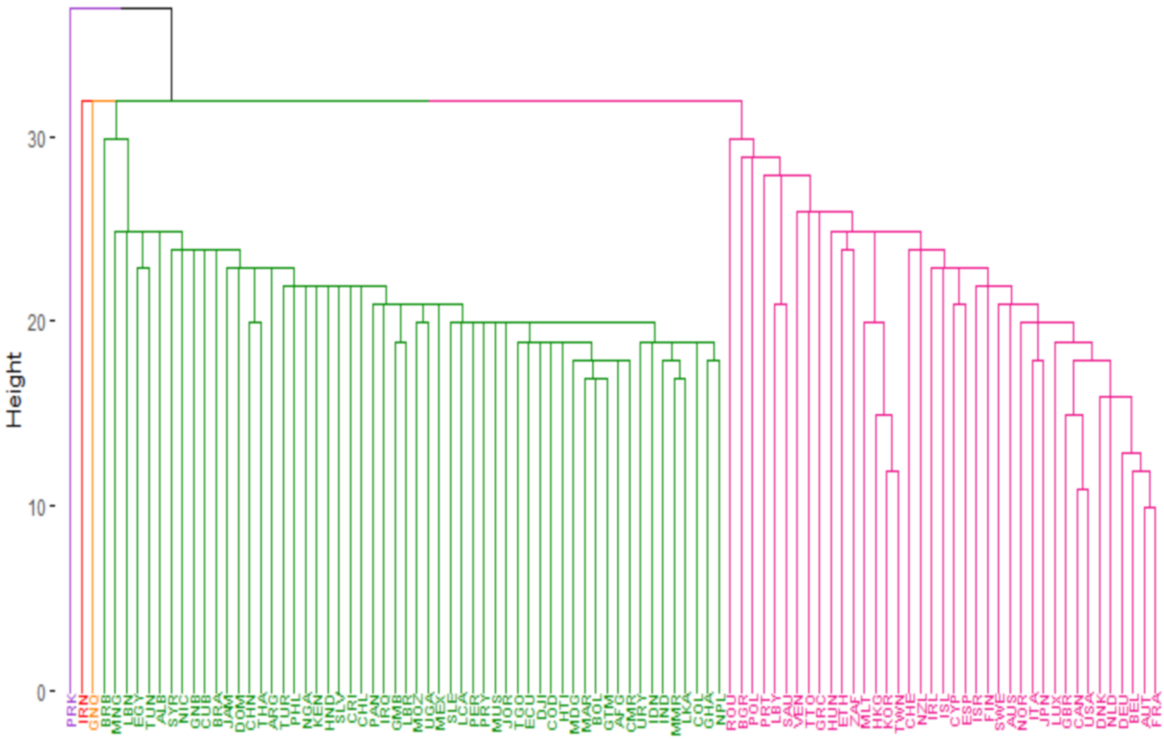


FIGURE 3:
Hierarchical tree of the set of 98 countries for the period 1951–2014.

Sources: Maddison project database (MPD) and Carbon Dioxide Information Analysis Center (CDIAC). Authors' calculations

