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Bachelor Thesis - BSc^2 Economics/Econometrics

Decomposing the R^2 in Models of Carbon Emission Growth: A Shapley-based Approach

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Abstract

This paper investigates the relative importance of economic and political variables in modelling carbon dioxide emission growth. Three different approaches to a Shapley-based decomposition of the R^2 are employed using a global panel of 115 or 119 countries covering the years 1970 to 2018. Next to the regular Shapley decomposition of the R^2 suggested by Lipovetsky and Conklin (2001), the joint importance of grouped variables are assessed using the Owen decomposition approach (Shorrocks, 2013) and the Nested Shapley appraoch (Chantreuil & Trannoy, 2011). Overall, the results suggest a higher importance of economic than political variables to explaining cross-country and time variations in carbon emission growth rates, but indicate an increase in the importance of political variables over time. In particular, measures of globalization are shown to be increasingly important determinants of carbon emission growth. Still, in historical datasets, energy consumption and GDP growth remain the main drivers of emission growth. Next to these topical findings, the applicability of a Shapley-based decomposition of the R^2 in quantifying explanatory variables' importance is demonstrated. Shapley values are found to offer a more robust alternative to assessing importance via t-statistics of regression coefficients. In grouped models, the Nested Shapley approach is found to be much preferred to the Owen approach, due to better computational performance and ease of application. Further research is recommended to apply Shapley decomposition to a broader set of explanatory variables and to incorporate the information from Shapley values in standard regression coefficient significance tests.

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1 Introduction

While efforts to bring down carbon emissions have increased substantially over the past years and the list of countries with a proclaimed goal of carbon neutrality keeps expanding, there are still striking disparities across national CO_2 emission growth rates. For example, in 2014 Chile reduced its national carbon emissions by 7.4% compared to the previous year, while its neighbour Bolivia saw an increase in emissions by 8.0% in the same year. What political and economic factors can explain such cross-country variation in carbon emissions? And what is the relative importance of these factors?

Understanding the influences and mechanisms of economic and political structures in curbing carbon emission growth is of crucial importance in global efforts to limit climate change. Numerous studies have thus attempted to answer the first question above, employing regression analysis and focusing on establishing significance of point estimates in order to prove importance of a certain explanatory variable. However, simple significance tests do not necessarily allow for a comparison of relative importance across variables and, therefore, cannot provide a clear answer to the second question. Moreover, multicollinearity of regressors may inflate standard errors and therefore lead to non-rejection of a false null hypothesis of ineffectiveness of the regressor. This paper therefore takes a novel approach and compares the contributions of different political and economic variables to explained variance of carbon emission growth using Shapley-based decomposition approaches. In doing so, it extends existing environmental economics literature on cross-country drivers of carbon emission growth beyond the use of simple regression analysis. Additionally, this paper contributes to the scientific literature on the applicability of Shapley-based decompositions of the R^2.

The main research question thus reads as follows:

> *What is the relative contribution of different economic and political variables to explaining carbon emission growth in a cross-country dataset?*

To answer this question, regression models will be estimated in a smaller, balanced 20-year panel of 115 countries and in a larger, unbalanced 48-year panel of 119 countries. Subsequently, weighted averages of the models' R^2 will be taken and allocated to the explanatory variables, following a Shapley-based decomposition approach as presented by Lipovetsky and Conklin (2001). Moreover, changes over time and across countries in the relative importance of different variables will be considered. Finally, parts of the analysis will be repeated using hierarchical models. In these models, related variables are grouped together and both the importance of variable groups and individual variables is assessed. To this end, the Owen decomposition and Nested Shapley decomposition will be employed. The comparative study of these approaches does not only allow for a more complete picture of the relative contribution of different variables to carbon emission growth, but also gives insight into the respective merits of the two approaches.

The analysis leads to the following main results. First, the relative contribution of economic variables significantly outweighs the contribution of political variables. Depending on the specifications, economic variables account for 52% to 80% of the explained variance of the dependent variable. GDP growth and electric power consumption growth bear the greatest explanatory importance in all model specifications, but are followed by measures of economic, social, and political globalization. Population growth and indicators of the degree of democracy bear limited importance in explaining cross-country variations in carbon emissions, while the share of industry and manufacturing in national GDP as well as human capital growth bear no explanatory power.

Second, estimations in sub-periods reveal an increase in the importance of political variables. Measures of globalization in particular gained importance between 1995 and 2005, while the contribution of electric power consumption growth has declined over the same period. This observation may reflect the ongoing decarbonization of electricity generation in many economies, as well as the increasing number of international agreements and intergovernmental cooperations to reduce global greehouse gas emissions.

Third, the analysis of hierarchical models highlights the usefulness of a grouped analysis, and the superiority of the Nested Shapley approach over the Owen approach. Grouping explanatory variables greatly saves computation time, however, only the Nested Shapley approach offers computational gains which are large enough to render computation feasible.

The main contribution of this paper is to demonstrate the applicability of Shapley-based decomposition of the R^2 in regression analysis, as well as to highlight the growing importance of political variables in explaining cross-country variation in carbon emission growth. Despite great differences across country and time period subsamples, the neglect of political covariates in modelling carbon emission growth substantially decreases goodness of fit.

The remainder of the paper is structured as follows. Section 2 summarizes the relevant literature, focusing on political and economic covariates of carbon emissions. Next, Section 3 presents the employed data and summary statistics. Sections 4 and 5 provide background and mathematical details of the employed decomposition approaches and outline the general methodology. Section 6 presents the results of the analysis, which are further discussed in Section 7. Section 8 concludes.

2 Literature review

The decomposition of carbon emissions has been studied abundantly by previous scholars. However, different groups of scholars have applied vastly different econometric techniques in decomposing emissions and attributed differing levels of importance to economic, political, and social factors in explaining emissions.

A large strand of the literature is concerned with the connection between economic growth and carbon emissions. This association is widely uncontested and has been confirmed for both cross-country studies (e.g Doda, 2014; Kammerlander & Schulze, 2020; Sharma, 2011) and intertemporal studies (e.g. Friedl & Getzner, 2003; Heutel, 2012; Shahiduzzaman & Layton, 2015). The seminal work of Grossman and Krueger (1995) has raised the important question of linearity in this relationship, forming the idea of an "Environmental Kuznets Curve" (EKC). This idea posits that the relationship between environmental degradation and income is characterized by an inverted U-shape, meaning that pollution initially increases with rising income but declines again beyond some point. However, empirical evidence for the case of carbon emissions is mixed. Using a global sample of 111 nations, Dietz and Rosa (1997) show that overall CO_2 emissions decline with further economic growth. Dutt (2009) confirm this result for a global panel of 125 nations spanning the years 1984-2002, but point out that only few nations have been experiencing sufficient economic growth to move beyond the turning point where emissions are falling again. Other scholars (e.g. Cole et al., 1997; Shafik, 1994) have found no turning point at all, but rather a monotonous relationship between economic growth and carbon emissions.

In attempts to explain tight association of national income and carbon emission, energy use has been paid considerable attention as a mitigating factor. Energy is a key input factor of economic activity and carbon emissions are an important by-product in most energy-generating processes (Sharma, 2011). Including energy use in regression models of carbon emissions is therefore common practice. However, some authors argue that the high correlation of energy use and carbon emissions requires instrumentalizing this variable (Joshi & Beck, 2018) or using decomposition analysis (Hamilton & Turton, 2002). A popular technique is to separate changes in carbon emissions (CE) into changes in carbon intensity of energy consumption (CE/EC), energy intensity of production (EC/GDP), GDP per capita (GDP/P), and population growth (P). First introduced by Kaya (1989), this "Kaya identity" has been studied for numerous regional and cross-country panels. In a study of OECD countries, Hamilton and Turton (2002) make use of a refined Kaya decomposition analysis, additionally accounting for fossil fuel-intensity of energy, in identifying the main drivers of CO_2 emission growth between 1982 and 1997. Overall, their findings suggest that increases in population and GDP per capita are primarily responsible for the observed growth in carbon emissions. This result is contested by Albrecht et al. (2002), who use a Shapley decomposition technique for 4 developed countries to show that the effect of economic growth on carbon emissions in the Kaya identity is frequently overestimated, due to large residuals.

Compared to measures of macroeconomic performance, the role of political factors in explaining environmental outcomes is less intuitive and conspicuous. Focusing on broader definitions of environmental quality, the question whether democracies are inherently "cleaner" has motivated several empirical studies (e.g. Li & Reuveny, 2006; Payne, 1995; Schultz & Crockett, 1990). Coining the "clean democracy hypothesis", these studies argue that the greater concern for citizens' freedoms and well-being, respect for international agreements, and the sparsity of corruption lead to stricter enforcement of environmental protection policies in democracies. For carbon emissions, this hypothesis is supported by Dutt (2009) and Farzin and Bond (2006), who find negative significant associations between measures of political freedom and carbon emissions in cross-country studies. By contrast, Kammerlander and Schulze (2020) fail to find a robust evidence of the clean democracy hypothesis when considering a wider set of air pollutants, including CO_2.

Unifying frameworks of economic and political covariates of carbon emissions, a few studies examine the role of globalization and economic freedom in explaining carbon emissions and come to dissimilar conclusions. Most prominently, the Pollution Haven Hypothesis (PHH) posits that emission-intensive production processes will be outsourced to jurisdictions with lax environmental regulation, implying that openness to trade will reduce emissions in countries with tight regulation but increase them in open economies with little regulation (Copeland & Taylor, 1994). However, empirical evidence of this hypothesis is inconclusive for the case of carbon emissions. Contradicting the PHH, Carlsson and Lundström (2001) find that economic freedom increases emissions in high-income countries but reduces them in low-income countries. Joshi and Beck (2018) find that the effect of economic freedom in emissions is dependent on the type of government but that the emission-enhancing effects of increased business prevail.

Even though a few studies (e.g. Albrecht et al., 2002; Henriques & Borowiecki, 2017) have used decomposition analysis to analyse the contribution of Kaya identity factors in explaining carbon emissions, the vast majority of empirical studies in this field focus on simple regression analysis to assess the relative importance of different variables. While economic and statistical significance of variables is usually established by comparing sign, magnitude, and t-statistics of regression coefficients, these figures do not necessarily allow for a ranking of the explanatory variables in order of importance (Israeli, 2007). Additionally, when explanatory variables are highly correlated, statements based on variable significance may be misleading, as standard errors are inflated. Scholars have therefore developed a strategic approach to allocating the overall goodness of fit of a regression model to its explanatory variables. This technique follows Shapley's (1953) approach of allocating utility to players in cooperative game theory. Technical details of this approach will be described in Section 4. Gaining popularity in decomposition analyses, Shapley-based decomposition has been employed to disentangle the contribution of various income sources to income inequality (e.g. Chantreuil & Trannoy, 2011; Sastre & Trannoy, 2002; Shorrocks, 2013). More recently, Shapley-based decompositions have also been employed to assess the contribution of the four Kaya identity factors to carbon emissions. Emphasising the attractiveness of a residual-free decomposition of carbon emissions, Albrecht et al. (2002) use a Shapley-based approach in a study of 4 European countries to show that the effect of economic growth on emissions is overestimated in conventional decomposition studies. Henriques and Borowiecki (2017) equally apply a Shapley decomposition to an extended Kaya identity and use historical data to show that changes in the energy mix account for rising carbon emissions in low-income countries and recently falling emissions in high-income countries.

