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The dependence between income inequality and carbon emissions: A distributional copula analysis.

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Abstract

High levels of carbon emissions and rising income inequality are interconnected challenges for the global society. Commonly-applied linear regression models fail to unravel the complexity of potential bi-directional transmission channels. Specifically, consumption, energy sources and the political system are potential determinants of the strength and direction of the dependence between emissions and inequality. To capture their impact, this study investigates the conditional dependence between income inequality and emissions by applying distributional copula models on an unbalanced panel data set of 154 countries from 1960 to 2019. A comparison of high-, middle-, and low-income countries contradicts a linear relationship and sheds light on heterogeneous dependence structures implying synergies, trade-offs and decoupling between income inequality and carbon emissions. Based on the conditional distribution, we can identify determinants associated with higher/lower probabilities of a country falling in an area of potential social and environmental sustainability.

Keywords: Bivariate distributional copula model, income inequality, carbon emission, social sustainability, ecological sustainability

JEL: C14, C46, D63, Q56

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1 Introduction

Climate change and rising income inequality are intersecting challenges for the global society that require joint attention for a transition into a socially and environmentally sustainable future. Recent studies provide increasing evidence on the interconnected nature of income inequality and carbon emissions (Torras and Boyce, 1998; Yohe and Tol, 2002; Harlan et al., 2015; Jorgenson et al., 2016, 2017; Grunewald et al., 2017). These analyses base their conclusions on unidirectional linear mean regressions, which conceal bi-directional relationships and differences of the dependence structure. The dependence between income inequality and carbon dioxide emissions exhibits a strong variation over the range of political systems, energy mix and income. Applying bivariate distributional copula models allows us to study such varying effects. Based on these regressions, we identify how these two challenges interact and calculate probabilities of falling into a space of potential social and environmental sustainability for specific country settings.

Different channels determine the dependence structure, which can lead to synergies, trade-offs or decoupling of income inequality and carbon emissions. Theories on the impact of income inequality on carbon emissions focusing on individual consumption behavior find either positive or negative effects (Veblen, 1899; Wilkinson et al., 2010; Boyce, 2018; Klasen, 2018). Political economy arguments centering around systemic structures like political framework or energy mix suggest a positive impact of income inequality on carbon emissions (Roemer, 1993; Martínez Alier, 2002; Roca, 2003; Boyce, 2018). These theories are supported by empirical studies that specifically condition on the countries' income level (Jorgenson et al., 2016, 2017; Grunewald et al., 2017). In the reverse direction, carbon dioxide emissions negatively influence inequality (Harlan et al., 2015). Furthermore, the carbon emissions of a country are closely linked to its GDP (Ravallion et al., 2000; Weil, 2012; Hickel and Kallis, 2020), which itself is discussed to be positively correlated with economic inequality. The relationship is thus not necessarily unidimensional. Due to the indeterminacy, we investigate the relationship itself to identify potential underlying structures focusing on the political setting, energy mix and income.

We use bivariate distributional copula models to analyze the conditional dependence structures between carbon emissions and income inequality. Mean regression techniques – which assume a normal distribution and stable effects over the range of the variables – investigate the transmission channels in one correlation direction. By contrast, the present study analyses the correlation by integrating income inequality and carbon emissions into a bivariate dependent vector. The copula captures the conditional dependence structure within the vector of carbon emissions and income inequality. The distributional regression techniques incorporated in the copula model make it possible to analyze non-linear effects of influencing factors on the relationship.

We apply the model to an unbalanced panel data set that comprises 154 countries over the period from 1960 to 2019. To measure income inequality, we use the widely-applied GINI measure, which estimates the average income inequality of a country (Solt, 2020). We use a consumption-based carbon measure, which locates the use of global carbon emissions by taking into account spatial separation of production and consumption (Peters et al., 2011). For GINI and carbon emissions, we determine threshold values that jointly define a potential socially and environmentally sustainable space. We argue that these national relationships proxy international relationships between carbon dioxide emissions and inequality based on the political economy argument that rich countries like rich elites can cushion the effects of climate change (Boyce, 1994). This accounts for the highly diverse regional impacts of climate change mainly driven by carbon emissions (IPCC, 2014, 2018). Therefore, we expect differences in the relation between income inequality and carbon emissions in high-, middle- and low-income countries.

The analysis identifies trade-offs, synergies and decoupling of income inequality and carbon emissions, indicating a higher potential to achieve social than environmental sustainability. Strong variation in the direction and strength of the relationship across the studied country groups reveals heterogeneous effects of the influencing factors of democracy score, fossil energy share and GDP per capita. A higher democracy score leads either towards synergy effects or decoupling of the two goals in all country cases under investigation. The decline of fossil energy leads to higher trade-offs in the middle-income countries investigated, while the low- and high-income countries studied demonstrate stronger synergies. At the same time, high-income countries have a higher probability of being below the GINI threshold for potential social sustainability. The reverse holds for middle- and low-income countries for an increasing democracy score as well as a falling share of fossil energy. None of the considered cases in high- and middle-income countries are likely to be below the carbon threshold nor in the potential socially and environmentally sustainable area. Only in low-income countries is change visible in the likelihood of being below the carbon threshold and in the potential social and environmental sustainability space. Consequently, decoupling from fossil energy is not hampering equality but is rather favorable for a more equal society in high-income countries. The reverse impact in middle- and low-income countries reflects the high dependence on carbon emissions for their development path (Klasen, 2018). The strong variation in the dependence structure and the changing effect size indicate that marginal, average effects are not representative for the dependence structure between carbon emissions and income inequality.

The following Section 2 theoretically studies the relation between inequality and emissions and lays out how current literature develops respective transmission channels. Section 3 explains the distributional copula model and the empirical strategy, including a description of the cross-country panel data set. Section 4 presents the different results by country groups, before finally Section 5 concludes.

2 Relationship between inequality and emissions

We consider potential channels and the associated direction of transmission in detail by distinguishing between three potential directions: synergies, tradeoffs and decoupling. These relationships are summarized in Table 1.

2.1 Synergies

A positive relation between the two variables indicates synergy effects, meaning that efforts in reducing one of them would help to reduce the other. One channel is the emulation effect, whereby poor people seek to imitate rich people who have carbon-intensive lifestyles, and the degree of emulation is stronger in more unequal societies. In turn, in more egalitarian societies individuals do not have to show their status by consuming carbon-intense status goods. Consequently, this leads to a positive relation between income inequality and carbon emissions (Veblen, 1899; Klasen, 2018).

As a second channel, higher income inequality leads to higher environmental degradation as the rich can lobby to block environmentally-friendly policies, due to higher political power in unequal societies. From a political economy perspective, political interests or policies shape individual behaviors, influencing the relationship between income inequality and carbon emissions. Unequal power distributions result in lobbies that favor the interests of the rich. These lobbies are most often in favor of less restrictive environmental policies. Rich people often benefit from high emissions but at the same time are less affected by them, as they can more easily adapt to a changing environment (Boyce, 1994, 2018). Given that power is correlated with wealth within and between countries, higher income inequality is most likely associated with higher power inequalities, leading to more environmental degradation. This leads to more losers of environmental damage, who lack the power to make the winners pay the cost of the damage that they cause (Boyce, 1994).

Environmental degradation can have an impact on income inequality. Human-made climate change leads to extreme weather events that cause drought, food and water shortage, infectious diseases, floods or storms (Harlan et al., 2015). These weather events disproportionately affect the poor. Social groups like people of color, women or indigenous people are often more severely affected in the long-term, due to discrimination, social norms or social hierarchies (Mileti, 1999; Kasperson and Kasperson, 2001). This vulnerability is associated with income inequality (Yohe and Tol, 2002).