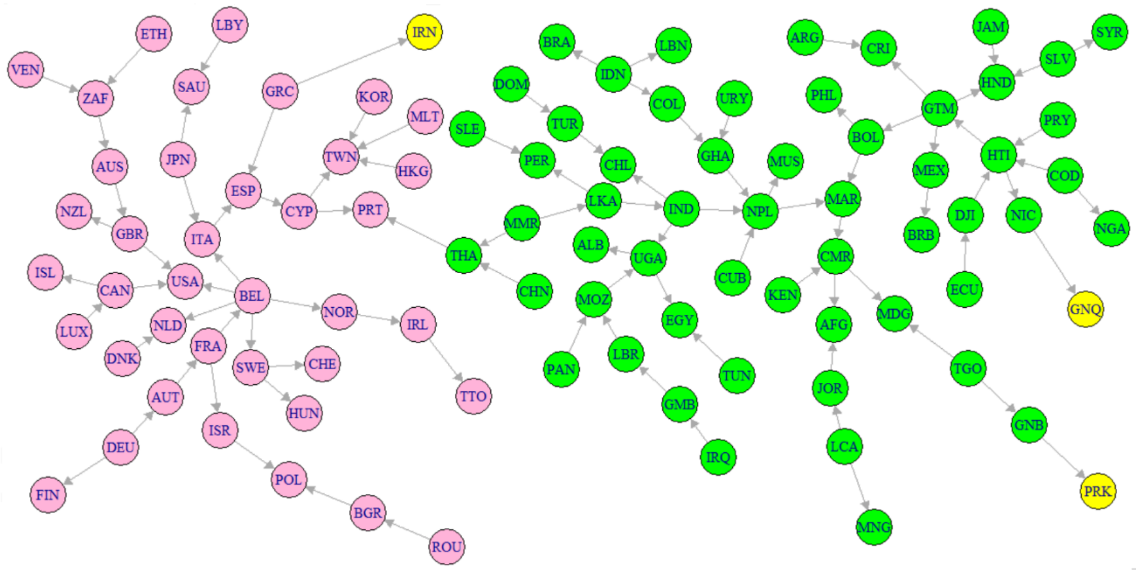
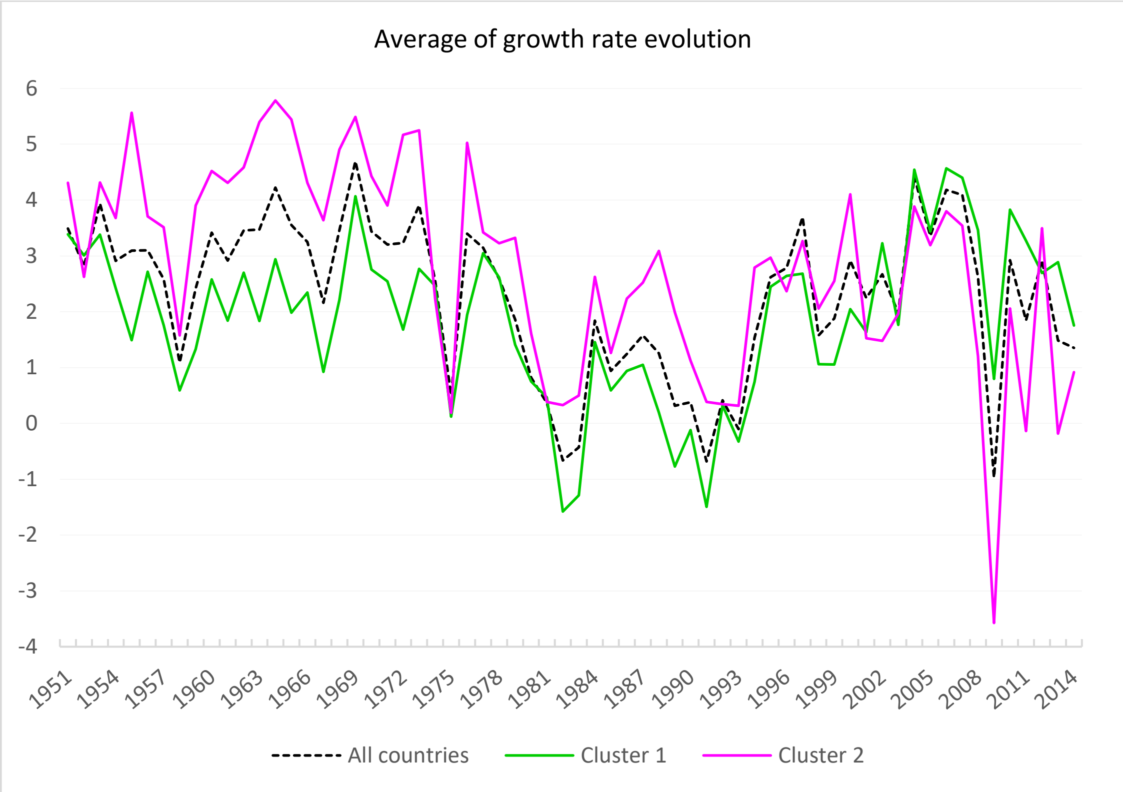


FIGURE 4:
Minimum Spanning Tree of the set of 98 countries for the period 1951–2014.

Sources: Maddison project database (MPD) and Carbon Dioxide Information Analysis Center (CDIAC). Authors' calculations



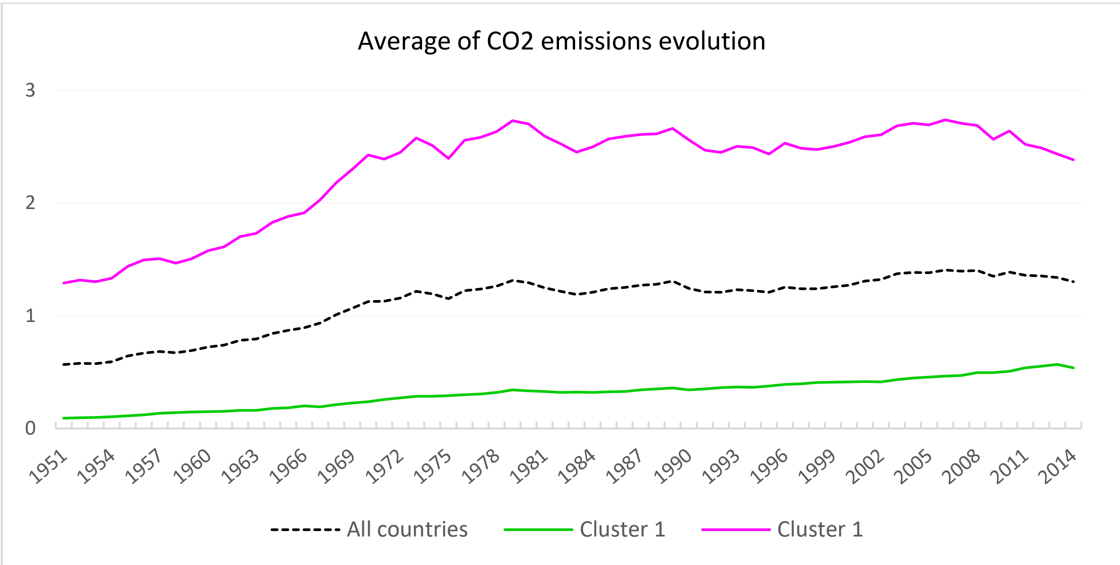


FIGURE 5:
Per capita GDP (annual rates of growth) and CO_2 emissions (metric tons of carbon, in levels)