While these applications of a Shapley-based decomposition help to shed light on the relative importance of Kaya identity factors in carbon emissions, the rigid focus on a perfect identity does not allow for an inclusion of more granular factors. In particular, the Kaya identity is inappropriate for the inclusion of political factors in a model of carbon emission. This paper therefore seeks to combine the benefits of a Shapley-based decomposition approach with the richness of political and economic variables found in conventional regression analysis studies. Using Shapley decomposition additionally allows for a grouping of variables and determining their joint importance, whereas no such exercise is possible in conventional regression analysis.

3 Data

This paper aims to study the relative importance of various political and economic factors in explaining cross-country and time variations in carbon emissions. Cross-sectional panel data on national carbon dioxide (CO_2) emissions is obtained from the Emissions Database for Global Atmospheric Research (EDGAR), which covers 215 countries for the period 1970-2018. EDGAR provides CO_2 emissions separately including and excluding short-cycle organic carbon emissions, like forest fires and biomass burning. Since organic emissions are frequently caused by external weather or climate conditions, they are assumed to be beyond regulatory control and therefore excluded from the study. To account for country-specific trends in carbon emissions and to normalize across countries, the CO_2 growth rate will be considered. The use of growth rates, rather than levels, is further corroborated by a Levin-Lin-Chu (LLC) test. For results, refer to Table 1 in the Appendix, which indicates the presence of unit root for national carbon emission levels, but not for growth rates.

Various political and economic variables are considered to explain time-varying differences in national carbon emission growth. As outlined in Section 2, GDP is an important predictor of carbon emissions and is therefore included in this study. As the dependent variable represents growth rates, the annual percentage growth rate of GDP as reported by the World Bank is used. Stationarity of this variable is again confirmed by an LLC test.

Many studies in the literature that analyse carbon emissions include measures of national population to capture the pollution arising from human non-industrial activities and to control for the size of a national economy. I therefore include population growth as a second dependent variable, which is calculated based on World Bank annual population figures.

Electric power consumption in kWh per capita is included, to capture the considerable impact of energy consumption on national emissions. This is in accordance with the literature, which frequently finds support for the role of changes in energy intensity in explaining changes in carbon emissions (e.g Kammerlander & Schulze, 2020; Kasman & Duman, 2015). Again, percentage growth rates are calculated based on level data reported by the World Bank.

Next, measures of size and output of national economies, variables capturing the sectoral structure of the economy help to explain cross-country differences in carbon emissions. I therefore include a human capital index as reported by the Penn World Tables (Feenstra et al., 2015), which combines information on average years of schooling and returns on education. The human capital index helps to proxy for the relative importance of the tertiary sector in a given country, which has been shown to reduce emissions in advanced economies (Friedl & Getzner, 2003). Moreover, I include the relative size of a country's industrial sector, which is retrieved from the World Bank. This indicator is reported as percentage of GDP and measures the value added from mining, manufacturing, construction, electricity, water, and gas. Combined, these variables paint a broader picture of an economy's structure and help to capture a potential focus on pollution-intensive production in capital-intensive and highly industrial economies.

A second group of variables is concerned with the political state of a country. Following the analysis of Kammerlander and Schulze (2021), who found a significant and robust effect of globalization measures on environmental performance, the KOF Globalization Index (KOFGI) is included in the model to account for trade and import effects on emissions and the national economy. The KOFGI is compiled by the Swiss Economic Institute at the ETH Zürich and quantifies the susceptibility of a country for economic, social, and political globalization on a scale from 0 (autarky) to 100 (fully globalized). Economic globalization measures the a country's openness to trade and the connectedness to the global financial market. Social globalization describes the existence of personal contacts, information flows, and cultural links. Political globalization describes a country's participation in treaties and organisations. The overall globalization index is the average of the three named subindices. In this paper, models using the overall index and models using the subindices are considered.

Additionally, a variable for democratic freedom in a country is included. I use the polity2 score of the PolityIV project. The PolityIV dataset has been commonly used in political science studies (e.g. Epstein et al., 2006); its polity2 indicator measures the competitiveness and openness of national elections and quantifies the degree of democracy on a scale from +10 (fully democratic) to -10 (fully autocratic). Following Kammerlander and Schulze (2020), I construct dummies for autocracies (polity2 value -10 to 0), partial democracies (+1 to +7), and full democracies (+8 to +10), which are included as independent variables in the regression model.

Using cross-country data from four sources results in a large number of missing values for several variables. This is particularly the case when considering political variables, due to changing national borders and jurisdictions in the course of the late 20^th century. To avoid sample selection bias, which may arise if there are commonalities among countries with missing values, two subsamples will be considered in comparison. First, a balanced yearly panel of 115 countries is constructed, which covers the time period from 1995 to 2014. The World Bank classifies 46 of these countries as high-income states, 41 as upper or lower middle income states, and 28 as lower income states. A full list of countries and a detailed description of the sample construction can be found in Appendix A.

Second, an unbalanced panel will be considered, where all country-year observations are included for which no variable has a missing value. This resulting sample contains 4,413 observations of 119 countries (that is, the same 114 countries of the balanced sample with Iraq, Ethiopia, Niger, Serbia, and Sudan). The number of observations per country varies between 8 and 44, with an average of 37 observations per country. A list with the number of observations per year can be found in Table A.3 in the Appendix.

Table 1. *Summary statistics in strongly balanced and unbalanced panel*

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Observations**
Strongly balanced panel					
CO_2 emissions*	0.312	0.105	-0.352	2.117	2,300
GDP*	0.0390	0.041	-0.263	0.262	2,300
population*	0.014	0.017	-0.044	0.191	2,300
electric power consumption*	0.044	0.084	-0.395	1.271	2,300
industry share	0.295	0.113	0.093	0.748	2,300
human capital*	0.009	0.006	-0.007	0.038	2,300
Globalization	61.923	14.769	23.563	90.440	2,300
Economic glob.	57.915	16.013	17.683	94.960	2,300
Social glob.	56.595	19.873	9.074	91.996	2,300
Political glob.	71.177	16.898	22.861	98.144	2,300
Polity2	4.734	6.062	-10	10	2,300
Full democracy	0.507	0.500	0	1	2,300
Partial democracy	0.239	0.427	0	1	2,300
Autocracy	0.243	0.429	0	1	2,300
Unbalanced panel					
CO_2 emissions*	0.328	0.118	-0.677	3.524	4,343
GDP*	0.0373	0.052	-0.640	0.578	4,343
population*	0.017	0.016	-0.044	0.191	4,343
electric power consumption*	0.037	0.094	-0.558	1.738	4,343
industry share	0.297	0.112	0.062	0.848	4,343
human capital*	0.010	0.007	-0.009	0.044	4,343
Globalization	54.850	16.709	14.885	90.440	4,343
Economic glob.	50.816	17.545	10.828	94.960	4,343
Social glob.	49.007	21.328	6.265	91.996	4,343
Political glob.	64.621	18.521	13.711	98.144	4,343
Polity2	2.936	7.162	-10	10	4,343
Full democracy	0.438	0.496	0	1	4,343
Partial democracy	0.196	0.397	0	1	4,343
Autocracy	0.356	0.478	0	1	4,343

Note. Variables marked with an asterisk (*) represent growth rates.

4 Introduction to Shapley values

To study the relative role of political and economic factors in explaining carbon emissions, a sequence of linear regression models is estimated and the R^2 is decomposed into the relative contributions of each explanatory variable. This is done by evaluating the R^2 for all possible deletion sequences of explanatory variables and taking a weighted average of each variables' contribution to the R^2. I consider three approaches to the weighing and sequential deletion of variables, which will be presented in sections 4.1-4.3. Thereafter, the models considered in this study will be presented.

4.1 Shapley decomposition

Initially referring to the allocation of utility to players in cooperative game theory (Shapley, 1953), the concept of "Shapley values" has found applications in numerous fields of mathematics, statistics, and economics. Its power lies in the fulfillment of the three axioms of symmetry, additivity, and efficiency of allocation. Moreover, Shapley values provide a methodologically simple and easily interpretable measure of the relative contribution of decomposition factors to an outcome measure.

In the case of regression analysis, explanatory variables may be seen as "players" who can form a "coalition" to improve model outcomes. That is, a regression model including all variables may lead to a different outcome in terms of explanatory power of the dependent variable than the sum of individual outcomes in regression models with one variable. This article focuses on the explained variance or R^2 as outcome measure to be decomposed. How much the joint outcome (that is, the R^2 in a model with all explanatory variables) differs from the sum of individual outcomes (that is, the sum of R^2 in models with just one explanatory variable) depends on the correlation of variables (Lipovetsky & Conklin, 2001). When regressors are highly correlated, the additional information from adding another variable to the model is limited and the R^2 only mildly increases in a joint model. At the same time, combinations of moderately correlated regressors may additionally inform the model and therefore result in a much higher R^2 for a joint model.