2.2 Trade-offs

A negative association between income inequality and carbon emissions is based on the so-called 'individual Kuznets curve'. Individual carbon emissions are low for both the very rich and the very poor, leading to a U-shape in the relationship between individual carbon emissions and income, and an overall negative relationship between income inequality and carbon emissions. This theory argues that rich people live more environmentally-conscious lives, while poor people drop out of the carbon economy as they have no direct access to energy other than biofuels (Klasen, 2018). Especially considering low-income countries, high inequality is coinciding with a higher share of persons without access to electricity induces lower emissions.

A negative relation indicates that there are trade-offs between inequality and carbon emissions. Consequently, working on one of them would demand further effort for dampening the negative side effects on the other goal.

2.3 Channels for trade-offs or synergies

Previous studies have found that the dependence between inequality and emissions varies across countries, depending on country income and other characteristics. In line with this result, we detect channels that lead to either a positive or negative association depending on further characteristics of the country. For instance, GDP per capita is one of the main drivers of carbon emissions. Worldwide carbon emissions are closely related to growth in GDP (Hickel and Kallis, 2020). Furthermore, the relation between GDP and income inequality is ambiguously described in the literature (see e.g. Chapter 13.3 of

Table 1: Summary of possible association structures between inequality and emissions with correlation coefficient ρ, the related characteristics and channels identified in the literature.

Association (Corr)	Characteristics & consequences	Channels (inequ $\leftrightarrow$ emissions)
positive ($\rho > 0$)	synergies, reducing both jointly	– emulation effect ($\rightarrow$) – political economy, lobbies ($\rightarrow$) – environmental degradation ($\leftarrow$)
negative ($\rho < 0$)	trade-offs, how to weaken relation	– individual Kuznet curve ($\rightarrow$)
positive or negative	synergies or trade-offs	– energy mix ($\leftarrow$) – GDP growth ($\leftrightarrow$)
decoupled ($\rho = 0$)	no synergies or trade-offs, effort in both, reducing separately	– none

Weil, 2012). We place a special focus on the impact of GDP per capita due to a strong dependence with inequality and carbon emissions by separating the analysis into income groups (namely high-, middle- and low-income countries). This separation accounts for heterogeneous effects between income groups of the covariates on the dependence. Including GDP as a covariate in the model additionally controls for country-specific differences and the varying impact over the observed time period.

Additionally, the energy mix can drive the relationship between income inequality and carbon emissions. The energy mix influences the amount of a country's carbon emissions. For instance, France and Germany are neighboring countries, with a similar standard of living and income inequality. However, the countries differ in carbon emissions, with France having a lower average than Germany. The share of fossil fuel energy varies between the countries as France – like Portugal and UK – uses more nuclear or renewable energy. In turn, Germany uses more fossil fuel energy, especially from coal plants (Ritchie and Roser, 2021, own data). This may lead to a larger range of carbon emissions in relation to one certain inequality level. Accounting for the relative share of fossil fuel energy can to some extent control for these differences.

2.4 Decoupled

If inequality and emissions are not related – i.e. the correlation is zero (or close to zero) – they are decoupled and the goals can be achieved independently of each other. This case is difficult to justify empirically as observing no relation might be caused by counteracting effects that conceal the underlying mechanisms. However, in our empirical analysis we can identify influencing factors that have a decoupling effect on either a positive or negative relationship between income inequality and carbon emissions.

2.5 Distributional description of the relation

A standard empirical model might face difficulties covering the large variety of channels between inequality and emissions and their interconnected nature. According to Oswald et al. (2020), energy use increases non-linearly with income, which suggests heterogeneous dependencies between income and carbon emissions. Thus, mean regressions do not appropriately account for the dependence and we apply distributional regression techniques instead.

Figure 1 displays possible examples of a negative, positive (with asymmetric distribution) and no association between inequality and carbon emissions, illustrated by contour lines. In general, the efforts for sustainable developments aim for low inequality and low emissions which is represented by the location of the red contour lines. No relation between inequality and emissions means decoupled variables (red), a positive association (yellow) implies synergies and a negative association (cyan) implies trade-offs. The intersecting area of the two thresholds defines the potential socially and environmentally sustainable space.

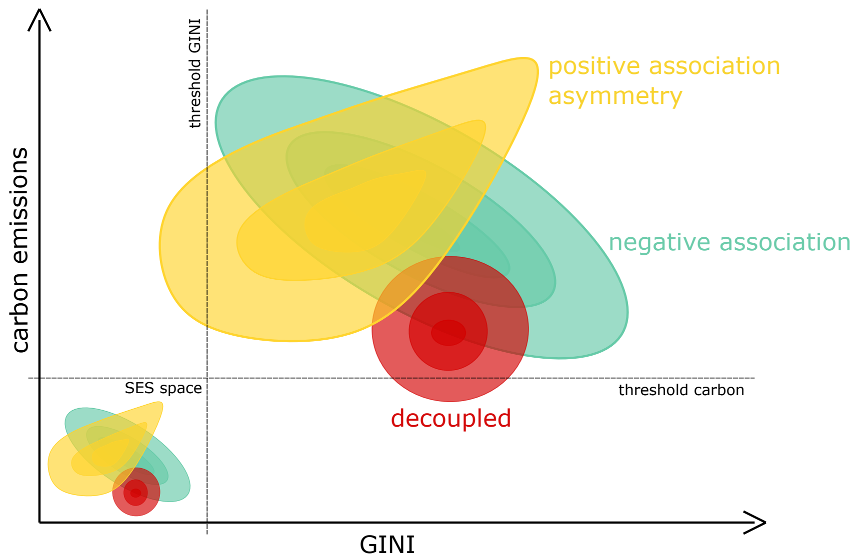

Figure 1: Schematic bivariate distribution of GINI and carbon emissions: positive association with asymmetric distribution (yellow), negative symmetric association (cyan) and decoupled (red); socially and environmentally sustainable (SES) space for low values of emissions and GINI (see Section 3.2 for more details).

3 Bivariate distributional copula regression

Bivariate distributional copula regression models focus analyzing the dependence structure and allow for varying effects over the range of the covariates. As a mathematical tool, the copula binds the marginal distributions of the two variables $GINI$ and *carbon* via a bivariate cumulative distribution function (CDF) to analyze their joint behavior. Bivariate distributional copula models incorporate generalized additive models for location scale and shape (GAMLSS) as building blocks for the marginals to study the shape of the marginal probability distributions of $GINI$ and *carbon* (Klein et al., 2019; Marra and Radice, 2017).

By contrast, predominantly-used univariate regression techniques analyze only mean effects and leave the varying dependence structure unconsidered. However, as outlined in Section 2, recent research suggests that income inequality and carbon dioxide emissions are interconnected. As no clear causal relation is identifiable, the strength and variety of the dependence matters to understand the relationship between income inequality and carbon dioxide emissions. Therefore, we apply bivariate distributional copula regression models.

3.1 Bivariate copula regression

Distributional copula regression for $GINI$ and *carbon* combines two features: first, it separately specifies the two marginal distributions, and subsequently it specifies the dependence between income inequality and carbon emissions with the option to model regression effects on all possible parameters of the resulting bivariate distribution.

Copula regression combines the ability to separate the specification for the marginal distributions and the dependence. It incorporates the option to model regression effects on possibly all parameters of the resulting bivariate distribution. More specifically, copulas allow specifying a bivariate distribution for the vector of responses $(Y_1.Y_2)$ via its CDF $F_{1,2}(Y_1, Y_2) = P(Y_1 \leq y_1, Y_2 \leq y_2)$ which can be represented as

$$F_{1,2}(y_1, y_2) = C(F_1(y_1), F_2(y_2)), \tag{1}$$

where $F_1(y_1) = P(Y_1 \leq y_1)$ and $F_2(y_2) = P(Y_2 \leq y_2)$ are the marginal CDFs and $C : [0,1]^2 \to [0,1]$ is the corresponding copula, i.e. a bivariate CDF with uniform marginals.