Sources: Maddison project database (MPD) and Carbon Dioxide Information Analysis Center (CDIAC). Authors' calculations

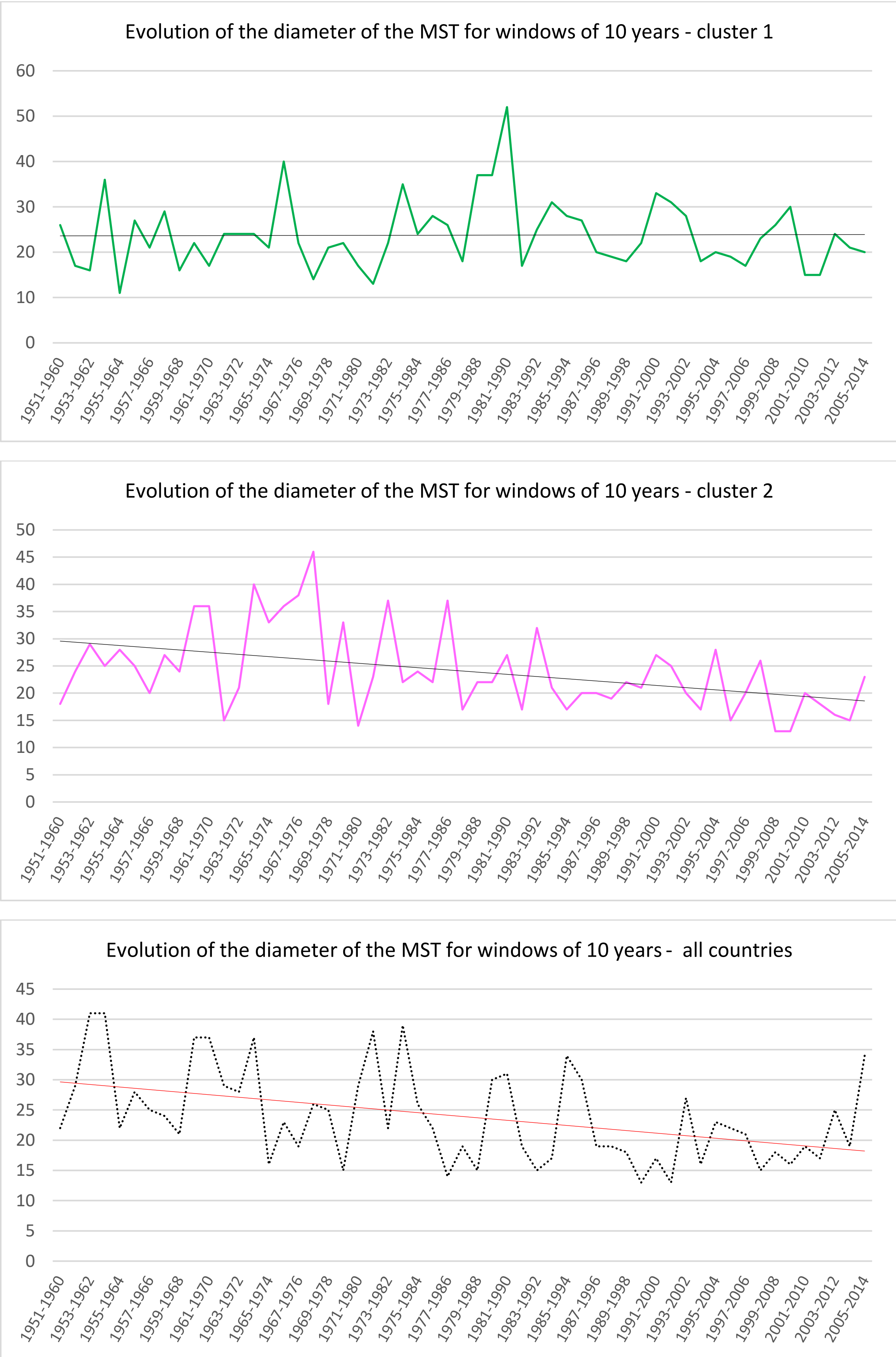
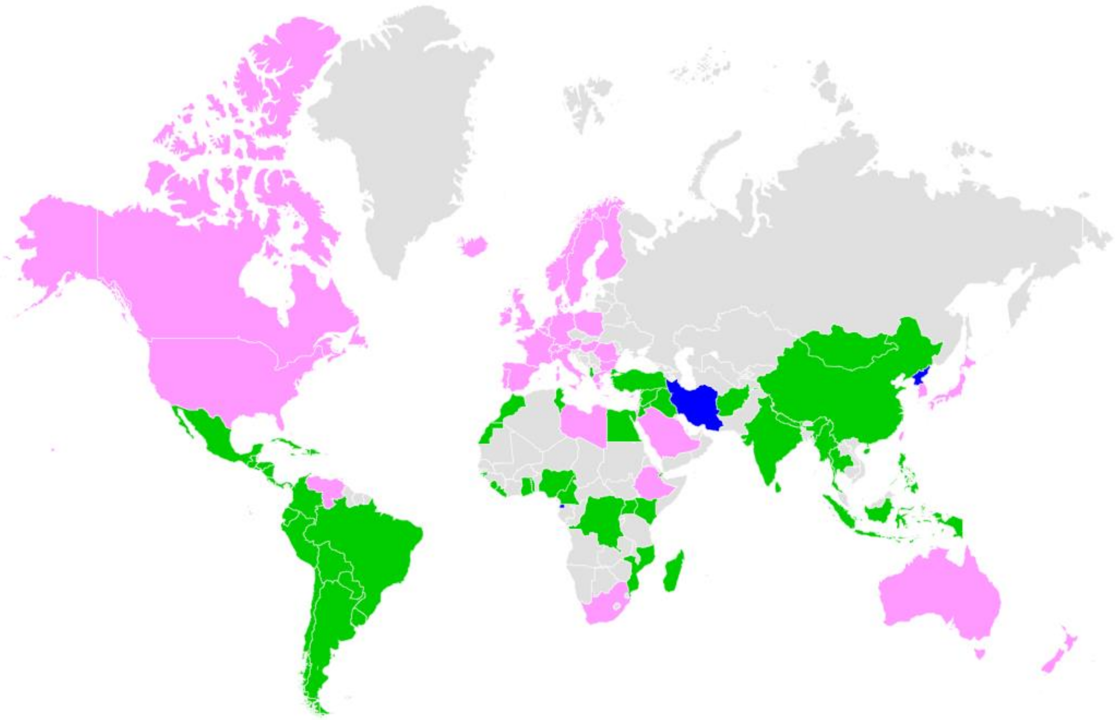
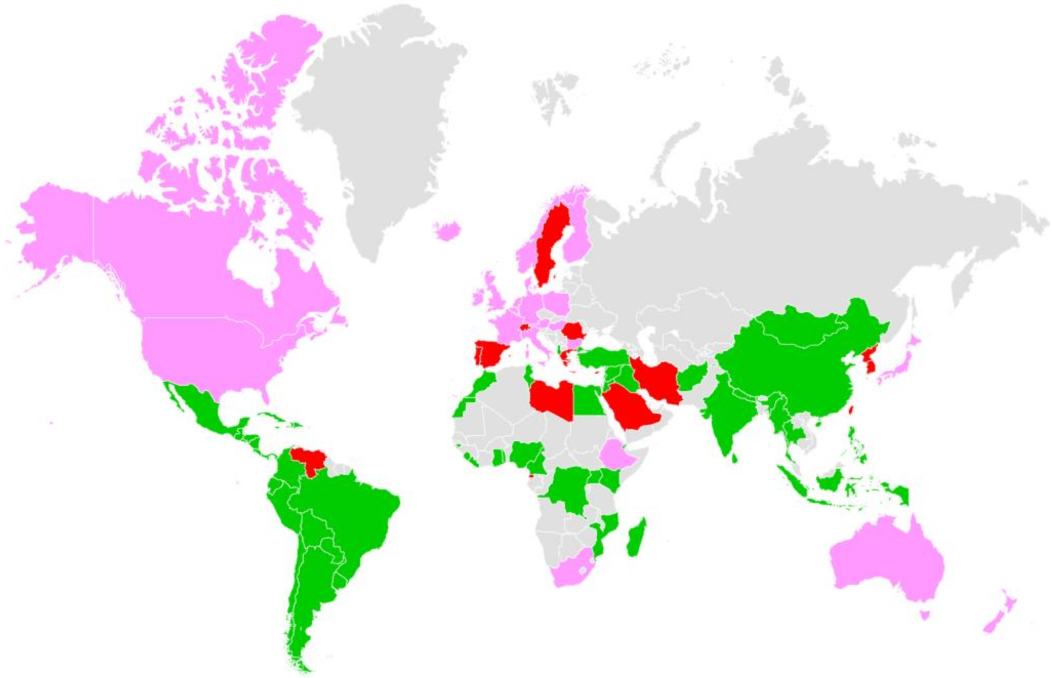