Measuring the contribution of an individual explanatory variable to the explanatory power of the model therefore requires careful weighting of all its contributions in combination with other variables. Shorrocks (2013) develops a generalized decomposition technique which draws upon the desirable features of the Shapley value and involves sequential elimination of "players" in all possible orders and averaging outcomes over all sequences. With k explanatory variables $x_1, x_2, ..., x_k$, there are 2^k possible model specifications. For general introduction, an example of $k = 3$ will be presented first. The regression equation therefore reads as:

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \epsilon \tag{1}$$

To evaluate the contribution of x_1 according to its Shapley value, $2^k = 2^3 = 8$ models need to be estimated. The R^2 of each model including x_1 is compared with the same model but excluding x_1, and a weight is assigned to this difference. The weight depends on the total number of possible elimination sequences $k!$ (in this case $3! = 6$) and the number of elimination sequences leading to a certain model. For example, the model containing only x_1 can be obtained by first eliminating x_2 and then x_3, or vice versa. Thus, when comparing the model containing only x_1 with the model containing no variable at all, the difference of R^2 receives the weight $\frac{2}{6} = \frac{1}{3}$, since there are two possible elimination sequences. By contrast, the model containing x_2 and x_3 can only be obtained by eliminating x_1 first, so the difference of R^2 receives weight $\frac{1}{6}$. Denoting the R^2 of a model containing variables x_i and x_j by $R^2(x_i, x_j)$, the Shapley value SH_1 of x_1 in the model of equation 1 is thus

$$\begin{aligned} SH_1 = \ & \tfrac{1}{3}R^2(x_1) + \tfrac{1}{6}[R^2(x_1,x_2) - R^2(x_2)] + \tfrac{1}{6}[R^2(x_1,x_3) - R^2(x_3)] \\ & + \tfrac{1}{3}[R^2(x_1,x_2,x_3) - R^2(x_2,x_3)] \end{aligned} \tag{2}$$

To formalize for a general set K of k explantory variables, $K = x_1, x_2, ..., x_k$, and following the notation of Chantreuil and Trannoy (1999), the Shapley value SH_j of explanatory variable x_j to the R^2 can be described as

$$SH_j = \sum_{\substack{S \subseteq K \\ j \in S}} \frac{(s-1)!\,(k-s)!}{k!} \left[R^2(S) - R^2(S \backslash \{j\})\right] \tag{3}$$

where $R^2(S)$ is the R^2 of a regression model with all explanatory variables in a set $S \subseteq K$. Dividing the Shapley values $SH_j, j = 1, ..., K$, by the R^2 of the complete model allows for an easily interpretable percentage figure indicating the relative contribution of explanatory variables to the overall explanatory power of the model.

But when is an explanatory variable "important" for model, as judged by its Shapley value? Lipovetsky and Conklin (2001) offer a formal approach of assessing "importance" for Shapley values of explanatory variables in regression analysis by deriving a lower threshold for Shapley values. Variables whose Shapley values surpasses this Lipovetsky threshold are then considered "important" to the modelling of the dependent variable.

Let N denote the sample size, K the number of considered explanatory variables, α the desired level of significance, and $t_{\gamma/2}$ the two-tailed t-statistic corresponding to γ. Then, the Lipovetsky lower threshold δ^2 for Shapley values can be expressed as follows:

$$\begin{aligned} \delta^2 &= \tfrac{1-R^2}{(N-K-1)R^2} t^2_{\gamma/2} \\ \text{with} \quad \gamma &= 1 - (1-\alpha)^{\frac{1}{K}} \end{aligned} \tag{4}$$

The intuition behind the expression for γ derives from the assumption of independence and equal importance of all explanatory variables in the regression model, assigning probability $1 - \gamma$ to each of them such that the joint probability $1 - \alpha$ can be expressed as the product of all observations' probabilities, $(1-\gamma)^K$. While the Lipovetsky threshold provides an easy tool to asssess the "significance" of a Shapley value, it also suffers from some structural drawbacks. Most importantly, it does not have an upper bound of 1. When the sample size N is small and the R^2 is low, the expression in Equation 4 may yield a threshold above 100%, which would declare all explanatory variables to be redundant by construction. Even when the Lipovetsky threshold does not exceed 100%, it may lead to inappropriately high threshold values in small samples, as a small divisor of (N-K-1) inflates the threshold value. To grasp whether the Lipovetsky value is inflated, one may compare it to the theoretical Shapley value of $SH_j = \frac{1}{K}$, which results in a model of K explanatory variables where all explanatory variables are of equal importance and perfectly uncorrelated.

One significant advantage of the Shapley approach over other decomposition techniques is the Shapley value's ability to deal with interactions. When the regression model contains interaction terms, it may be unclear how the additional explanatory power of the interaction should be divided among the interacted variables. The Shapley value always divides this additional contribution symmetrically among the components. Take, for example, the following linear regression with $k=2$ and one interaction:

$$y = \alpha + \beta_1 \bar{x}_1 + \beta_2 \bar{x}_2 + \beta_3 \bar{x}_1 \bar{x}_2 + \epsilon \tag{5}$$

where $\bar{x}_1$ and $\bar{x}_2$ are the demeaned transformations of x_1 and x_2, respectively. Then, following the standard Shapley approach, eliminating x_1 from the regression equation involves eliminating both x_1 and $x_1 x_2$. In this case,

$$\begin{aligned} SH_1 = & \ \tfrac{1}{2}[R^2(\bar{x}_1, \bar{x}_2, \bar{x}_1\bar{x}_2) - R^2(\bar{x}_2)] + \tfrac{1}{2}[R^2(\bar{x}_1)] \\ SH_2 = & \ \tfrac{1}{2}[R^2(\bar{x}_1, \bar{x}_2, \bar{x}_1\bar{x}_2) - R^2(\bar{x}_1)] + \tfrac{1}{2}[R^2(\bar{x}_2)] \end{aligned} \tag{6}$$

In this fashion, the contribution of the interaction term is divided equally between x_1 and x_2, due to the symmetry of the Shapley decomposition. Other approaches are, however, possible, and can be advantageous in cases where there is a hierarchy between interacted variables. The Owen decomposition (Shorrocks, 2013) and the Nested Shapley decomposition (Sastre & Trannoy, 2002) offer two such approaches and will be presented below.

4.2 Owen decomposition

For simplicity, this section begins with a simple example of a a hierarchical model with three variables, $K = \{x_1, x_2, x_3\}$, which can be partitioned into a set of two primary factors, $P = \{S_1, S_2\}$. For illustration, let x_1 and x_2 constitute the first primary factor, $S_1 = \{x_1, x_2\}$, and x_3 constitute the second primary factor, $S_2 = \{x_3\}$. The decomposition of the R^2 into the two primary factors then simply follows the Shapley approach described above, but using just two factors.

$$
\begin{aligned}
SH_{S_1} &= \tfrac{1}{2}R^2(S_1) + \tfrac{1}{2}[R^2(S_1, S_2) - R^2(S_2)] \\
&= \tfrac{1}{2}R^2(x_1, x_2) + \tfrac{1}{2}[R^2(x_1, x_2, x_3) - R^2(x_3)] \\
SH_{S_2} &= \tfrac{1}{2}R^2(S_2) + \tfrac{1}{2}[R^2(S_1, S_2) - R^2(S_1)] \\
&= \tfrac{1}{2}R^2(x_3) + \tfrac{1}{2}[R^2(x_1, x_2, x_3) - R^2(x_1, x_2)]
\end{aligned}
\tag{7}
$$

Note that the contribution of primary factor S_2 differs from the contribution of x_3 in a non-hierarchical model. Next, the primary factors are decomposed into the contribution of secondary factors. It is in this second step where the Owen approach and the Nested Shapley approach differ: the Owen decomposition uses both primary and secondary factors, whereas the Nested Shapley decomposition only uses secondary factors. The merit of these two procedures, rather than a simple Shapley decomposition into secondary factors only, is that the decomposition is aggregation-consistent. Aggregation consistency describes the property of the sum of contributions of the secondary factors to perfectly add up to the contribution of their primary factor. This does not necessarily hold for the regular Shapley decomposition, and therefore complicates the assessment of the importance of variable groups when using the regular Shapley decomposition. Note, however, that the sum of regular Shapley values *may* equal the value assigned to the primary factor if the secondary factors are uncorrelated.

For the above-mentioned example with three variables x_1, x_2, and x_3, partitioned into two sets $S_1 = \{x_1, x_2\}$ and $S_2 = \{x_3\}$, the Owen decomposition yields the following Shapley values for the secondary factors x_1 and x_2.

$$
\begin{aligned}
OW_1 &= \tfrac{1}{4}R^2(x_1) + \tfrac{1}{4}[R^2(x_1, x_3) - R^2(x_3)] + \tfrac{1}{4}[R^2(x_1, x_2) - R^2(x_2)] + \\
&\quad \tfrac{1}{4}[R^2(x_1, x_2, x_3) - R^2(x_2, x_3)] \\
OW_2 &= \tfrac{1}{4}R^2(x_2) + \tfrac{1}{4}[R^2(x_2, x_3) - R^2(x_3)] + \tfrac{1}{4}[R^2(x_1, x_2) - R^2(x_1)] + \\
&\quad \tfrac{1}{4}[R^2(x_1, x_2, x_3) - R^2(x_1, x_3)]
\end{aligned}
\tag{8}
$$

Note that this expression is very similar to the Shapley decomposition in Equation 2, but that the respective weights of each difference vary. This is to ensure aggregation-consistency of the Owen decomposition, which does not hold for the expression in Equation 3. Generalizing the notation and following Chantreuil and Trannoy (1999), let $P = \{S_1, S_2, ..., S_m\}$ be a partition of $K = \{x_1, x_2, ..., x_k\}$. Each set $S_j \in P$ contains s_j secondary factors. Then the Owen R^2 decomposition for each secondary factor $x_j \in S_l$ can be expressed as

$$
OW_j = \sum_{\substack{C \subseteq P \\ S_l \notin C}} \sum_{\substack{S \in S_l \\ j \notin S}} \frac{c!(m-c-1)!s!(s_l - s - 1)!}{m!s!} [R^2(C \cup S \cup \{j\}) - R^2(C \cup S)] \tag{9}
$$

where c, s_l, s, and m denote the cardinality of C, S_l, S, and P, respectively.

4.3 Nested Shapley decomposition

As mentioned above, the Nested Shapley decomposition and the Owen decomposition do not differ in the decomposition of primary factors, but in allocating the contribution of the primary factors to the secondary factors. Specifically, the Owen decomposition uses both primary and secondary factors in this second step, while the Nested Shapley decomposition only uses secondary factors. Using a hierarchical three-variable model with primary factors $S_1 = \{x_1, x_2\}$ and $S_2 = \{x_3\}$ for illustration, the Nested Shapley approach yields the following decompositions:

$$\begin{aligned} NSH_1 &= \tfrac{1}{2}R^2(x_1) + \tfrac{1}{4}[R^2(x_1, x_2, x_3) - R^2(x_3) - R^2(x_2)] + \\ &\quad \tfrac{1}{4}[R^2(x_1, x_2) - R^2(x_2)] \\ NSH_2 &= \tfrac{1}{2}R^2(x_2) + \tfrac{1}{4}[R^2(x_1, x_2, x_3) - R^2(x_3) - R^2(x_1)] + \\ &\quad \tfrac{1}{4}[R^2(x_1, x_2) - R^2(x_1)] \end{aligned} \tag{10}$$

Note that the main difference between the Owen decomposition in Equation 8 and the Nested Shapley decomposition in Equation 10 concerns the elimination of the variable of interest from the full model. While the Owen decomposition simply treats the other primary factor as a secondary one and subtracts the model containing both primary and secondary factors, the Nested Shapley decomposition does not allow for such a mixture of primary and secondary factors after elimination of the variable of interest. Specifically, when eliminating x_1 from the model, the Owen decomposition evaluates the difference to $R^2(x_2, x_3)$ while the Nested Shapley decomposition considers the difference to $R^2(x_2) + R^2(x_3)$. Generalizing the notation, let x_j be a secondary factor belonging to some primary factor S_l and let s_l denote the dimension of S_l. Let NSH_{S_l} be the Shapley value belonging to the primary factor S_l as derived above. Then, the Nested Shapley value of x_j can be described as

$$NSH_j = \sum_{\substack{S \subseteq S_l \\ j \in S}} \frac{(s-1)!\,(s_l - s)!}{s_l!} \left[R^2(S) - R^2(S \backslash \{j\})\right] + \frac{1}{s_l}\left[NSH_{S_l} - R^2(S_l)\right] \tag{11}$$

Note that this expression of the Nested Shapley closely ressembles the regular, non-hierarchical Shapley value expression in Equation 3. In colloquial terms, the Nested Shapley approach computes the regular Shapley value of Equation 3 considering *only* variables in the same group of secondary factors, and adds the weighted difference of the primary factor value and the primary factor R^2 to ensure aggregation consistency. The computation of Nested Shapley values can therefore be described as a two-step procedure: first, the values for primary factors are computed, using all possible combinations of primary factors. Second, the values for secondary factors are computed using all possible combinations of secondary factors within the same group.