Copula regression now links the parameters of both the marginals and the copula to regression predictors. Let $\boldsymbol{\theta} = (\boldsymbol{\theta}_1', \boldsymbol{\theta}_2', \boldsymbol{\theta}_c')'$ be the J-dimensional vector of parameters characterizing the marginals ($\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$) and the copula ($\boldsymbol{\theta}_c$). Then we assume that each of the parameters is a function of the covariates $\boldsymbol{z}$ such that $\theta_{ij} = \theta_j(\boldsymbol{z}_i)$, $j = 1, \dots, J$ for observations $i = 1, \dots, n$.

In our application, we will consider various types of response distributions for continuous, non-negative responses including $normal$, $log-normal$, $gumbel$, $reverse\,gumbel$, $dagum$ and $singh-maddala$. For the copula, we will consider all possible copula specifications provided by the $GJRM$ package in R (Marra and Radice, 2017). Copula regression then allows us to make any aspect of the bivariate distribution covariate-dependent. Further, we can flexibly specify the marginal distribution with different types of dependencies, and in particular use forms of dependence that are not reflected by linear correlation.

To achieve flexibility in the regression specification, we extend beyond purely linear regression predictors in a semi-parametric specification where the partially-linear predictor

$$\eta_i^{\theta_j} = \boldsymbol{z}_i'\boldsymbol{\beta}^{\theta_j} + \sum_{k=1}^{K} f_k^{\theta_j}(x_{ik}) \tag{2}$$

is linked to the distributional parameter θ_j via a strictly monotonically increasing response function h_j such that

$$\theta_j(\boldsymbol{z}_i) = h_j(\eta_i^{\theta_j}). \tag{3}$$

The predictor combines linear effects $\boldsymbol{z}_i'\boldsymbol{\beta}^{\theta_j}$ based on covariates $\boldsymbol{z}_i$ and regression coefficients $\boldsymbol{\beta}^{\theta_j}$ with non-linear effects $f_k^{\theta_j}(x_{ik})$ of continuous covariates x_{ik}. For the latter, we employ penalized splines, i.e. cubic B-splines of moderate size supplemented with a second-order difference penalty to achieve a data-driven amount of non-linearity in the effect estimates.

We continue by studying the worldwide data for GINI and consumption-based carbon emissions per capita and introduce relevant covariables for the analysis. Subsequently, we describe the model specification that allows us to estimate the bivariate distribution in (1).

3.2 Data

The data studied comprise an unbalanced panel data set including 154 countries for the 1960–2019 period, collected from different sources. We focus our analysis on the relationship between carbon dioxide emissions per capita and GINI, which composes the bivariate outcome vector for our distributional copula model.

3.2.1 Measures of carbon emissions and GINI

We use a consumption-based measure of carbon dioxide emissions to account for trade. This measure assigns carbon emissions to the consuming rather than the producing country. The Global Carbon Atlas provides the data on carbon emissions. Carbon dioxide emissions are measured in millions of metric tons, combining emissions from fossil fuel combustion, cement production, and gas flaring (Peters et al., 2011; Global Carbon Project, 2020).

The GINI index is a country-level average measure of income inequality which ranges from 0 (perfect equality) to 100 (perfect inequality). Other than specific quantile measures of inequality, the GINI measure provides no information about the location of the inequality, i.e. whether it is between the richest 10 percent and the rest or between other quantiles. It rather measures the average inequality of a country (Jorgenson et al., 2017). This feature serves our exploratory purposes. The GINI measure is particularly attractive due to its internationally comparable data availability (Solt, 2016, 2020). The Standardized World Income Inequality Database (SWIID) comprises an adjusted panel data set for inter-country comparison of the GINI based on the Luxembourg Income Study. For our analysis, we apply the *gini_disp* variable, which measures equalized (using the square root scale), post-tax and post transfer household disposable income (Solt, 2016).

3.2.2 Factors influencing the relationship

Following the theoretically-specified channels and previous literature on the topic (Jorgenson et al., 2016; Grunewald et al., 2017; Jorgenson et al., 2017), we condition the relationship between GINI and carbon emissions on the following control variables. The World Development Indicators (World Bank, 2020b) provide the variables GDP per capita in constant 2010 US Dollars, agriculture ($agri$), service ($serv$), and manufacturing ($manu$), with the reference category construction measured in the share of value added as a percentage of total GDP. Furthermore, the $urban$ variable is defined as the percentage of the total population of a country living in cities (following Grunewald et al., 2017; Jorgenson et al., 2017) and the share of fossil fuel consumption $fossil$ is given in percentage of the total energy use (Dunlap and Brulle, 2015; Jorgenson et al., 2017). The polity measure proxies institutional differences and power relations in countries (Boyce, 1994; Torras and Boyce, 1998; Grunewald et al., 2017). The *polity* measure is provided by the Center for Systemic Peace (2020) and varies between -10 (strongly autocratic) and 10 (strongly democratic).

3.2.3 Country groups and summary statistics

We classify the countries into low-, lower- and upper-middle- and high-income countries as suggested by the World Bank (World Bank, 2020a), as we expect differences between country groups in the influencing factors. For the further analysis, we combine low- and lower-middle- (from here onwards, low-) income countries due to a lack of observations in the group of low-income countries and a rather similar pattern in comparison with lower- and upper-middle- (from here middle-) income countries. A detailed list of the included countries is provided in Table A1 in the Appendix.

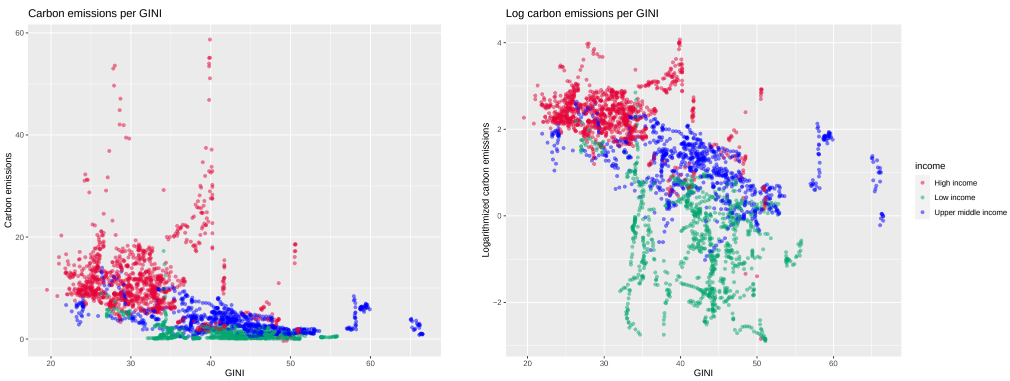

Figure 2: Scatter plot of the variables $GINI$ and *carbon*, pooled over all years and separated into the three income groups of, low- (red), middle- (blue) and high-income countries (green).

Figure 2 displays the variables $GINI$ and *carbon* as well as logarithmized *carbon* in a scatter plot, revealing considerable heterogeneity between the three income groups. The right-hand side plot displays the *carbon* variable in its logarithmized form due to scaling reasons. Furthermore, the empirical analysis in Section 3.3 suggests a logarithmized distribution of *carbon*. We can identify heterogeneity between the three displayed income groups (low-, middle- and high-income countries) in the level of both inequality and carbon emissions. This finding suggests separating the analysis into these country groups, which is in line with the empirical literature finding that the direction of correlation depends on the level of income (see e.g. Grunewald et al., 2017; Jorgenson et al., 2016). While the level of inequality decreases with higher income, the level of emissions increases. Figure 2 indicates that certain countries follow a path of rising emissions with fairly constant $GINI$ indexes. It further suggest differences in the strength of the dependence according to the level of income.

The summary statistics in Table 2 support the assumption of heterogeneity over the country groups and increasing emissions from low-income countries with a $mean = 1.27$ MtCO2 per capita over middle-income countries with a *mean* = 3.57 MtCO2 per capita, to high-income countries with a *mean* = 12.02 MtCO2 per capita. The variation in *carbon* is strongest in high-income countries with a standard deviation $sd = 7.17$ MtCO2 per capita compared with middle- and low-income countries, with $sd = 2.18$ and $sd = 1.94$ MtCO2 per capita, respectively. Inequality is highest in middle-income countries with a $mean = 42.59$ and lowest in high-income countries with a $mean = 30.51$ with low-income countries in between $mean = 42.08$. The variation in the $GINI$ variable is strongest in middle-income countries $sd = 8.16$ and similar over the other country groups.