FIGURE 6: Evolution of the diameter of the MST and the diameter of the portion of the MST corresponding to each cluster, for windows of 10 years. Sources: Maddison project database (MPD) and Carbon Dioxide Information Analysis Center (CDIAC). Authors' calculations



Map 1. Regime Clusters for the whole period (1951-2014). In green cluster 1, pink cluster 2, in blue we show single-country clusters. Finally, we use gray color for not included countries in our dataset.



Country	1951-1999	2000-2014
Barbados	1	3
Cyprus	1	2
North Korea	3	1
Equatorial Guinea	1	2
Greece	3	2
Hong Kong	1	2
Iran	1	2
South Korea	1	2
Libya	3	2
Malta	1	2
Portugal	1	4
Romania	2	1
Saudi Arabia	3	2
Spain	1	2
Sweden	2	3
Switzerland	2	3
Taiwan	1	2
Venezuela	3	2

Map 2. Mobility between clusters. Periods 1951-1999 and 2000-2014. In green, countries that remain in cluster 1 when compared to the previous period. In pink, the same information regarding cluster 2. In red, we show countries that have switched their group when comparing to the period 1951-1999. Finally, gray represents countries not included in our dataset. The lower table shows the countries' changes between periods. Group 1 corresponds to the green group while number 2 is the pink group. Groups 3 and 4 correspond to different, smaller groups.