The Nested Shapley approach requires much less computations than the Owen approach. Additionally, Sastre and Trannoy (2002) raise concerns about the interpretation of mixed subsets of primary and secondary factors, which may be doubtful in certain economic contexts. At the same time, the Nested Shapley approach has the important disadvantage of being able to produce negative values. This complicates interpretation, as it seems illogical to state that an explanatory variable "takes away" explanatory power. The application on both approaches in this study therefore aims to shed light on their relative performance in practice. An important drawback of both approaches, however, is the lack of a "critical value" for Shapley values, like the Lipovetsky threshold in a simple non-hierarchical model. Since both the number of primary and secondary factors can be considered as the number of explanatory variables K, different Lipovetsky threshold values would arise. This may lead to different conclusions for individual variables and the variable group they belong to.

5 Empirical strategy

This paper aims to study the relative contributions of economic and political factors to carbon emission growth through a Shapley-based decomposition of the R^2. To ensure sound model specifications, the stationarity of all variables in the balanced panel is tested using a panel unit root test as proposed by Levin et al. (2002). This test is particularly useful for cross-country econometric studies using moderately sized panels and is therefore considered appropriate for the setting of this study. The results of these tests can be found in Table C.1 in the Appendix. Using growth rates, rather than levels, removes non-stationarity from the variables capturing carbon emissions, electric power consumption, and human capital. For all other variables, including GDP growth, the Levin-Lin-Chu test does not indicate the existence of a unit root.

The first part of the analysis focuses on two general models, which gives equal weight to all considered variables. The smaller model only uses the aggregated KOF globalization index and the polity2 index, while the larger model uses the KOF sub-indices and the democracy dummies constructed from the polity2 index. These general models will be considered for both the balanced and unbalanced sample.

Given the use of a global panel, an important consideration in standard regression analysis would be to use two-way fixed effects to account for non-time-varying differences of countries and period-specific effects. However, simply including 20 year-specific or 115 country-specific fixed effects would increase the number of regressions' R^2 that need to be calculated from 2^{11} = 2,048 in the larger model to $2^{31} = 2.147 \times 10^9$ or even $2^{126} = 8.507 \times 10^{37}$ calculations. Clearly, including fixed effects is thus not feasible using standard computing tools, which usually have a limited memory space of $2^{31} - 1$. A grouping of variables may however provide a remedy to this problem and will further be elaborated on below.

The second part of the analysis investigates heterogeneity in Shapley values across time and country groups. To evaluate changes in importance of variables across time, year-by-year analyses will be conducted. While no time-varying unobserved variables risk to flaw the analysis in this approach, using yearly subsamples significantly reduces the sample size. To find middle grounds in this trade-off, the panel will be sampled using a moving window approach. A window size of 3 years is chosen to ensure a sufficiently large number of observations per subsample while allowing year-specific conditions to influence the results. The robustness of these results is further verified by analysing non-overlapping 5-year windows. Comparing Shapley values across these windows will shed light on possible changes over time in the relative importance of various factors of carbon emissions.

Next to changes across time, there may be substantial differences in the relative importances of explanatory variables in different country groups. For example, electric power consumption growth is less likely to contribute to carbon emissions in a country that derives a large share of its electricity from renewable sources. Moreover, GDP growth is more likely to contribute to carbon emissions in countries with a large secondary sector. Two approaches are considered to deal with these potential heterogeneities. First, following the methodology of Sharma (2011), the set of countries will be split into three groups according to income classification by the World Bank. Upper middle income countries and lower middle income countries are hereby considered as one group. The second approach does not split the sample but adds interaction terms to the model. In particular, interactions between GDP growth and industry share, as well as between democratic status dummies and electric power consumption.

Finally, the contribution of different variable groups will be studied, using the Nested Shapley and Owen approach. Variables will be split in economic and political factors (see Table 1). Moreover, sub-indices of globalization and dummies indicating democratic status will be considered as separate groups. To improve overall model fit, two-way fixed effect will be added to the general model and considered as one group. In all hierarchical models, the Nested Shapley and Owen decomposition values will be compared. Next to painting a more complete picture of the relative contribution of different variables, this comparison will also help to illuminate the respective merits of the two decomposition approaches.

6 Results

Table 2 presents the results of a simple Shapley decomposition using two sets of explanatory models and the two subsamples described in Section 3. It is worth noting first that the total R^2 of the models is relatively low: only around 20% of the variance in carbon emissions in the balanced panel can be explained by the employed independent variables. For the unbalanced panel, this number even falls to approximately 15%. The lower explanatory power in the unbalanced panel is, however, no surprise when considering that this sample spans a time period from 1970 to 2018 and the model does not contain country- or time-specific intercepts. Moreover, while a low R^2 indicates poor model fit and should therefore raise some concerns with regards to the selection of explanatory variables, a Shapley value decomposition is a suitable approach to such models (Israeli, 2007).

Overall, the results in Table 2 suggest that economic variables explain a much larger share of the cross-country and cross-time variance in carbon emission growth than political variables. In the balanced panel, electric power consumption shows the largest Shapley value, with 46.46%

Table 2. *Shapley values (in percent) of economic and political variables in non-hierarchical model of carbon emission.*

	balanced panel		**unbalanced panel**	
	(1)	(2)	(1)	(2)
Economic				
GDP*	29.31	27.60	54.30	53.39
population*	7.50	6.60	8.52	7.36
electric power consumption*	46.46	43.47	27.83	27.03
industry share	0.57	0.46	0.40	0.34
human capital	0.69	0.48	0.55	0.38
Political				
KOF Globalization index	13.47		6.36	
Economic glob.		4.70		2.22
Social glob.		6.59		3.67
Political glob.		3.61		1.78
Polity2	1.99		2.04	
Full democracy		2.84		2.00
Partial democracy		2.86		0.94
Autocracy		0.78		0.88
total R^2	0.202	0.205	0.148	0.149
observations	2,300	2,300	4,343	4,343
Lipovetsky threshold	1.24	1.36	0.96	1.06

Note. Variables marked with an asterisk (*) represent growth rates. Percentages may not add up to 100% due to rounding. Lipovetsky threshold values are based on a significance level of $\alpha = 0.05$, resulting in $\gamma = 0.0073$ for the small model and $\gamma = 0.0047$ for the large model.

in the small model and 43.47% in the large model. The second largest contribution is made by GDP growth, which accounts for 29.31% (27.6%) of the R^2 in the small (large) model. For the unbalanced panel, this ranking reverses, with GDP growth and electric power consumption growth contributing around 54% and 27%, respectively. Other variables show comparatively low Shapley values. The contribution of industry share and human capital growth are close to negligible and consistently fall below the Lipovetsky threshold, which fluctuates around 1%, depending on the sample size and number of regressors. With contributions between 6% and 13%, depending on the size of the model, the KOF Globalization Index and population growth show Shapley values well above the threshold and can therefore be considered to be of significant importance to the model of carbon emission growth. Notably, social globalization has the largest contribution among the globalization sub-indices for both samples.

Turning towards the yearly analysis, the low number of observations in each yearly subsample needs to be emphasized. Large differences between estimation results of different years are therefore to be expected. Figure 6.1 plots the Shapley values in percentages for each yearly subsample of the balanced panel dataset. The corresponding values can be found in Table C.3

in the Appendix. There are great fluctuations in the Shapley values of all variables, and no variable seems to follow a clear trend across the considered time period. With the exception of 2005 and 2014, the largest share of explained variance is always allocated to electric power consumption growth or GDP growth. The share of GDP growth mainly fluctuates between 20% and 40%, while values for electric power consumption growth are highly volatile across years and range from 5.03% in 1996 to 80.22% in 1995. The contributions of human capital growth, industry share, and polity2 are consistently low and mainly fluctuate between 0% and 10%. This further confirms the previous finding of relatively low importance of these variables in explaining carbon emissions. Finally, Shapley values for globalization generally seem to increase in the second half of the considered time period, with the highest five values of this variable being reached after 2004. However, the high volatility of Shapley values for globalization in this time period does not warrant a definite conclusion here.

Due to the small sample size of 115 observations per yearly subsample and a low R^2 in most of the samples, the Lipovetsky threshold for importance of regressors is inflated. Assuming equal importance of all regressors, a Lipovetsky threshold of approximately 100% divided by the number of regressors seems reasonable. With 7 regressors, this would correspond to a threshold of around 14%. However, as Table C.3 indicates, the Lipovetsky threshold exceeds this value in 14 out of the 20 yearly subsamples, and even surpasses the logical upper bound of 100% in 2002. Using Lipovetsky thresholds in the yearly analysis to make binary judgements on the importance of explanatory variables thus seems inappropriate.