To identify a potential ecologically and socially sustainable space, we specify thresholds for $GINI$ and *carbon*.

Table 2: Summary statistics of the outcome variables $GINI$ and *carbon* for high-, middle- and low-income countries.

Variable	N	mean	sd	min	max
		High-income countries			
carbon	1087	12.02	7.17	1.58	58.70
$GINI$	1626	30.51	5.77	19.50	50.60
		Middle-income countries			
carbon	840	3.57	2.18	0.36	13.98
$GINI$	1375	42.59	8.16	21.90	66.50
		Low-income countries			
carbon	939	1.27	1.94	0.06	17.26
$GINI$	1761	42.08	5.84	26.30	55.80

3.2.4 Socially and environmentally sustainable space

The target for a sustainable future comprises low levels of carbon emissions and income inequality. To investigate the attainability of this goal, we define two separate thresholds for $GINI$ and *carbon*. The overlapping area defines the potential socially and environmentally sustainable area. In order to limit global temperature rise to 1.5 degrees, studies suggest a life within a necessary global carbon budget. In this scenario, an individual could emit 0.5 MtCO2 per capita per year. This is an approximate value for a person born in 2017 with a life expectancy of 85 years. The estimated life budget is 45 metric tons. However, the current global average emissions are at 4.9 MtCO2 per capita per year. Thus, following the calculations, carbon emissions need to be reduced to one-tenth. The carbon budget calculation assumes an equal budget for every global citizen, independent of their place of birth. Country differences and historical responsibilities are not taken into account, which not only means that some people have to cut drastically but also that some could increase their footprint (Hausfather, 2019). Despite these limitations, we consider this threshold as an example for a desirable equitable and sustainable distribution of carbon emissions. For a socially sustainable future, we estimate the optimal GINI coefficient as the lowest quantile of the GINI distribution of countries with a polity score of 10. The estimated GINI threshold is 25.7.

Jointly, the limit of 0.5 MtCO2 per capita yearly carbon emissions and a GINI of 25.7 define the potential socially and environmentally sustainable space, which is schematized in Figure 1. The definition of a sustainable area in terms of our two outcome variables can help to quantify these targets along the lines of studies like O'Neill et al. (2018). The joint probability of being in the socially and environmentally sustainable space is derived from our bivariate distributional copula model specified in the following section.

3.3 Model specification

We define the model following the two-step procedure described in Section 3.1. First, we identify the marginal distributions of the variables $GINI$ and $carbon$ to build a GAMLSS model for each of the two variables. Second, we determine the copula, which (together with the marginals) defines the joint distribution of $GINI$ and $carbon$. All selections of the specific type of the distribution are made by comparing the values of the AIC and BIC selection criterion and QQ plots of the model residuals for different choices of the distribution. We select the distributions and copulas with the lowest values. We do not consider specifications whose models do not converge since this usually indicates that the dependence observed in the data does not comply with the structure assumed by the given copula.

The specific marginals and copulas are described by a set of parameters $\theta_j, j = 1, \ldots, J$, as specified in Equations (2) and (3). The predictor η^{θ_j} of parameter θ_j depends on the set of covariates introduced in Section 3.2. For each of the three income groups $i = 1, 2, 3$, we obtain a set of predictors

$$\begin{aligned}\eta_i^{\theta_j} = \beta_{0i}^{\theta_j} + s_i(GDP)^{\theta_j} + \beta_{3i}^{\theta_j} manu + \beta_{4i}^{\theta_j} serv + \beta_{5i}^{\theta_j} agri + \beta_{6i}^{\theta_j} urban \\ + \beta_{7i}^{\theta_j} fossil + \beta_{8i}^{\theta_j} polity + s_i(year)^{\theta_j}.\end{aligned} \tag{4}$$

The intertemporal variation of the GINI index is small within countries and varies more across countries (see 2). For this purpose, we apply a fixed grouping for the countries following the income classes and control for non-linear variation in time by applying a nonlinear effect (modeled as a penalized spline) for the years. Using the panel data structure, we implement splines s_i with ten inner knots for year effects $year$. Likewise, we model GDP by using a penalized splines with ten inner knots to account for non-linear effects. Splines enable us to smooth the effects between knots and therefore allow for more flexibility compared to a standard quadratic relation (Fahrmeir et al., 2013). According to the distribution of the model residuals (see Figures A12, A17, and A22), the explanatory variables seem to sufficiently control for heterogeneity between the countries, which was directly observable as country-specific paths in Figure 2. The parameters in (4) are estimated using the R package *GJRM* (Marra and Radice, 2020).

Table 3 displays the selected marginal distributions and copula specifications for the three country groups based on the specification of the predictor and the corresponding parameters. $Carbon$ exhibits a log normal distribution in all three income groups. $GINI$ exhibits a normal distribution in middle- and low-income countries, while it reveals a log normal distribution in high-income countries. All selected distributions are determined by two parameters. Conditioned on these choices for the marginal distribution, the copula specification is a normal copula for high-income countries and a Frank copula for low- and middle-income countries.

Table 3: Selected marginal distributions for $GINI$ and $carbon$ and type of the copula by country groups. The full list of AIC and BIC values for all model specifications is displayed in Tables A2-A4, A10-A12 and A18-A20 for high-, middle- and low-income countries, respectively.

Marginal distr.	High-income	Middle-income	Low-income
$GINI$	Log Normal	Normal	Normal
$carbon$	Log Normal	Log Normal	Log Normal
Copula	Normal	Frank	Frank

With the specified marginal distributions and copulas, all resulting bivariate distributions $D = F_{1,2}$ depend on five parameters $\theta_j, j = 1, \ldots, 5$: two parameters for each of the two marginal distributions and one parameter for the copula. These five parameters specify the bivariate distribution for each income group $i = 1, 2, 3$, i.e.

$$\begin{pmatrix} GINI \\ Carbon \end{pmatrix} \sim D_i(\theta_1, \theta_2, \theta_3, \theta_4, \theta_5). \tag{5}$$

We are primarily interested in the effect of the covariates on the dependence. For this reason, our analysis focuses on the estimation output of Equation (4) for the copula parameter θ_5. The results display the impact of the covariates on the dependence. The following section presents the results for the three country groups.

4 Results

The dependence structure exhibits a strong variation over the set of influencing factors and widely differs from the mean prediction. Thus, the mean is not representative for the full range of the influencing factors. We therefore take specific country cases into account to better illustrate the dependence structure. In the groups of high-, middle- and low-income countries, effect significances on the dependence parameter and the analysis of model residuals (displayed in Figure A12, A17 and A22) support the grouping by income group. In this sense, the grouping results in effect homogeneity on the dependence but variety in the dependence structures. Most of the covariates included show a significant impact but we do not further concentrate on their interpretation. Our analysis specifically focuses on the covariates *polity*, $fossil$ and GDP as drivers of the relationship to deduce potential policy implications in line with a sustainable future. The flexible copula model enables us to analyze the covariate effects in specific settings, with a focus on the varying impact over the range of the variables. For each country group, we consider the mean copula prediction – i.e. the prediction based on the average over all predictions for the parameters θ_1-θ_5 – and compare it to a selection of country-specific predictions.

The country cases allow studying the effect on different aspects of the resulting distributions. In particular, the resulting bivariate copula prediction enables us to calculate joint probabilities for falling below both thresholds for GINI (25.7) and carbon (0.5 MtCO2 per capita), specified as a potential socially and environmentally sustainable space in Section 3.2.4. Besides the joint probability, we additionally investigate the likelihood of falling below each of the thresholds separately.