Country	Code	R1	R2	R3	R4	TOTAL
AFGHANISTAN	AFG	0%	0%	30%	70%	100%
ALBANIA	ALB	0%	0%	62%	38%	100%
ARGENTINA	ARG	0%	0%	47%	53%	100%
AUSTRALIA	AUS	62%	38%	0%	0%	100%
AUSTRIA	AUT	41%	59%	0%	0%	100%
BARBADOS	BRB	11%	0%	56%	33%	100%
BELGIUM	BEL	44%	56%	0%	0%	100%
BOLIVIA	BOL	0%	0%	34%	66%	100%
BRAZIL	BRA	0%	0%	55%	45%	100%
BULGARIA	BGR	38%	48%	9%	5%	100%
REPUBLIC OF CAMEROON	CMR	0%	0%	23%	77%	100%
CANADA	CAN	52%	48%	0%	0%	100%
CHILE	CHL	0%	0%	56%	44%	100%
CHINA (MAINLAND)	CHN	0%	13%	62%	25%	100%
COLOMBIA	COL	0%	0%	47%	53%	100%
COSTA RICA	CRI	0%	0%	55%	45%	100%
CUBA	CUB	2%	0%	48%	50%	100%
CYPRUS	CYP	27%	20%	37%	16%	100%
D. P. R. KOREA	PRK	17%	26%	16%	41%	100%
D. R. CONGO	COD	0%	0%	30%	70%	100%
DENMARK	DNK	59%	41%	0%	0%	100%
DJIBOUTI	DJI	0%	0%	27%	73%	100%
DOMINICAN REPUBLIC	DOM	0%	0%	58%	42%	100%
ECUADOR	ECU	0%	0%	47%	53%	100%
EGYPT	EGY	0%	0%	53%	47%	100%
EL SALVADOR	SLV	0%	0%	36%	64%	100%
EQUATORIAL GUINEA	GNQ	8%	14%	44%	34%	100%
ETHIOPIA	ETH	58%	41%	0%	1%	100%
FINLAND	FIN	41%	51%	3%	5%	100%
FRANCE (INCLUDING MONACO)	FRA	38%	61%	0%	1%	100%
GAMBIA	GMB	0%	0%	33%	67%	100%
GERMANY	DEU	45%	55%	0%	0%	100%
GHANA	GHA	0%	0%	45%	55%	100%
GREECE	GRC	30%	31%	31%	8%	100%
GUATEMALA	GTM	0%	0%	36%	64%	100%
GUINEA BISSAU	GNB	0%	0%	50%	50%	100%
HAITI	HTI	0%	0%	28%	72%	100%
HONDURAS	HND	0%	0%	30%	70%	100%
HONG KONG	HKG	12%	30%	41%	17%	100%
HUNGARY	HUN	40%	50%	5%	5%	100%
ICELAND	ISL	41%	59%	0%	0%	100%
INDIA	IND	0%	0%	62%	38%	100%
INDONESIA	IDN	0%	0%	67%	33%	100%
IRAQ	IRQ	0%	0%	47%	53%	100%
IRAN	IRN	16%	17%	37%	30%	100%
IRELAND	IRL	42%	58%	0%	0%	100%
ISRAEL	ISR	33%	67%	0%	0%	100%
ITALY (INCLUDING SAN MARINO)	ITA	39%	42%	19%	0%	100%
JAMAICA	JAM	0%	0%	41%	59%	100%
JAPAN	JPN	33%	51%	16%	0%	100%
JORDAN	JOR	0%	0%	39%	61%	100%
KENYA	KEN	0%	0%	33%	67%	100%
REPUBLIC OF KOREA	KOR	5%	37%	45%	13%	100%
LEBANON	LBN	0%	0%	53%	47%	100%
LIBERIA	LBR	0%	0%	31%	69%	100%
LIBYAN ARAB JAMAHIRIYAH	LBY	47%	26%	22%	5%	100%
LUXEMBOURG	LUX	44%	56%	0%	0%	100%
MADAGASCAR	MDG	0%	0%	14%	86%	100%