Figure 6.1. *Shapley values (in percent) in non-hierarchical model for yearly subsamples*

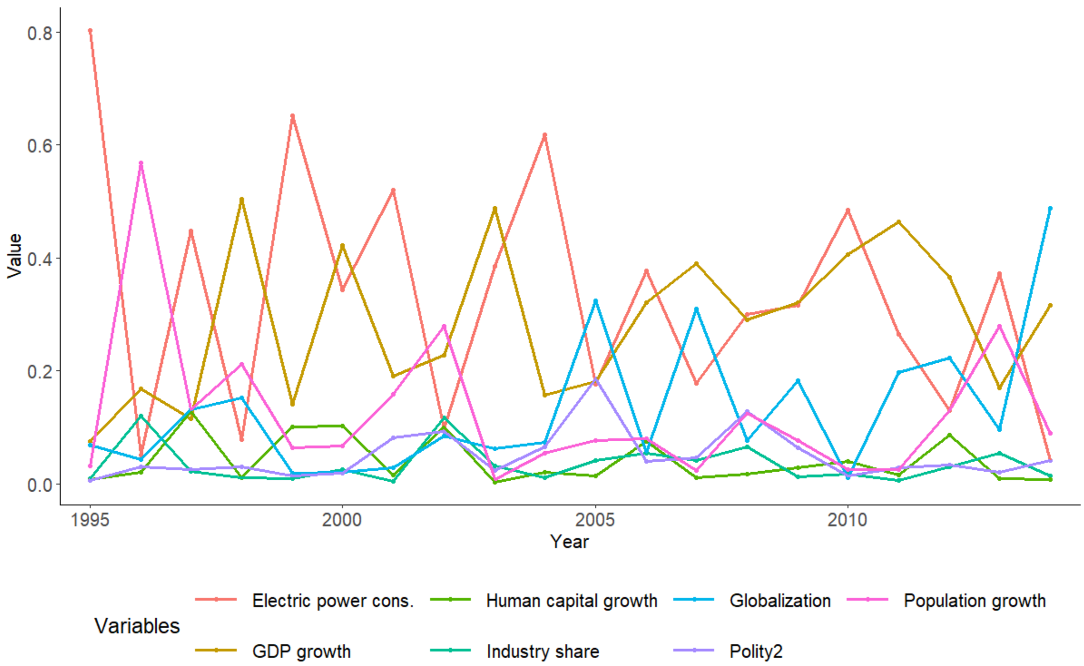
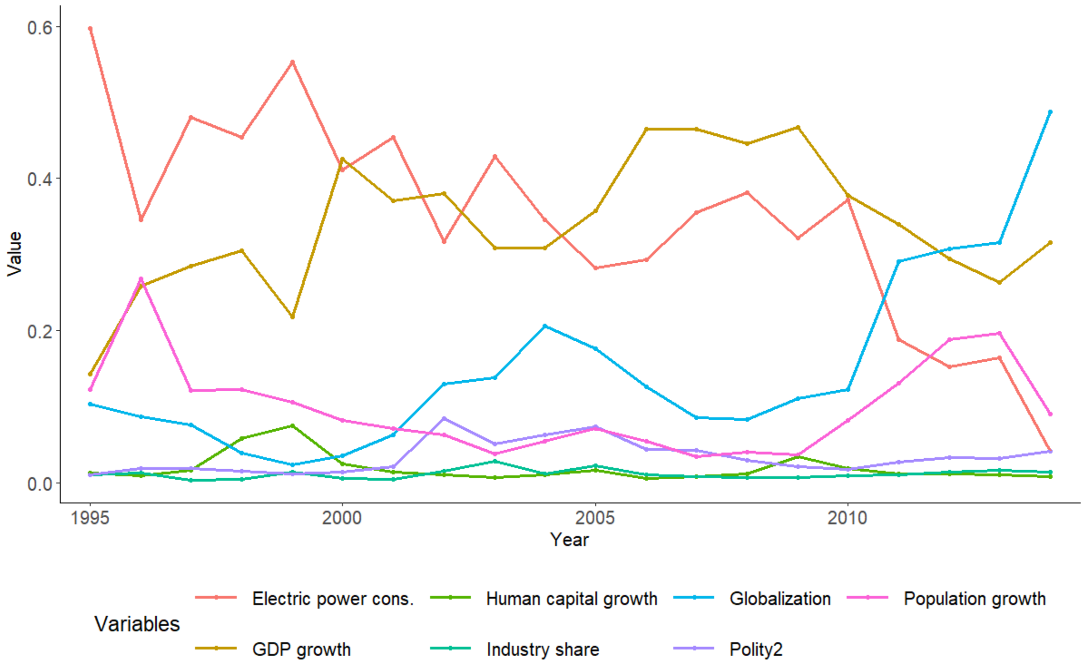


Figure 6.2. *Shapley values (in percent) in non-hierarchical model for 3-year moving window subsamples*



As stated above, the yearly analysis suffers from small sample problems. To alleviate this issue, a moving-window approach is considered. Figure 6.2 shows the Shapley values in percentages for a 3-year moving window. Values are plotted on the left edge of the window. That is, the value shown for year j is calculated using a subsample of the years j through $j + 2$. As the entire sample only covers years up until 2014, the values for 2013 and 2014 represent values of a 2-year and 1-year subsample, respectively. In comparison with Figure 6.1, the values are much smoother, and some broad trends can be observed. Confirming earlier indications, there seems to be an increase in the relative importance of globalization over time, with Shapley values showing an upward trend after 2005. Again, human capital growth, industry share, and the polity2 index are consistently found to be of low importance. With two exceptions (for human capital growth in 1998 and 1999), their Shapley values stay well below 5% for all years. With Lipovetsky threshold values varying between 3% and 11%, human capital growth and industry share can reasonably be called unimportant to the model of carbon emission growth. GDP growth does not seem to follow a trend, but consistently exceeds the Lipovetsky threshold and reaches particularly high Shapley values between 2006 and 2010. Finally, the importance of electric power consumption appears to be following a slight downward trend, falling from Shapley values up to 60% for the 1995-1997 time window to around 16% in the most recent considered windows.

These results are further corroborated by Table 3, which presents the Shapley values for the

Table 3. *Non-hierarchical Shapley values (in percent) of economic and political variables in 5-year subsamples*

	Small model				Large model			
years	1995-99	2000-04	2005-10	2010-14	1995-99	2000-04	2005-10	2010-14
Economic								
GDP*	15.85	38.44	44.07	38.23	15.48	34.28	41.83	34.22
population*	12.03	7.21	5.38	9.17	10.15	6.03	5.14	7.34
Electric power*	60.40	45.40	28.48	26.09	57.09	41.10	26.53	22.91
Industry share	0.76	0.56	1.31	0.81	0.50	0.61	1.20	0.67
Human capital*	0.56	2.50	0.59	1.30	0.50	2.05	0.54	0.80
Political								
KOF Global.	9.37	4.27	14.73	22.03				
Economic global.					3.13	1.73	5.35	6.70
Social. global.					5.48	2.59	7.55	13.29
Political global.					1.86	1.78	5.52	5.04
Polity2	1.02	1.62	5.43	2.38				
Full democracy					1.83	3.50	3.43	4.33
Part. democracy					3.06	5.10	0.86	3.79
autocracy					0.91	1.22	2.05	0.91
total R^2	0.229	0.159	0.238	0.299	0.236	0.167	0.239	0.302
observations	575	575	575	575	575	575	575	575
Lipovetsky threshold	4.30	6.77	4.10	3.00	4.64	7.16	4.56	3.31

Note. Variables marked with an asterisk (*) represent growth rates. Percentages may not add up to 100% due to rounding. Lipovetsky threshold values are based on a significance level of $\alpha = 0.05$, resulting in $\gamma = 0.0073$ for the small model and $\gamma = 0.0047$ for the large model.

small and large model in 4 non-overlapping 5-year windows of the balanced panel. Considering the subindices of globalization and democratic status dummies, rather than the aggregate variables, also sheds light on their changes in their relative importance over time. For all four subsamples, social globalization is allocated the largest share of explanatory power among the three subindices. However, there does not seem to be a clear ordering of economic and political globalization in terms of explanatory power. For the democratic status dummies, the autocracy intercept has the lowest explanatory power in all subsamples, but there are no clear differences between the full and partial democracy intercept. The dissection of the sample in 4 subsamples also highlights the previous finding of a downward trend in the explanatory power of electric power consumption growth. Meanwhile, the picture is less clear for a potential upward movement of globalization.

The relative importance of political and economic variables in explaining carbon emission growth is likely to differ not only across time periods, but also across country groups. While 20 observations per country do not suffice for a country-by-country analysis, it is possible to split the sample into subgroups of countries with similar characteristics. Following the methodology of Sharma (2011), countries are grouped by income level, which serves as a proxy for a wider array of socioeconomic and political characteristics. Analysing Shapley values in the three

Table 4. *Non-hierarchical Shapley values (in percent) of economic and political variables in country subsamples*

Model	**High income countries** (1)	**Middle income countries** (2)	**Low income countries** (3)	**All with interactions** (4)
Economic				
GDP*	21.51	31.26	27.39	26.89
population*	4.55	9.25	8.65	6.40
electric power consumption*	52.60	45.09	44.37	42.97
industry share	4.13	2.54	0.33	0.90
human capital	0.76	0.19	0.69	0.45
Political				
Economic glob.	1.65	2.18	3.60	4.35
Social glob.	3.89	4.17	2.40	6.06
Political glob.	5.83	1.52	0.48	3.29
Full democracy	2.32	1.11	-	3.24
Partial democracy	0.14	2.02	8.81	4.10
Autocracy	2.62	0.68	3.28	1.34
total R^2	0.332	0.162	0.200	0.219
observations	920	1,220	160	2,300
Lipovetsky threshold	1.78	3.46	22.35	1.25
interactions				✓

Note. Variables marked with an asterisk (*) represent growth rates. Percentages may not add up to 100% due to rounding. A dummy for full democracy is omitted in the sample of low income countries (column (3)) due to the absence of full democracies in this subsample. Column (4) uses the entire set of countries and includes the following four interaction terms: GDP growth * industry share, electric power consumption * full democracy, electric power consumption * partial democracy, electric power consumption * autocracy. Interacted variables in column (4) are demeaned.

subsamples of countries may therefore also improve the overall R^2, since unobservables may differ less between countries in the same income group.

The results of the country group analyses can be found in columns (1) through (3) of Table 4. Analysing the contribution of the considered variables per group of countries reveals substantial differences between high, middle, and low income countries. In all country subsamples, GDP growth remains well above the Lipovetsky threshold but greatly loses in importance, which is likely to be due to the greater homogeneity in GDP growth rates within the country groups. Electric power consumption growth seems to have larger explanatory power in high income countries than in the other country groups, whereas population growth is a much better predictor in middle income countries than in other groups. Another interesting result is that while social globalization contributes the most to the R^2 in the global sample and in the subsample of middle income countries, it is political and economic globalization that respectively contribute the most in high and low income countries. Note, however, that with 22.35%, the Lipovetsky value in the sample of low income countries by far exceeds the equalized importance value of $1/K = 10\%$. It is therefore unclear which variables in the low income countries subsample should be labelled as "important" or "unimportant" in explaining carbon emission growth.

Column (4) of Table 4 shows the Shapley values of the large model in the strongly balanced sample, but with the additional inclusion of four interaction terms. Interactions are between GDP growth and industry share, as well as between all democratic status dummies and electric power consumption growth. Since the additional explanatory power gained from the inclusion of an interaction term is divided over the interacted variables, no separate Shapley values for interaction terms are reported. However, regression coefficients of the model with interactions can be found in column (5) of Table C.2 in the Appendix.