We describe our interpretation strategy in detail for the group of high-income countries, which is studied first. The analysis for middle- and low-income countries proceeds analogously.

4.1 High-income countries

The results for high-income countries reveal significant effects of *polity*, $fossil$ and GDP on the relationship between $GINI$ and *carbon*. Table 4 displays the estimates for the copula parameter θ_5. Due to the distributional focus, the estimates cannot be interpreted as mean effects, but they still indicate the direction of the impact and its significance. To analyze the economic relevance, we take into account specific cases later in the chapter.

Higher scores of polity – and hence democracy score – have a negative effect on the predictor of the dependence between $GINI$ and *carbon*. We deduce this from the significant negative effect of the variable *polity* on the relationship (c.f. Table 4). This can lead to an increase or decrease of the dependence, depending on the intercept and level of the other variables. More specifically, if the predictor for a given country is initially negative, then an increase in polity leads towards an even stronger negative relationship, while if the predictor is initially positive, an increase in polity leads to a weaker positive relation and can result in a negative or decoupling scenario. Positive and negative impacts have to be placed in relation to the initial predictor and can thus indicate strengthening or weakening effects at the same time. Kendall's τ measures the change in the dependence, which we study for country-specific cases to account for different covariate settings. The fossil variable – representing the share of fossil energy in the energy mix – exhibits a significant decreasing impact on the dependence parameter displayed in Table 4.

Table 4: High-income countries, $n = 864$: equation for copula parameter θ_5. The results for the other model parameters θ_1-θ_4 are in Table A5-A8.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.837	0.781	1.071	0.284
Manu	0.024	0.010	2.332	0.020
Serv	0.076	0.010	7.557	0.000
Agri	0.187	0.046	4.064	0.000
Urban	-0.037	0.004	-8.778	0.000
fossil	-0.031	0.004	-8.506	0.000
polity	-0.157	0.017	-9.347	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	8.782	8.977	503.95	$<$ 2e-16
s(Year)	7.424	8.389	21.68	0.00642

For different levels of GDP, we can identify a varying impact on the dependence. The effect of GDP – like the years effect – is estimated non-parametrically by a spline, i.e., the smooth effects over the range of the variable on the relationship between *carbon* and $GINI$. The estimated centered spline is displayed in the left-hand graphic of Figure 3. The spline indicates that GDP per capita has a non-linear effect on the dependence, which is statistically significant, as indicated in Table 4. By contrast, the spline for the year effect (right-hand graphic in Figure 3) does not strongly vary over the time period, suggesting no variation in the dependence due to year effects.

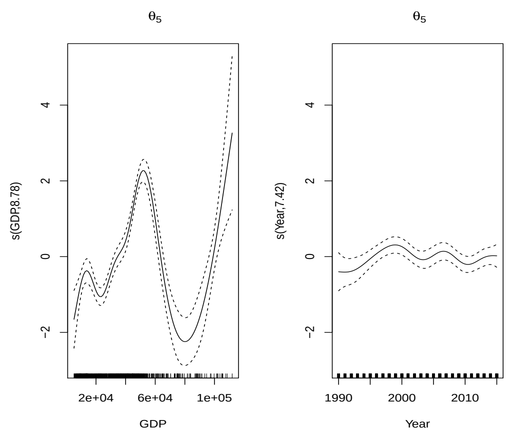

Figure 3: High-income countries: splines for GDP and $year$ for the copula parameter. The splines for the other model equations are in Figures A13-A16.

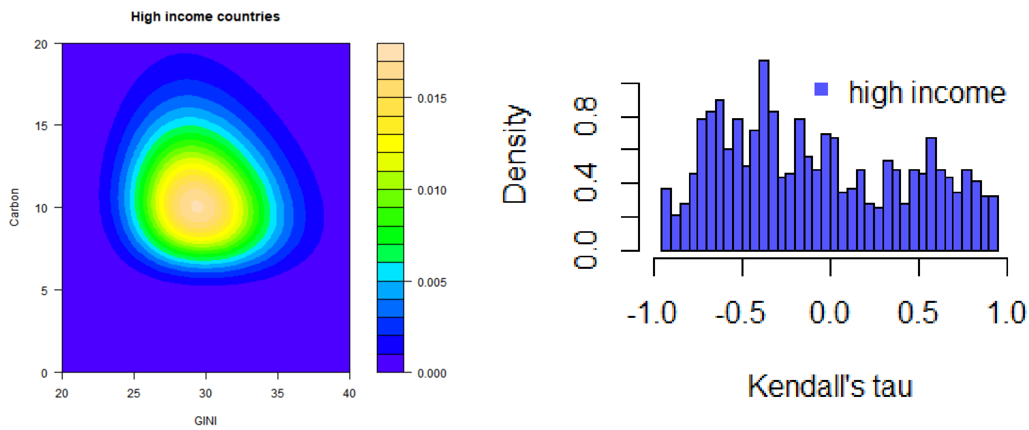

Figure 4: Average copula prediction for the conditional dependence between $GINI$ and $carbon$ (left) and the histogram for the distribution of Kendall's τ of the individual predictions in high-income countries (right).

The strength and direction of the dependence between $GINI$ and $carbon$ shows a strong deviation between the mean prediction and the prediction for different country settings. The left-hand side of Figure 4 displays the mean dependence structure as an average over the predictions of the parameters $\theta_j, j = 1, \dots, 5$. The right-hand side shows a histogram of the distribution of the dependence structures for all observations, which is measured by Kendall's τ from the predicted copula for these observations. The average predicted copula for high-income countries shows a weak association between carbon emissions and GINI. More precisely, in mean the relation is -0.08 with a confidence interval containing zero, $(-0.23, 0.08)$, suggesting that there is hardly any relation between inequality and emissions. However, the widely spread distribution in the histogram of Kendall's τ indicates a large variety of positive and negative relations covering nearly all possible values, i.e. ranging from $-.95$ to 0.93, whereby these values average to a mean around zero. This uncovers the discrepancy between the average association and the possible range of associations between $GINI$ and *carbon*. Thus, the sole analysis of the mean prediction is misleading and not representative for the entire distribution of the relationship. Next, we consider different covariate settings and the resulting copula prediction.

The results of exemplary copula predictions for Germany and the US displayed in Table 5 support the analysis of the covariate effects from the pooled estimation for the whole country group in Table 4. Cases 1,2,3 and 4 for Germany and 5,6,7 and 8 for the US represent real cases, while cases including letters represent fictive changes in *polity* and $fossil$. The variation in the strength of the dependence underpins the economic relevance, as – for instance – a lower polity score leads to higher positive associations of $GINI$ and *carbon*. Specifically, cases 4c and 4d as well as 8c and 8d show the changes in the relationship for lower polity score in Germany and the US, respectively. Likewise, cases 4a and 4b as well as 8a and 8b demonstrate fictive cases for lower fossil share in Germany and the US, respectively. These fictive cases indicate a strongly increasing relationship for lower fossil energy shares. For Germany, this increase is around 0.5 points in Kendall's τ and for the US around 0.1 points, adding to an already-high level of dependence.

We find a recognizable difference in the relationship between $GINI$ and *carbon* between 2008 and 2009, indicating the relevance of a change in GDP. Between these two years, most macroeconomic factors remained stable, while due to the financial crisis GDP fell in Germany and the US. The drop in GDP per capita led to a change from a positive relationship between $GINI$ and *carbon* in 2008 to a negative relationship in 2009 in Germany. This amounts to approximately 0.24 points in Kendall's τ. For the US, the relationship reduced by approximately 0.05 points in Kendall's τ.

For all investigated cases in Table 5, Germany and the US are highly unlikely to fall into the socially and environmentally sustainable area. The last three columns of the table display the estimated probability of being below the GINI threshold, the carbon threshold or both, i.e. in the socially and environmentally sustainable area. Choosing a lower polity score for Germany, the likelihood of being below the GINI threshold decreases, while with a falling

Table 5: Specific copula prediction for high-income countries: Germany and the US with the respective choices of the variables *year*, *polity* and $fossil$ (the remaining covariates are set to their actual value). In the last four columns: Kendall's τ (K's τ) and the probability to of being the threshold for $GINI$ and *carbon* and in the socially and environmentally sustainable (SES) area in the specific setting. Additional case studies in Table A9.