MALTA	MLT	16%	28%	44%	12%	100%
MAURITIUS	MUS	0%	0%	58%	42%	100%
MEXICO	MEX	0%	0%	53%	47%	100%
MONGOLIA	MNG	5%	11%	42%	42%	100%
MOROCCO	MAR	0%	0%	36%	64%	100%
MOZAMBIQUE	MOZ	0%	0%	48%	52%	100%
MYANMAR (FORMERLY BURMA)	MMR	0%	0%	67%	33%	100%
NEPAL	NPL	0%	0%	45%	55%	100%
NETHERLANDS	NLD	53%	47%	0%	0%	100%
NEW ZEALAND	NZL	58%	42%	0%	0%	100%
NICARAGUA	NIC	0%	0%	34%	66%	100%
NIGERIA	NGA	0%	0%	45%	55%	100%
NORWAY	NOR	47%	53%	0%	0%	100%
PANAMA	PAN	0%	0%	59%	41%	100%
PARAGUAY	PRY	0%	0%	41%	59%	100%
PERU	PER	0%	0%	50%	50%	100%
PHILIPPINES	PHL	0%	0%	50%	50%	100%
POLAND	POL	38%	62%	0%	0%	100%
PORTUGAL	PRT	17%	9%	55%	19%	100%
ROMANIA	ROU	24%	39%	23%	14%	100%
SAINT LUCIA	LCA	0%	0%	45%	55%	100%
SAUDI ARABIA	SAU	45%	30%	22%	3%	100%
SIERRA LEONE	SLE	0%	0%	44%	56%	100%
SOUTH AFRICA	ZAF	80%	20%	0%	0%	100%
SPAIN	ESP	31%	33%	28%	8%	100%
SRI LANKA	LKA	0%	0%	53%	47%	100%
SWEDEN	SWE	45%	47%	2%	6%	100%
SWITZERLAND	CHE	58%	30%	0%	12%	100%
SYRIAN ARAB REPUBLIC	SYR	0%	0%	45%	55%	100%
TAIWAN	TWN	6%	39%	50%	5%	100%
THAILAND	THA	0%	0%	75%	25%	100%
TOGO	TGO	0%	0%	34%	66%	100%
TRINIDAD AND TOBAGO	TTO	41%	58%	0%	1%	100%
TUNISIA	TUN	0%	0%	61%	39%	100%
TURKEY	TUR	0%	0%	66%	34%	100%
UGANDA	UGA	0%	0%	45%	55%	100%
UNITED KINGDOM	GBR	61%	39%	0%	0%	100%
UNITED STATES OF AMERICA	USA	53%	47%	0%	0%	100%
URUGUAY	URY	0%	0%	50%	50%	100%
VENEZUELA	VEN	58%	41%	1%	0%	100%

Table 1. 98 Selected countries, acronyms and percentage of time every country in each regime. 1951-2014.

ANNEX. SUPPLEMENTARY FIGURES/TABLES

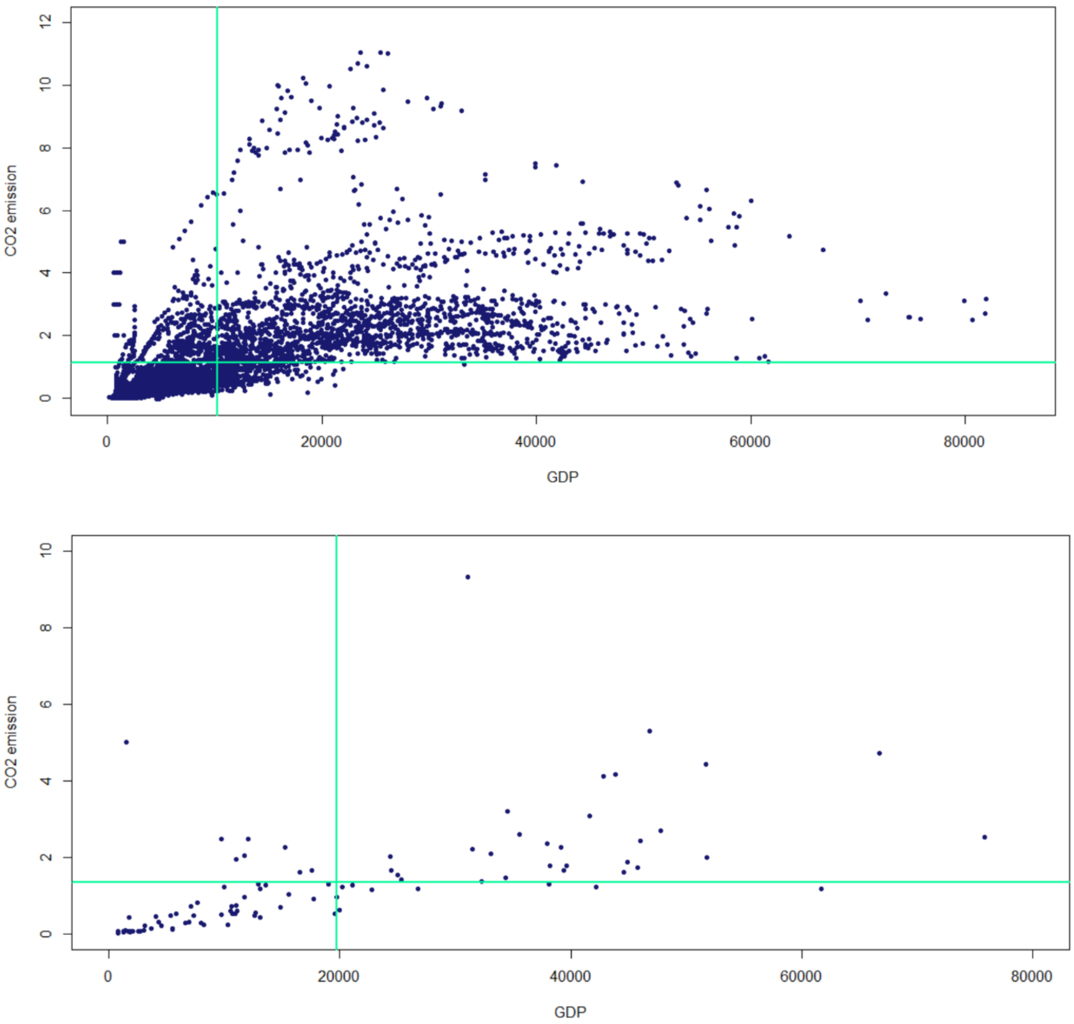


FIGURE S1: GDP and CO2 emissions per capita levels.
Upper part: Data partition in the state space for the set of 98 countries for the whole period
Lower part: Data partition in the state space for the set of 98 countries during 2014
Sources: Maddison project database (MPD) and Carbon Dioxide Information Analysis Center (CDIAC). Authors' calculations