Comparing the interacted model with the regular model in column (2) of Table 2, the majority of variables seems unaffected by the inclusion of interaction terms. The Shapley value of GDP growth slightly reduces but remains high, while the value industry share slightly increases from 0.46% to 0.9%, thus remaining below the Lipovetsky threshold of 1.25%. Including an interaction between industry share and GDP growth therefore did not increase the explanatory power of industry share substantially, and the variable remains unimportant to the model of carbon emission growth. By contrast, including interactions between democratic status dummies and electric power consumption growth raises the Shapley values of all democratic status dummies and causes the autocracy dummy to exceed the Lipovetsky threshold. Moreover, while full and partial democracy seemed to be of comparable importance in the model without interactions, the inclusion of interaction terms results in a higher gain in Shapley values for the partial democracy dummy than for the full democracy dummy. This finding is also reflected in column (5) of Table C.2, which presents the regression coefficients of the model with interactions. Though both significant, the coefficient of the interaction with partial democracy is 30% higher than the coefficient of the interaction with full democracy. This implies that an increase in electric power consumption growth rates raises carbon emissions much more in partial democracies than in full democracies. This may be a sign of higher carbon intensity of electricity production in partial democracies.

Turning towards model results of a grouped analysis, Table 5 presents the Shapley values of the hierarchical models using the Nested Shapley and Owen approach. Unlike the regular Shapley approach used in above, the Nested Shapley and Owen decompositions allow for aggregation consistency, meaning that the sum of values assigned to factors of one group equals the value assigned to the entire group. Here, the two decomposition approaches were considered for three divisions of variables. In Model (1), all economic and political variables were respectively grouped together. In Model (2), political variables were further split into democracy variables and globalization variables. In Model (3), all economic variables were additionally considered as their own subgroup.

The results in columns 1 through 6 in Table 5 illustrate the properties of the Nested Shapley and Owen decomposition as described in Sections 4.2 and 4.3. Both approaches assign equal values to primary factors (i.e. groups of variables), but typically lead to differing results for secondary factors (i.e. individual variables). In the present case, these differences between values of secondary factors are particularly apparent, due to the Nested Shapley approach's ability of producing negative values. The autocracy dummy and the variables capturing industry share and human capital growth are all allocated a negative value by the Nested Shapley decomposition, ranging from -0.77% for autocracy in the first model to -2.08% for industry share in the second model. The Owen approach, on the other hand, only produces positive values by construction. Owen values for industry share, human capital growth, and autocracy, are therefore positive but very small in magnitude, ranging from 0.53% to 1.05%.

Due to aggregation consistency, the presence of variables with negative Nested Shapley values in a group requires an inflation of the other variables in the same group. Comparing Nested Shapley and Owen values in groups where the Nested Shapley decomposition resulted in a few negative values, it is therefore visible that the positive Nested Shapley values are larger in magnitude than the Owen values. In Models (1) and (2), all economic variables are grouped together, and the Nested Shapley approach produces negative values for industry share and human capital growth, resulting in a combined "negative contribution" to the group's explanatory power of -3.09% and -3.83%, respectively. This negative contribution is offset by a larger contribution of GDP growth and electric power consumption growth, whose values are approximately 1 and 4 percentage points larger than under the Owen decomposition. In the subgroup of democracy variables, the negative Nested Shapley values for the autocracy dummy mainly benefit the full democracy dummy, whose contribution is approximately 2 percentage points higher than under the Owen approach. Finally, in the subgroup of globalization variables, the Nested Shapley approach reduces the contribution of economic and political globalization in models (2) and (3), and therefore inflates the contribution of social globalization. Compared to the Owen approach, the Nested Shapley values of social globalization are approximately 2 percentage points higher.

Finally, the grouped analysis allows for an incorporation of two-way fixed effects in the model. While the calculation of secondary factor Shapley values was computationally not possible, with the number of possible permutations 2^{146} far exceeding the maximum memory of $2^{31} - 1$ of the employed statistical software, a convenient feature of the Owen and Nested Shapley decomposition could be used. Retrieving the values of primary factors is relatively efficient and by construction, the value of a primary factor equals the value of its secondary factor if it consists of only one secondary factor. Columns 7 through 9 of Table 5 present the results of a grouped analysis including an additional group capturing all country- and year-specific fixed effects. Including these fixed effects clearly reduces the importance of economic and political variables. Their respective Shapley values drop by approximately 27 and 8 percentage points, meaning that fixed effects alone are responsible for more than a third of the explanatory power of the model. Increasing the number of primary factors by decomposing the group of economic and political variables further shows which specific variables lose importance upon the inclusion of fixed effects. With the exception of the group of democratic status variables, industry share,

Table 5. *Hierarchical Shapley values (in percent) of economic and political variables*

	Nested Shapley			**Owen**			**Nested Shapley/Owen**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Economic variables	80.49	78.63		80.49	78.63		53.21	52.45	
GDP*	28.80	28.43	28.31	27.63	27.27	28.31			20.48
population*	6.95	6.58	7.26	7.22	6.55	7.26			4.37
Electric power*	47.83	47.45	45.02	44.54	43.84	45.02			30.95
Industry share	-1.71	-2.08	0.52	0.54	0.53	0.52			0.27
Human capital*	-1.38	-1.75	0.67	0.56	0.43	0.67			0.46
Political variables	19.51			19.51			11.21		
Globalization variables		14.27	12.18		14.27	12.18		7.77	6.78
Economic globalization	3.63	2.87	2.18	4.00	4.16	3.85			
Social globalization	8.52	8.59	7.89	6.13	6.50	5.47			
Political globalization	4.00	2.81	2.11	3.48	3.61	2.87			
Democracy variables		7.09	6.05		7.09	6.05		5.17	4.56
Full democracy	2.21	5.06	4.71	2.45	3.11	2.49			
Part. democracy	1.93	2.88	2.53	2.66	2.94	2.71			
autocracy	-0.77	-0.84	-1.19	0.81	1.05	0.86			
Two-way fixed effects							35.57	34.61	32.12
number of groups	2	3	7	2	3	7	3	4	8
variables	11	11	11	11	11	11	146	146	146
fixed effects							✓	✓	✓
computation time (in min.)	0.005	0.004	0.036	48.25	7.987	342.7			

Note. Variables marked with an asterisk (*) represent growth rates. The hierarchical structure of variables is indicated by indentation in the first column. In model (3), all variables of the group "Economic variables" are treated as a group consisting of one variable. Computation times represent average computation times of 10 runs.

and human capital growth, all variable groups considerably lose in importance. When comparing the 7-group model in columns (3) and (6) with the 8-group model in column (9), electric power consumption experiences the largest absolute drop in Shapley value, falling from 45.02% to 30.95%. Not considering industry share and human capital growth, whose contributions are well below 1% in *all* models, the group of globalization variables shows the largest relative drop in Shapley value with around 63%. GDP growth and electric power consumption growth experience a drop of around 30%.

Including country- and year-specific fixed effects highlights the benefits of a grouped analysis, which allows for the inclusion of a large number of additional explanatory variables. Even though the group of two-way fixed effects largely reduces the relative importance of other variable groups, it is reassuring that the ordering of variables in terms of their importance remains unaffected.

7 Discussion

Overall, the findings presented in the previous section give a clear account of the relative contribution of economic and political factors to national carbon emissions. Additionally, these findings help to evaluate the performance of different decomposition techniques in practice. In the following, the practical implications of the results will be discussed.

7.1 The importance of economic and political factors in predicting carbon emissions

In the quest for lowering carbon emissions, it is important to understand what the main drivers of national CO_2 growth rates are and how these have developed over time. The analysis in this paper has resulted in four main findings.

The first main finding is that economic variables are much more predictive of carbon emission growth rates than political variables. In grouped models, economic variables account for around 80% of the explanatory power of the model, with electric power consumption growth and GDP growth alone accounting for approximately 70%. While in the balanced panel datasets spanning the years 1995 to 2014, electric power consumption growth clearly had a larger contribution than GDP growth, the reverse is true for the dataset including observations from the period 1970 to 2018. It is therefore tempting to conclude that the importance of electric power consumption growth in explaining carbon emission growth must have increased. However, these differences can also partially be explained by the structural differences of the two samples. As the analysis of income groups of countries reveals, electric power consumption bears more explanatory power in high income countries. A comparison of income in the two panels results in average GDP in mio. current US$ amounting to 422,546.3 in the balanced panel and to 289,738.0 in the unbalanced panel. The large role of electric power consumption growth in the balanced panel is therefore not necessarily due to differing time frames, but also due to differing underlying characteristics of the units in the sample.

Additionally, an analysis of three-year subsets of the balanced panel data reveals a decline in importance of electric power consumption over time. From 1995 to 2014, the share of explanatory power of electric power consumption growth declined from well above 40% to less than 10%. A possible explanation for this observation is the decline of fossil fuels and the growing importance of renewable energies in electric power generation. In 2018, the combustion of fossil fuels was responsible for about 60 % of global greenhouse gas emissions (IEA 2020). However, the share of wind, solar, and other renewable energy sources in world electricity generation has risen from 18.3% in 1995 to 23% in 2015 (IEA 2021), indicating a clear trend in reducing the carbon intensity of electricity. As a result, changes in electric power consumption have become less susceptible to affect national carbon emissions.

Next to the prevalence of economic variables and the declining importance of electric power consumption growth, the increasing importance of globalization in explaining carbon emission growth constitutes an important finding. Even though the Shapley values for globalization seem to have plummeted in the years of the great financial crisis, they seem to have risen sharply after 2009, reaching a share of more than 20% for the 5-year subsample covering the period from

2010 to 2014. In particular, the importance of social globalization, measuring information flows, cultural proximity, and personal contacts, seem to have risen over the period covered by the sample. This result corroborates previous findings of Kammerlander and Schulze (2021), who found that "the mobility of ideas rather than the mobility of goods and investment matters for environmental performance".

An interesting side result is the reduced importance of globalization in explaining carbon emissions between 2005 and 2009, as portrayed in Figure 6.2. This temporary decline in importance seems to be accompanied by an increase in importance in GDP growth. Considering the large impact of the Great Financial Crisis in this time period, which caused both GDP growth and carbon emissions to plummet (Peters et al., 2012), it seems likely that the increase in explanatory power of GDP growth reflects recession-related effects. But why is it globalization then that is losing explanatory power? One possible explanation is that while globalization generally has a negative effect on carbon emissions, as shown in Table 2 in the Appendix, highly globalized countries' economies and thus emissions were more negatively affected by the financial crisis. Two opposing effects of globalization on carbon emissions may thus be at work during global financial crises, reducing the overall explanatory power of the globalization variables.