Case	Country	*year*	*polity*	$fossil$	K's τ	TH $GINI$	TH *carbon*	SES Area
1	Germany	1997	10	84.63	-0.302	0.079	0	0
2	Germany	2008	10	80.8	0.052	0.027	0	0
3	Germany	2009	10	79.97	-0.187	0.005	0	0
4	Germany	2015	10	78.86	0.428	0.101	0	0
4a	Germany	2015	10	50	0.749	0.168	0	0
4b	Germany	2015	10	10	0.925	0.436	0	0
4c	Germany	2015	9	78.86	0.502	0.068	0	0
4d	Germany	2015	3	78.86	0.797	0.001	0	0
5	USA	1997	10	86.46	0.311	0	0	0
6	USA	2008	10	84.97	0.827	0	0	0
7	USA	2009	10	84.15	0.775	0	0	0
8	USA	2015	10	82.43	0.877	0	0	0
8a	USA	2015	10	50	0.954	0	0	0
8b	USA	2015	10	10	0.986	0	0	0
8c	USA	2015	9	82.43	0.895	0	0	0
8d	USA	2015	3	82.43	0.959	0	0	0

fossil energy share the likelihood increases. However, in none of the settings does Germany have a non-zero likelihood of falling below the carbon threshold or in the socially and environmentally sustainable area. The US does not show a positive likelihood of falling under the threshold of any of the target variables.

Focusing on the shape of the copula prediction in different settings, Figure 5 illustrates the changes in the contour lines for changing polity scores, showing a higher dependence for lower polity scores and fossil share. For example, we take the case of Germany and compare the real situation in 2015 to a fictive situation with a different polity score in Figure 5. All other factors correspond to the actual values in 2015. For more autocratic frameworks, Germany exhibits weaker variation in the relationship, and thus a higher dependency. Varying the fossil energy share to a lower share in the same setting, the variation is also lower. The contour plots for the US present a similar direction but the shape of the contour lines differs, indicating the relevance of distributional aspects. Both country settings lead to a distribution with higher variation in higher levels of $GINI$. The center of the contour lines – which represents the highest density of the correlation – is located in higher levels of $GINI$ for the US. The plots for Germany expose a stronger dependence at the lower tails of the joint distribution, which is driven by the choice of the marginal distributions.

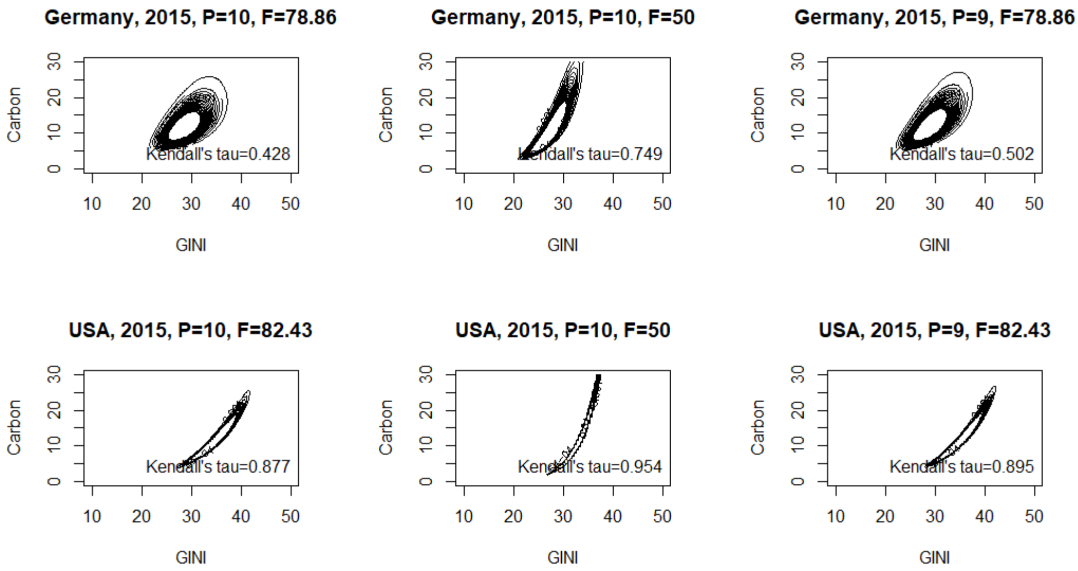

Figure 5: Contour plots for Germany and the US in 2015, different choices of *polity* (P) and *fossil* (F), the remaining covariates are set to their actual value.

The results support the political economy argument described in Section 2. The increasing likelihood of being below the $GINI$ threshold for falling fossil share and polity score as well as the increasing relationship for falling polity score and fossil share suggests that the relationship is determined by political settings, which also influence environmental policy and thus the fossil energy share. In less democratized countries, the political economy argument suggests that the rich benefit more from short-term environmental degradation and spending, while the reverse holds in more democratic and more egalitarian countries. Higher income inequality is associated with higher power inequality (Boyce, 1994). Accordingly, the rich are likely able to block a shift away from fossil fuels and thereby increase emissions. Further, the emulation effect focusing on the individual basis suggests a more carbon-intensive lifestyle for richer people in more unequal societies, strengthening the mechanisms of the political economy argument. The higher disposable income in high-income countries compared to the average of middle- and low-income countries strengthens the effect in richer countries, as GDP and carbon emissions are strongly correlated (Hickel and Kallis, 2020). Most cases under investigation (Table 5) have a positive Kendall's τ, whereby lower fossil energy shares strengthens the relation between *carbon* and $GINI$. This implies that reducing the fossil energy share likely leads to synergy effects between social and environmental sustainability.

4.2 Middle-income countries

In the analysis of middle-income countries, *polity*, $fossil$ and GDP significantly influence the relationship between $GINI$ and *carbon*, as displayed in Table 6. In contrast to high-income countries, the impact of the variables *polity* and $fossil$ is positive.

Table 6: Middle-income countries, $n = 636$: equation for the copula parameter θ_5. Tables A13 -A16 report the results for the model parameters θ_1-θ_4.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	10.654	7.425	1.435	0.151
Manu	-0.635	0.124	-5.120	0.000
Serv	-0.188	0.078	-2.395	0.017
Agri	0.009	0.134	0.066	0.948
Urban	-0.389	0.040	-9.611	0.000
fossil	0.279	0.056	4.996	0.000
polity	0.777	0.177	4.398	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	7.696	8.499	127.52	<2e-16
s(Year)	4.557	5.584	56.74	2e-10

The impact of GDP on the dependence varies over the range of the variable. GDP exhibits a non-linear impact on the relationship between $GINI$ and *carbon*, illustrated by the centered spline in Figure 6. The centered spline for the year effect in Figure 6 indicates a non-linear impact on the relationship between $GINI$ and *carbon*. Both effects are statistically significant, as displayed in Table 4.

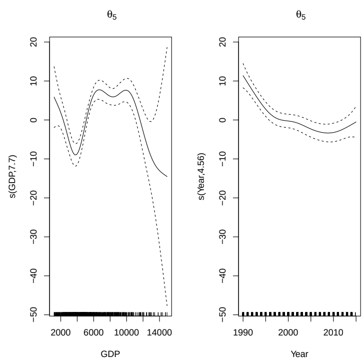

Figure 6: Middle-income countries: splines for GDP and *year* for the copula parameter. The splines for the other model equations are in Figure A18-A21.