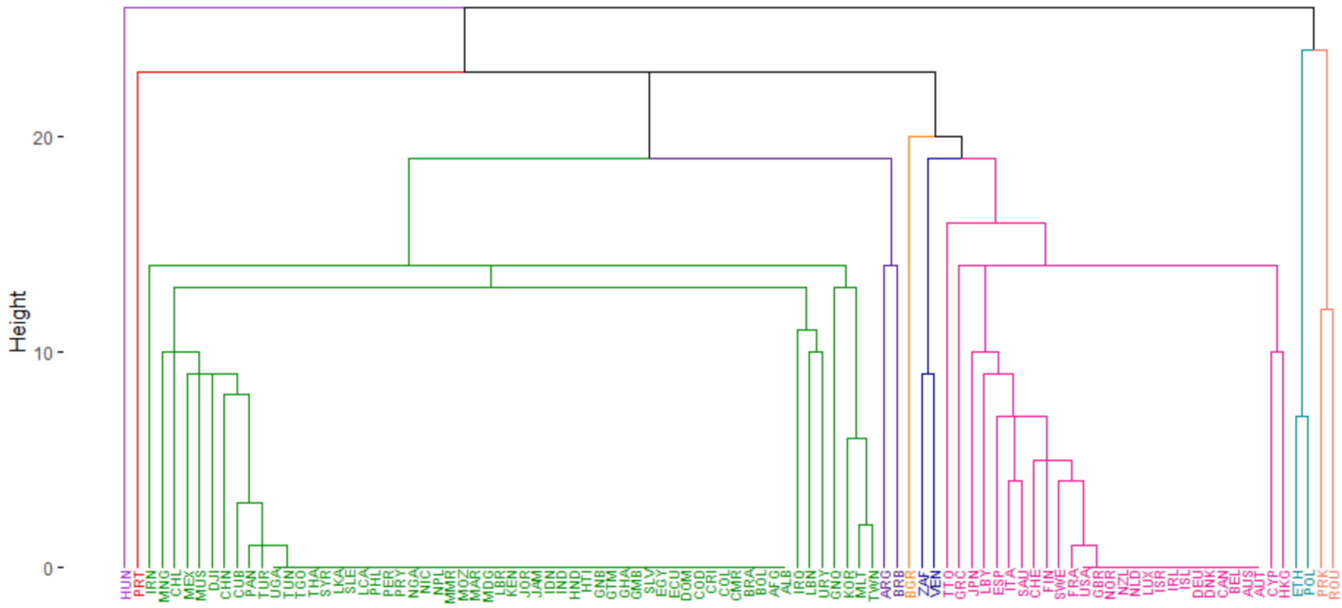


FIGURE S2: GDP and CO2 emissions per capita levels. Hierarchical tree of the set of 98 countries for the period 1951–2014.
Sources: Maddison project database (MPD) and Carbon Dioxide Information Analysis Center (CDIAC). Authors' calculations

Country	Code	R1	R2	R3	R4	TOTAL
Afghanistan	AFG	0%	0%	0%	100%	100%
Albania	ALB	0%	0%	0%	100%	100%
Argentina	ARG	0%	0%	84%	16%	100%
Australia	AUS	0%	100%	0%	0%	100%
Austria	AUT	0%	100%	0%	0%	100%
Barbados	BRB	9%	2%	84%	5%	100%
Belgium	BEL	0%	100%	0%	0%	100%
Bolivia	BOL	0%	0%	0%	100%	100%
Brazil	BRA	0%	0%	0%	100%	100%
Bulgaria	BGR	34%	52%	2%	13%	100%
Cameroon	CMR	0%	0%	0%	100%	100%
Canada	CAN	0%	100%	0%	0%	100%
Chile	CHL	0%	0%	30%	70%	100%
China	CHN	13%	0%	0%	88%	100%
Colombia	COL	0%	0%	0%	100%	100%
Costa Rica	CRI	0%	0%	0%	100%	100%
Cuba	CUB	2%	0%	3%	95%	100%