The final main finding from the grouped analysis is that even though the importance of different economic and political variables may be changing over time, GDP growth and electric power consumption remain the main drivers of emission growth in historical data sets. The Kaya identity thus remains an appropriate model of carbon emission growth, but may need adjustment for political factors in more recent data sets. Specifically, factors measuring globalization and ideational spillovers may help to inform models of carbon emissions in a world that is increasingly marked by intergovernmental efforts to fight global warming.

7.2 Shapley value decomposition techniques

Next to topical implications for modelling carbon emission growth, this study bears some scientific implications for the use of Shapley values in regression analysis. First, the utility of Shapley values for evaluating the relative importance of explanatory variables in a regression model was demonstrated. Even though a large number of explanatory variables was found to be insignificant using OLS regression analysis, their relative contribution to the R^2 of the model could still amount to up to 9 %. Following the standard convention in regression analysis of sequentially deleting insignificant variables from the model ("general-to-specific approach") may therefore lead to an important loss of information.

How can Shapley values then inform regression analysis and support variable selection? This paper employed lower thresholds for Shapley values as presented by Lipovetsky and Conklin (2001), which provide a clear critical value for the Shapley value of explanatory variables. However, two important considerations arise from this. First, there are cases where the Lipovetsky threshold may be inappropriate for judging the importance of explanatory variables. Most notably, the results in this paper have shown that the Lipovetsky threshold may yield inflated values in small samples, and that application of the Lipovetsky threshold is ambiguous when a hierarchical model of variables is employed. Second, even when the Lipovetsky threshold yields reasonable values, should variables whose Shapley values fall below the threshold be deleted from the model? As the Lipovetsky threshold classifies the explanatory variable according to their percentage shares of the R^2, which increase by construction as the number of variables decreases, it is possible that a step-wise deletion of variables from the regression model results in all variables being declared as "unimportant".

Moreover, this paper demonstrated the usefulness of grouped analysis in the presence of a large number of variables. Since the number of possible elimination sequences grows exponentially as the number of explanatory variables increases, including a full set of two-way fixed effects is usually not computationally feasible. However, grouping fixed effects together and using the first step of the Owen and Nested Shapley decomposition allowed for the computation of "fixed effects adjusted" Shapley values of other explanatory variables. To this end, explanatory variables were considered as their own one-element group. The computation of secondary factor Shapley values was, however, not computationally feasible, due to insufficient memory in the employed statistical software.

When comparing the Owen and Nested Shapley approach, a striking result is the vast difference in computation time. While the Nested Shapley approach only requires the evaluation of elimination sequences across groups or across variables within the same group, the Owen approach considers all possible elimination sequences across groups and individual variables. The Nested Shapley decomposition therefore by far outperforms the Owen decomposition when the number of variables and variable groups is large. Even though the Nested Shapley decomposition has the structural weakness of possibly assigning negative values to explanatory variables, which renders interpretation dubious, the negative values obtained in this study were rather small in magnitude. Other values were thus only mildly inflated in comparison to the Owen decomposition, and overall results did not seem to suffer from this structural weakness. The Nested Shapley approach therefore seems to be preferential to the Owen approach when analysing the contribution of explanatory variables to the R^2 in a regression model.

8 Conclusion

This paper investigated the relative contributions of political and economic variables to the overall R^2 in a regression model of carbon emission growth. To this end, the R^2 was allocated to the explanatory variables using three Shapley-based decomposition approach. Next to a regular Shapley decomposition of the R^2 following Lipovetsky and Conklin (2001), explanatory variables were grouped together and evaluated with the Owen approach (Shorrocks, 2013) or the Nested Shapley approach (Chantreuil & Trannoy, 2011). Analyses were conducted using yearly data from 1995 to 2014 in a global panel of 115 states.

Overall, a much higher contribution of economic variables was found, ranging from 52% to 80% of the R^2 depending on the inclusion of fixed effects. Political variables showed a contribution of ranging from 11% to 20%. Looking at individual variables, GDP growth and electric power consumption growth were found to be the main drivers of carbon emission growth. An interesting result was that the group of variables measuring economic, social, and political globalization was the third-largest contributor, contributing between 12% and 14% of the explanatory power of the model. Especially social globalization, which measures ideational spillovers and cultural connectedness, had a surprisingly high importance in explaining cross-country variations in carbon emissions.

Using Shapley-based decomposition of the R^2 to judge the importance of variables, rather than evaluating their individual significance level, bore some important advantages. Even though a large number of variables were found to be insignificant using standard t-tests of coefficients, their relative contribution as judged by the Shapley value still amounted to up to 9%. Eliminating these variables from the model, following a classic general-to-specific modelling approach, would therefore imply a considerable loss of information. Shapley values should be considered as important additional tool to judge a variable's importance, and further theoretical research is encouraged to develop a formal approach for combining t-statistics of regressors with their Shapley values.

The comparative use of the Nested Shapley and Owen decomposition approaches highlighted the superiority of the Nested Shapley approach. Even though this approach has the inconvenient feature that it may assign negative contributions to individual variables, which leads to dubious interpretations, its computational performance outperforms the Owen approach by far. This is due the fact that in the Nested Shapley approach, the contribution to the R^2 of an individual variable is independent of the disaggregation of other variable groups. While the Owen approach considers all possible elimination sequences across different variable groups, the Nested Shapley approach does not mix subsets of individual variables and variable groups.

Due to the use of a global sample of 115 countries in the balanced panel and 119 countries in the unbalanced panel, this study exhibits great external validity. In other words, it is likely that the obtained Shapley values indeed represent global trends in variable contributions to carbon emission growth. However, the great external validity comes at the expense of internal validity. In all considered (sub-)samples and models, the overall R^2 reached a value of 0.302 at most, and usually fluctuated around 0.2. Re-estimating the model for subsamples of 5 years somewhat increased the overall fit of the model, but still left a large share of variation in the dependent variable unexplained. In an attempt to address this issue, Shapley values were studied separately for high, middle, and low income countries. However, a focus on other important subsamples may offer further insights and is therefore recommended for further research. Moreover, the inclusion of additional economic variables may improve goodness of fit of the model, but comes at the expense of much higher computation times for the Shapley values.

A second important limitation concerns the possibility of measurement errors. In particular, statistics on growth rates of national GDP growth, carbon emissions, electric power consumption, and population may only be observed with a substantial error margin. While use of growth rates cancels out constant measurement errors (like strategic over- or underreporting), it is likely that in a sample covering 20 years, random measurement errors occur. Reassurance is, however, offered by the fact that such measurement errors in the explanatory variables lead to underestimation of the R^2 (Meijer et al., 2021). This means that in the case of random measurement errors in an explanatory variable, its Shapley value will be underestimated, as including the variable with measurement error does not substantially raise the R^2.

Finally, while measures of globalization and democratic status somewhat reflect the political state of a country, they do not fully embody all political dimensions which may affect environmental policy-making. For example, the prevalence of corruption and lobbying, political stability, or the government's political orientation may significantly affect companies' ability to pollute, but have not been included in the models of this paper due to data availability and the requirement of a parsimonious model for computation efficiency. Further research is thus recommended to derive a parsimonious model of carbon emission growth which incorporate a larger array of political elements. Principal component analysis may be a useful tool for this purpose, allowing to condense the information of a large number of political variables into a smaller number of covariates.

9 References

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Appendix

A Data and sample selection

The data employed in this study is obtained from five open-source datasets: the Emission Database for Global Atmospheric Research (Crippa et al., 2021), the World Bank Open Data, the Penn World Tables (Feenstra et al., 2015), the Polity5 project (**polity5**), and the KOF Globalization Index (Gygli et al., 2019). For all datasets, the latest version as of May 2022 was used. Table 1 shows the original names of retrieved variables in the respective dataset. In a first step, all observations before 1970 and after 2018 were deleted from the datasets. Then, each dataset's country codes were adjusted to enable merging. All datasets, with the exception of the Polity5 dataset, were merged sequentially according to year and ISO 3166 A3 country code. The ISO 3166 A3 is a country identifier code consisting of three capital letters. However, changes in countries' jurisdictions throughout the time frame of the data led to inconsistencies in the identifiers. In the World Bank, Penn World Tables, and KOFGI Globalization Index datasets, observations with ISO code "SRB", representing Serbia, were changed to "SCG", to match observations from the EDGAR dataset. In the same way, observations with code "ROU" (representing Romania) and "COD" (representing the Democratic Republic of Congo, formerly Zaire) were changed to "ROM" and "ZAR" in the KOF dataset, respectively.

As the Polity5 dataset uses a different country coding system than ISO 3166, its observations were merged to the aggregate dataset using the countries' string name, rather than identifier code. As expected, this led to a large number of mismatches, which were resolved manually. Specifically, observations were recoded to have the same country name as the World Bank dataset. Table 2 shows the matching of country names from the Polity5 dataset with the World Bank dataset. All observations in the Polity5 dataset that could not be merged to the other datasets in this way were dropped. These 243 (out of 7,520) observations either describe jurisdictions that do not exist at present, such as Czechoslovakia, or that are not contained in the World Bank's dataset for political reasons, such as Taiwan.

After merging the datasets, the two considered subsamples are created. The first subsample is a strongly balanced panel of 115 countries capturing the years 1995 to 2014, thus resulting in 2,300 observations. In a first step, all relevant final variables are calculated using the raw data from the merged datasets. That is, growth rates of CO_2 emissions, electric power consumption, human capital, and population levels are calculated. Since data on electric power consumption is retrieved as per capita variable, it is first multiplied with population levels. Then, to unify the scale of variables, GDP growth and industry share are divided by 100, since these variables were retrieved as percentages.

Second, missing values are addressed. Here, a strategic decision is made to infer values for certain variables to avoid a large loss of observations. Specifically, missing values for GDP growth are proxied by the self-derived growth rate in real GDP, which is provided in the Penn World

Tables (variable name: *rgdpna*). Missing values for the year 1995 in electric power consumption growth are replaced with their lead value. Missing values for industry share are replaced with the country mean of the variable. The scope of all these alterations is relatively small when comparing it to the size of the final panel. Of the final 2,300 observations, 16 observations previously had a missing value in GDP growth, 2 in electric power consumption, and 77 in industry share. These adjustments are therefore unlikely to result in bias, but help avoiding a large loss of countries from the dataset in the subsequent step, which involves deleting observations with missing values. All observations missing GDP growth, the globalization index, human capital, electric power consumption growth, or the Polity2 index, are deleted from the sample. Then, all observations from years earlier than 1995 or after 2014 are deleted from the sample. The resulting panel is verified for balanced, and countries with less than 20 observations are deleted. These include Ethiopia, Serbia, Niger, Sudan, and Iraq. Finally, all non-essential variables are deleted from the dataset. An overview of summary statistics with all essential variables can be found in Table **??**. The 115 countries contained in this panel are: Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Bahrain, Bangladesh, Belgium, Benin, Bolivia, Botswana, Brazil, Bulgaria, Cambodia, Cameroon, Canada, Chile, China, Colombia, Democratic Republic Congo, Republic of Congo, Costa Rica, Cote d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Finland, France, Gabon, Germany, Ghana, Greece, Guatemala, Haiti, Honduras, Hungary, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kuwait, Kyrgyz Republic, Latvia, Lithuania, Luxemburg, Malaysia, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Nigeria, North Korea, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russia, Saudi Arabia, Senegal, Singapore, Slovakia, Slovenia, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Syria, Tajikistan, Tanzania, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe.