The mean copula prediction in middle-income countries (right graphic of Figure 7) shows a negative dependence i.e. trade-offs between *carbon* and

$GINI$. The Frank copula implies an oval shape. A Kendall's τ of -0.39 joint with a confidence interval of $(-0.55, -0.21)$ indicate that there is a negative relation between $GINI$ and $carbon$. The presence of primarily negative associations is supported by the histogram of country-specific Kendall's τ's in the right-hand graphic of Figure 7. However, the values range between a Kendall's τ of -0.89 to 0.75. Although we can state that the mean effect better represents the relationship for middle-income countries than its equivalent for high-income countries, the diversity of the relationship justifies the need for specific case studies.

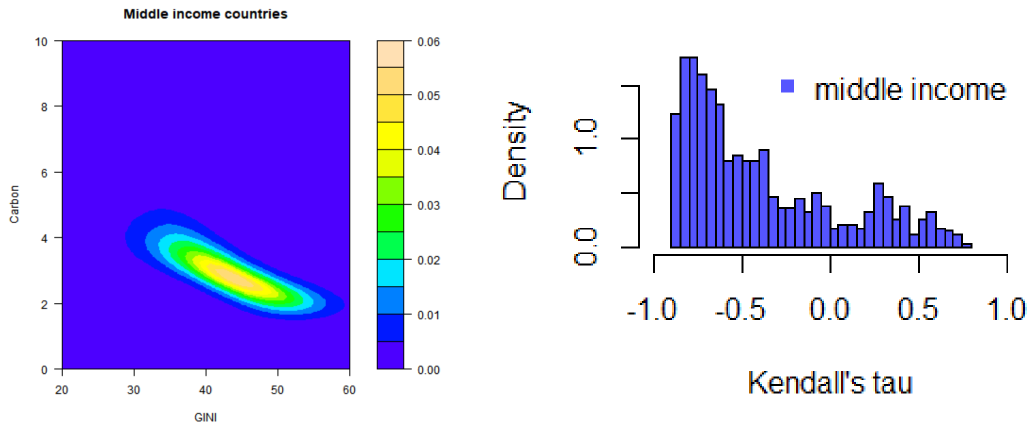

Figure 7: Average copula for the conditional dependence between $GINI$ and $carbon$ (left) and the histogram for the distribution of Kendall's τ in middle-income countries (right).

The specific cases of interest – China and South Africa – expose the economic relevance of the impact of $polity$, $fossil$ and GDP, as displayed in Table 7. Cases 9, 10 and 11 for China and 12, 13, 14 and 15 for South Africa represent real cases, while cases including letters represent fictive changes in $polity$ and $fossil$. Keeping $fossil$ at its actual value for China in 2014, an increase in the democracy score from the actual value of -7 to 10 increases the Kendall's τ from -0.75 to -0.09. Thus, in this alternative setting with a high level of democratization, the dependence is close to decoupling. An increase in the polity score from 9 to 10 in South Africa leads to a 0.06 point increase. A decrease in fossil energy share leads to a higher negative relation for China (cases 11a and 11b) as well as South Africa (15a and 15b), ranging from a 0.1 to 1.0 point change in Kendall's τ. The change in the relationship between 2008 and 2009 ranges between a positive impact of 0.1 for China and 0.02 for South Africa. These significant changes support the economic impact of the variables.

Table 7: Specific copula prediction for middle-income countries: China and South Africa with the respective choices of the variables *year*, *polity* and *fossil* (the remaining covariates are set to their actual value). In the last four columns: Kendall's τ (K's τ) and the probability of being below the threshold for *GINI* and *carbon* and in the socially and environmentally sustainable (SES) area in the specific setting. Additional case studies in Table A17.

Case	Country	*year*	*polity*	*fossil*	K's τ	TH *GINI*	TH *carbon*	SES Space
9	China	2008	-7	87.22	-0.87	0.213	0	0
10	China	2009	-7	87.64	-0.869	0.21	0	0
11	China	2014	-7	87.67	-0.747	0.303	0	0
11a	China	2014	-7	50	-0.848	0.091	0	0
11b	China	2014	-7	10	-0.893	0.001	0.032	0
11c	China	2014	10	87.67	-0.088	0.229	0	0
11d	China	2014	3	87.67	-0.522	0.261	0	0
12	South Africa	1997	9	84.91	0.338	0.036	0	0
13	South Africa	2008	9	88.15	0.196	0.047	0	0
14	South Africa	2009	9	87.68	0.216	0.065	0	0
15	South Africa	2014	9	86.79	0.327	0.089	0	0
15a	South Africa	2014	9	50	-0.562	0.001	0	0
15b	South Africa	2014	9	10	-0.799	0	0.057	0
15c	South Africa	2014	10	86.79	0.385	0.085	0	0
15d	South Africa	2014	3	86.79	-0.15	0.115	0	0

For South Africa, the likelihood of falling below the *GINI* threshold slightly decreases with an increasing level of democracy, and it strongly decreases with falling shares of fossil energy. The likelihood of being below the carbon threshold is only different from zero for a low fossil energy share. Considering the likelihood of falling in the potential socially and environmentally sustainable space, none of the country settings in Table 7 show a positive probability. Additionally, the probability of falling below the carbon threshold is zero or very low in all cases. The probability for the threshold of *GINI* changes with the macroeconomic setting. For higher levels of democracy, the likelihood of falling below the *GINI* threshold slightly declines, while it more strongly declines for changing fossil energy shares. However, a low fossil energy share increases the likelihood of falling below the carbon threshold.

The contour plots for predictions based on variable choices represented in cases 11a and 11c for China and 15a and 15c for South Africa in Figure 8 illustrate the varying dependence structure for changing fossil share and polity score. The contour plots illustrate a stronger dependence for a falling fossil energy share and a decoupling for changes in *polity* in China. The contour plots for South Africa show a change in the direction and strength of the dependence for a reduced fossil energy share. The same plots expose a stronger dependence at the tails of the joint distribution, which is driven by the choice of the marginal distributions.

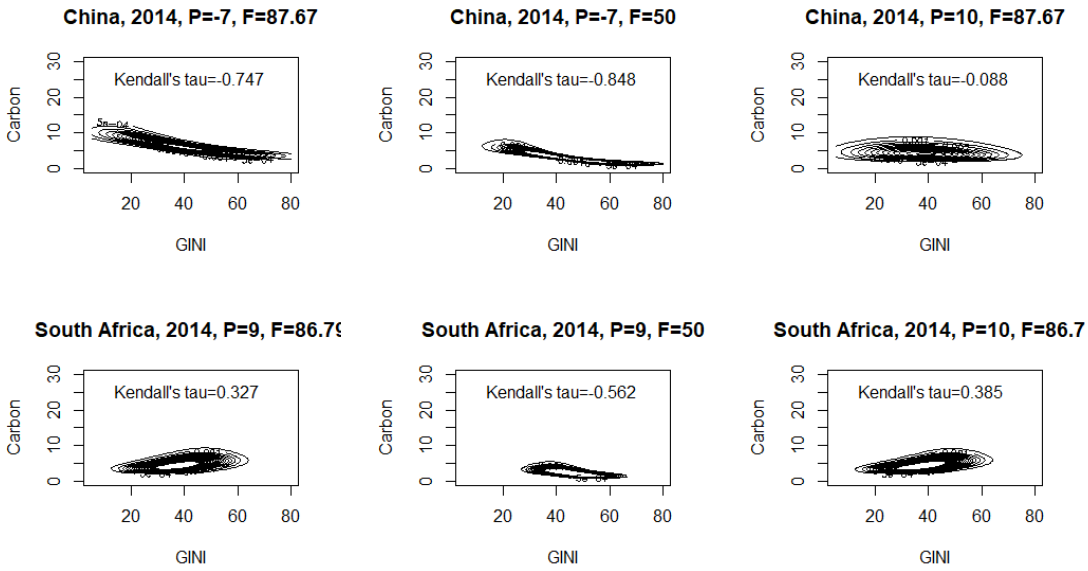

Figure 8: Contour plots for China and South Africa in 2014, different choices of *polity* (P) and *fossil* (F), the remaining covariates are set to their actual value.