Cyprus	CYP	0%	47%	44%	9%	100%
North Korea	PRK	44%	0%	0%	56%	100%
Democratic Republic of the Congo	COD	0%	0%	0%	100%	100%
Denmark	DNK	0%	100%	0%	0%	100%
Djibouti	DJI	0%	0%	17%	83%	100%
Dominican Republic	DOM	0%	0%	0%	100%	100%
Ecuador	ECU	0%	0%	0%	100%	100%
Egypt	EGY	0%	0%	0%	100%	100%
El Salvador	SLV	0%	0%	0%	100%	100%
Equatorial Guinea	GNQ	0%	22%	0%	78%	100%
Ethiopia	ETH	98%	0%	0%	2%	100%
Finland	FIN	0%	92%	8%	0%	100%
France	FRA	0%	98%	2%	0%	100%
Gambia	GMB	0%	0%	0%	100%	100%
Germany	DEU	0%	100%	0%	0%	100%
Ghana	GHA	0%	0%	0%	100%	100%
Greece	GRC	0%	61%	20%	19%	100%
Guatemala	GTM	0%	0%	0%	100%	100%
Guinea-Bissau	GNB	0%	0%	0%	100%	100%
Haiti	HTI	0%	0%	0%	100%	100%
Honduras	HND	0%	0%	0%	100%	100%
Hong Kong	HKG	0%	42%	53%	5%	100%
Hungary	HUN	36%	55%	9%	0%	100%
Iceland	ISL	0%	100%	0%	0%	100%
India	IND	0%	0%	0%	100%	100%
Indonesia	IDN	0%	0%	0%	100%	100%
Iraq	IRQ	0%	0%	55%	45%	100%
Iran	IRN	28%	5%	2%	66%	100%
Ireland	IRL	0%	100%	0%	0%	100%
Israel	ISR	0%	100%	0%	0%	100%
Italy	ITA	0%	81%	19%	0%	100%
Jamaica	JAM	0%	0%	0%	100%	100%
Japan	JPN	0%	84%	3%	13%	100%
Jordan	JOR	0%	0%	0%	100%	100%
Kenya	KEN	0%	0%	0%	100%	100%
South Korea	KOR	0%	42%	0%	58%	100%
Lebanon	LBN	0%	0%	44%	56%	100%
Liberia	LBR	0%	0%	0%	100%	100%
Libya	LBY	5%	69%	19%	8%	100%
Luxembourg	LUX	0%	100%	0%	0%	100%
Madagascar	MDG	0%	0%	0%	100%	100%
Malta	MLT	0%	44%	8%	48%	100%
Mauritius	MUS	0%	0%	14%	86%	100%
Mexico	MEX	0%	0%	14%	86%	100%
Mongolia	MNG	16%	0%	0%	84%	100%

Morocco	MAR	0%	0%	0%	100%	100%
Mozambique	MOZ	0%	0%	0%	100%	100%
Myanmar	MMR	0%	0%	0%	100%	100%
Nepal	NPL	0%	0%	0%	100%	100%
Netherlands	NLD	0%	100%	0%	0%	100%
New Zealand	NZL	0%	100%	0%	0%	100%
Nicaragua	NIC	0%	0%	0%	100%	100%
Nigeria	NGA	0%	0%	0%	100%	100%
Norway	NOR	0%	100%	0%	0%	100%
Panama	PAN	0%	0%	3%	97%	100%
Paraguay	PRY	0%	0%	0%	100%	100%
Peru	PER	0%	0%	0%	100%	100%
Philippines	PHL	0%	0%	0%	100%	100%
Poland	POL	91%	9%	0%	0%	100%
Portugal	PRT	0%	27%	44%	30%	100%
Romania	ROU	63%	0%	0%	38%	100%
Saint Lucia	LCA	0%	0%	0%	100%	100%
Saudi Arabia	SAU	0%	75%	25%	0%	100%
Sierra Leone	SLE	0%	0%	0%	100%	100%
South Africa	ZAF	61%	39%	0%	0%	100%
Spain	ESP	0%	64%	36%	0%	100%
Sri Lanka	LKA	0%	0%	0%	100%	100%
Sweden	SWE	0%	92%	8%	0%	100%
Switzerland	CHE	0%	88%	13%	0%	100%
Syria	SYR	0%	0%	0%	100%	100%
Taiwan	TWN	0%	45%	8%	47%	100%
Thailand	THA	0%	0%	0%	100%	100%
Togo	TGO	0%	0%	0%	100%	100%
Trinidad and Tobago	TTO	23%	75%	2%	0%	100%
Tunisia	TUN	0%	0%	0%	100%	100%
Turkey	TUR	0%	0%	2%	98%	100%
Uganda	UGA	0%	0%	0%	100%	100%
United Kingdom	GBR	0%	100%	0%	0%	100%
United States	USA	0%	100%	0%	0%	100%
Uruguay	URY	0%	0%	38%	63%	100%
Venezuela	VEN	50%	48%	2%	0%	100%

Table S1. GDP and CO2 emissions per capita levels. 98 Selected countries, acronyms and percentage of time in each regime. 1951-2014.

Italics and underlined: countries that moved from group (comparing to analysis of per capita GDP rate of growth)

Light grey cells: countries staying in the same regime the overall period

Argentina and Barbados become outliers (previously placed in the green group) Bulgaria, Ethiopia, Hungary, Poland, Portugal, Romania, South Africa and Venezuela become outliers (previously placed in the pink group) Equatorial Guinea and Iran join the green group (previously outliers) South Korea, Malta and Taiwan moved away from pink to green group (these are the only countries moving between groups)

Table S2. Switching countries information