The unbalanced panel contains 4,343 observations of 119 countries. These contain the previously listed 115 countries, and additionally Ethiopia, Iraq, Niger, Serbia, and Sudan. The process to obtain this panel follows the same steps as the first (strongly balanced) panel, with the exception of two steps: only missing values for industry share are proxied, and no observations of specific countries or years are deleted. Summary statistics of the resulting panel can be found in Table 1.

A.1. *Overview of variable names in original and final data*

variable	**original dataset**	**original name**	**final variable name**
Carbon emissions*	EDGAR	CO2_excl_short-cycle_org_C	$CO2_{gr}$
Electric power consumption	WB	eg_use_elec_kh_pc	electric_gr
Industry share	WB	nv_ind_totl_zs	industry_share
Population	WB	sp_pop_totl	pop_gr
GDP per cap.	WB	ny_gdp_pcap_cd	gdp_gr
Human capital	PWT	hc	hc_gr
Globalization	KOFGI	KOFGI	KOFGI
Economic Globalization	KOFGI	KOFEcGI	KOFEcGI
Social Globalization	KOFGI	KOFSoGI	KOFSoGI
Political Globalization	KOFGI	KOFPoGI	KOFPoGI
Polity2	Polity5	polity2	polity2

A.2. *Matching of country names across datasets*

Polity5	World Bank	Polity5	World Bank
Congo-Kinshasa	Congo, Dem Rep	Swaziland	Eswatini
Congo Brazzaville	Congo, Rep	Macedonia	North Macedonia
Congo-Brazzaville	Congo, Rep	Cote D'Ivoire	Cote d'Ivoire
Egypt	Egypt, Arab Rep	Ivory Coast	Cote d'Ivoire
Kyrgyzstan	Kyrgyz Republic	UAE	United Arab Emirates
United States*	United States	Yemen	Yemen, Rep
Korea South	Korea, Rep	Laos	Lao PDR
Venezuela	Venezuela, RB	Iran	Iran, Islamic Rep
Timor Leste	Timor-Leste	Gambia	Gambia, The
Syria	Syrian Arab Republic	Russia	Russian Federation
Myanmar (Burma)	Myanmar		

A.3. *Number of observations per year in unbalanced panel*

Year	Observations	Year	Observations	Year	Observations
1971	20	1987	92	2003	117
1972	78	1988	93	2004	117
1973	79	1989	94	2005	117
1974	79	1990	93	2006	117
1975	79	1991	96	2007	118
1976	81	1992	103	2008	118
1977	82	1993	104	2009	118
1978	82	1994	108	2010	119
1979	83	1995	108	2011	119
1980	83	1996	117	2012	118
1981	88	1997	117	2013	118
1982	89	1998	117	2014	118
1983	89	1999	117	2015	1
1984	89	2000	117	2016	1
1985	90	2001	118	2017	1
1986	92	2002	118	2018	1

A.4. *Summary statistics in raw data set*

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Observations**
CO_2 emissions*†	5,331.7	11,919.5	< 0.1	204,334.4	9,847
Economic					
GDP*†	9,493.6	17,681.7	20.0	189,432.4	8,634
electric power consumption*†	3,192.8	4,513.6	5.8	54,799.2	5,644
industry share	26.97	12.65	3.15	90.51	7,103
human capital	2.18	0.72	1.01	4.15	6,786
Political					
Globalization	49.26	16.35	14.15	90.73	9,422
Economic glob.	49.10	16.41	10.59	94.96	9,091
Social glob.	49.74	21.41	4.75	91.99	9,703
Political glob.	49.16	24.90	1.19	98.14	9,703
Polity2	1.30	7.32	-10	10	7,494
Full democracy	0.34	0.47	0	1	7,494
Partial democracy	0.20	0.40	0	1	7,494
Autocracy	0.43	0.49	0	1	7,494

Note. Variables marked with an asterisk (*) represent growth rates.

B Statistical software use

The creation of final datasets from the primary data, computation of summary statistics, and the conduct of panel unit root tests was performed using STATA. All further analyses were performed using R Statistical Software (v4.0.4; R Core Team 2021). The ”shapley” package by Elbers (2019) was used to compute simply Shapley values and the Owen decomposition values. Alterations were made to the functions in this package to compute percentages corresponding to individual values, to report the Lipovetsky threshold corresponding to a regular Shapley calculation, and to separately report aggregate Shapley values in case of a hierarchical structure in the variables. The computation of Nested and Interacted Shapley values was implemented by the author of this paper, but based losely on the code of the ”shapley” package.

C Additional material

C.1. *Levin-Lin-Chu panel unit root tests*

Variable	**LLC test statistic**	**adjusted t***	**p-value**
levels			
CO_2 emissions	-0.6724	6.1757	1.0000
electric power consumption	3.8198	9.7058	1.0000
population	1.9484	3.5201	0.9998
industry share	-13.2177	-4.3026	0.0000
human capital	-0.5790	1.5944	0.9446
KOFGI	-16.8547	-12.7378	0.0000
polity2	-15.9947	-2.8150	0.0024
growth rates			
CO_2 emissions	-36.0776	-16.9060	0.0000
GDP	-29.9371	-15.9872	0.0000
population	-23.4758	-18.6123	0.000
electric power consumption	-30.6155	-14.5959	0.0000
human capital	-14.4643	-2.3381	0.0097
null hypothesis	panels contain unit root		
panels	115		
number of periods	20		

Note. The Levin-Lin-Chu (LLC) unit root tests may be viewed as a pooled Augmented Dickey-Fuller (ADF) test, where the null hypothesis assumes that the time series of each unit in the panel contains a unit root. In this study, the LLC unit root test was conducted in the balanced panel dataset, consisting of 115 panels and 20 periods, using 1 lag and the Bartlett kernel.

C.2. *Regression results of economic and political variables in non-hierarchical model of carbon emission.*

Variable	balanced panel (1)	balanced panel (2)	unbalanced panel (1)	unbalanced panel (2)	balanced panel (3)
GDP†	0.472***	0.467***	0.594***	0.593***	0.513***
	(0.052)	(0.052)	(0.034)	(0.034)	(0.053)
population†	0.530***	0.532***	0.740***	0.730***	0.586***
	(0.139)	(0.140)	(0.133)	(0.134)	(0.140)
electric power consumption†	0.335***	0.333***	0.202***	0.202***	-0.138
	(0.026)	(0.026)	(0.019)	(0.019)	(0.123)
industry share	-0.037	-0.041	-0.030	-0.030	-0.027
	(0.021)	(0.021)	(0.016)	(0.016)	(0.021)
human capital†	-0.937	-0.141	-0.032	-0.080	-0.109
	(0.330)	(0.335)	(0.262)	(0.263)	(0.332)
Globalization	-0.009***		-0.006***		
	(0.002)		(0.001)		
Economic globalization		-0.004*		-0.002	-0.005*
		(0.002)		(0.002)	(0.002)
Social globalization		-0.002		-0.002	-0.001
		(0.002)		(0.002)	0.002
Political globalization		-0.002		0.000	-0.002
		(0.001)		(0.001)	(0.001)
Polity2	0.001		0.001		
	(0.000)		(0.000)		
Full democracy		0.028		-0.005	0.023
		(0.020)		(0.017)	(0.020)
Partial democracy		0.037		0.004	0.030
		(0.020)		(0.016)	(0.019)
Autocracy		0.022		-0.009	0.019
		(0.020)		(0.016)	(0.019)
GDP#industry share					-0.750*
					(0.349)
electric power#full democracy					0.447***
					(0.133)
electric power#partial democracy					0.582***
					(0.127)
electric power#autocracy					0.309*
					(0.133)
constant	0.057***	0.027	0.030***	0.028	0.048*
	(0.012)	(0.022)	(0.009)	(0.018)	(0.021)
total R^2	0.202	0.205	0.148	0.149	0.219
observations	2,300	2,300	4,343	4,343	2,300

Note. Significance of coefficients is indicated at *5% level, **1% level, or ***0.1% level. Standard errors are reported in brackets. Variables marked with a dagger (†) represent growth rates. Globalization variables are scaled by factor 10^{-1} and range between 0 and 10. In column 5, the variables GDP growth, electric power consumption, and industry share are demeaned.

C.3. *Year by year results*

Year	**GDP***	**population***	**Elec. power***	**industry**	**HC***	**Global.**	**Polity2**	*Lipovetsky*
1995	7.48	3.13	80.22	0.90	0.72	6.94	0.62	4.74
1996	16.89	56.74	5.03	11.97	2.11	4.26	3.01	47.18
1997	11.47	13.17	44.84	2.18	12.79	13.11	2.45	14.40
1998	50.42	21.20	7.88	1.03	1.13	15.27	3.07	25.50
1999	14.08	6.32	65.25	0.85	10.13	1.94	1.41	13.29
2000	42.28	6.67	34.41	2.46	10.21	2.11	1.87	9.71
2001	19.10	15.89	51.95	0.50	1.56	2.79	8.21	27.90
2002	22.83	27.84	9.69	11.74	10.09	8.50	9.30	125.32
2003	48.75	0.78	38.47	3.10	0.24	6.30	2.37	16.75
2004	15.65	5.45	61.81	1.02	2.11	7.41	6.56	34.83
2005	18.17	7.60	17.68	4.19	1.34	32.48	18.53	31.14
2006	32.05	7.92	37.64	5.41	7.53	5.51	3.95	52.95
2007	39.03	2.36	17.84	4.07	1.01	31.04	4.64	27.36
2008	28.98	12.44	29.95	6.56	1.65	7.69	12.73	22.31
2009	32.06	7.70	31.57	1.22	2.82	18.31	6.32	14.76
2010	40.65	2.55	48.48	1.71	4.04	1.09	1.47	21.66
2011	46.35	2.54	26.46	0.53	1.58	19.74	2.81	9.38
2012	36.59	13.01	12.97	3.08	8.62	22.32	3.41	21.16
2013	17.03	27.89	37.25	5.37	0.95	9.53	1.99	6.93
2014	31.59	9.02	4.15	1.43	0.84	48.78	4.20	7.05

Note. Variables marked with an asterisk (*) represent growth rates.