The results for middle-income countries support the political economy argument as an increase in democracy has a positive effect on the relationship between $GINI$ and *carbon*. Due to primarily negative relationships, an increase in the democracy score leads to a decline in the negative relationship in most cases. Further, with an increasing level of democracy, the likelihood of being below the $GINI$ threshold increases. Although the direction of the impact is opposite to high-income countries, most cases under investigation exhibit negative Kendall's τ, and thus the strength of the negative relationship falls and may become positive with higher levels of democracy. Thus, more democratic societies are more equal, which is associated with a decoupling or positive effect on the relationship. This can be explained by less powerful elites and democratic mechanisms that enable better environmental and income equality supporting policies. However, falling fossil shares lead to higher negative relationships. The individual Kuznet curve may hold in this case as poor individuals drop out of the carbon economy. This is indicated by a decrease in the likelihood of being below the $GINI$ threshold and an increase in the likelihood of being below the carbon threshold. The overall significant negative relationship suggests that higher levels of carbon emissions are realized with less inequality, and thus more people can afford a carbon-intensive lifestyle. Further, middle-income countries strongly rely on fossil energy to realize their development path (Klasen, 2018).

4.3 Low-income countries

The output table of the estimated copula equation (Table 8) shows that the share of fossil energy has a significant negative impact on the copula parameter, while *polity* is statistically insignificant.

Table 8: Low-income countries: equation for the copula parameter, n = 898. All results for the model parameters are in Table A21-A24.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-22.475	6.782	-3.314	0.001
Manu	0.446	0.104	4.271	0.000
Serv	0.245	0.072	3.401	0.001
Agri	0.028	0.095	0.292	0.770
Urban	0.147	0.049	3.020	0.003
fossil	-0.103	0.021	-4.968	0.000
polity	-0.060	0.072	-0.839	0.402
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	8.485	8.889	77.927	3.92e-13
s(Year)	1.000	1.000	1.393	0.238

GDP per capita exhibits a non-linear impact on the relationship, while the year effect is less pronounced (see Figure 9). Table 8 indicates that both effects are statistically significant.

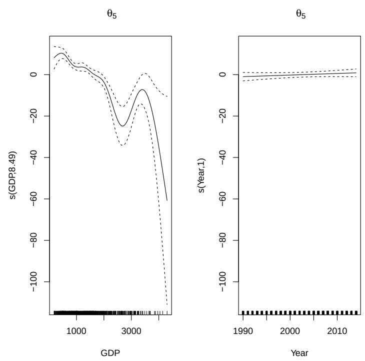

Figure 9: Low-income countries: splines for *GDP* and *year* for the copula parameter. The splines for the other model equations are in Figures A23-A26.

The average copula prediction in low-income countries exhibits a negative dependence, as displayed in Figure 10. The probability mass is located around a *GINI* of 40 to 45 and *carbon* around 1 MtCO2 per capita. The Frank copula itself suggests an oval shape, which – due to the marginal distributions – is slightly higher at higher $GINI$ values, and hence with a lower variation in emissions. A Kendall's τ of -0.097 joint with a confidence interval of -0.27 to 0.08 suggests that there is hardly any relation. The individual-specific dependence values range from a strongly negative association of -0.93 up to a positive association of 0.67 (displayed in the histogram of Figure 10). The mean effect is thus not representative for the strongly varying relationship, which supports the need for case studies to better understand the relationship.

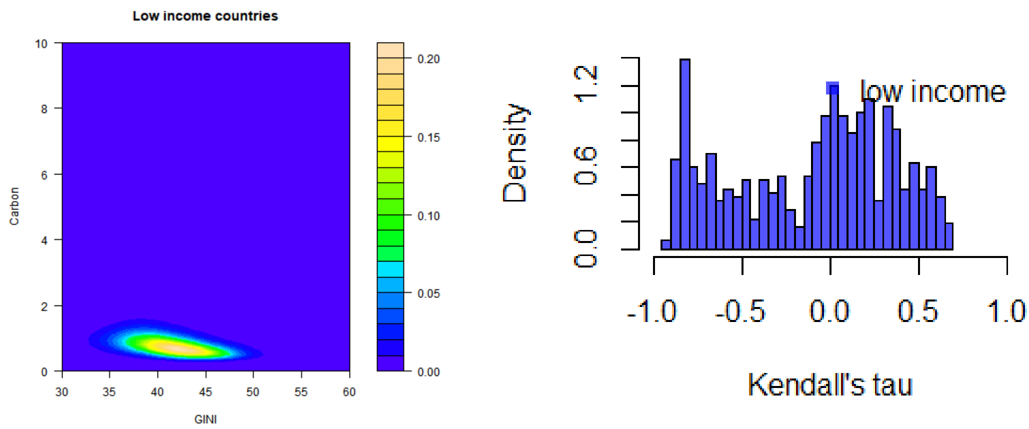

Figure 10: Average copula for the conditional dependence between $GINI$ and $carbon$ (left graphic) and the histogram for the distribution of Kendall's τ in high-income countries.

The results for the specific cases of Bangladesh and Tanzania underpin the economic relevance of the impact of $fossil$ and GDP. Cases 16, 17, 18 and 19 for Bangladesh and 20, 21, 22 and 23 for Tanzania represent real cases, while cases including letters represent fictive changes in $polity$ and $fossil$. Even though $polity$ is insignificant in the parameter estimation in Table 8, a change in $polity$ leads to a sizable change in Kendall's τ (see cases 19c and 19d compared to 19 for Bangladesh and 23c and 23d compared to 23 for Tanzania). Cases 19a and 19b show changes in Kendall's τ for a lower fossil energy share in Bangladesh, which leads to a strong increase in the relationship. Kendall' τ is 0.06 for a share of fossil energy of 73.77 percent of the total energy mix and rises to a Kendall's τ of 0.567 for a fossil share of 10 percent, holding all other variables fixed in Bangladesh. For Tanzania, the relationship even becomes negative. Compared to the other country groups, it is difficult to follow an impact of GDP from the change between 2008 and 2009. Specifically in Bangladesh, the strong shift from a negative to positive polity score might dominate any changes in the resulting prediction from 2008 to 2009.

Within all country-specific investigations, Bangladesh is the only country that exhibits a small likelihood of 0.1-0.4 percent of falling into the socially and environmentally sustainable space in 2008-2014, although this probability decreases over time. The considered cases for Tanzania exhibit no probability of being in the socially and environmentally sustainable area. The likelihood of being below the $GINI$ thresholds increases and being below the *carbon* threshold decreases over the years under consideration. A strong decrease in $fossil$ drastically increases the likelihood of being below the carbon threshold. Tanzania is unlikely to be below the $GINI$ threshold. However, a rise as well as a decline in the share of fossil energy increases the likelihood of falling below the $GINI$ threshold, being higher for an increase in the fossil share. Likewise, the likelihood of being below the carbon threshold decreases.

Table 9: Specific copula prediction for low-income countries: Bangladesh and Tanzania with the respective choices of the variables *year*, *polity* and $fossil$ (the remaining covariates are set to their actual value). In the last four columns: Kendall's τ (K's τ) and the probability of being below the threshold for $GINI$ and *carbon* and in the socially and environmentally sustainable (SES) area in the specific setting. Additional case studies in Table A25.

Case	Country	*year*	*polity*	$fossil$	K's τ	TH $GINI$	TH *carbon*	SES Space
16	Bangladesh	1997	6	56.57	0.359	0	0.543	0
17	Bangladesh	2008	-6	67.58	0.328	0.014	0.114	0.004
18	Bangladesh	2009	5	69.01	0.244	0.016	0.049	0.002
19	Bangladesh	2014	1	73.77	0.06	0.051	0.009	0.001
19a	Bangladesh	2014	1	50	0.306	0.004	0.057	0.001
19b	Bangladesh	2014	1	10	0.567	0	0.774	0
19c	Bangladesh	2014	10	73.77	0	0.045	0.003	0
19d	Bangladesh	2014	3	73.77	0.046	0.05	0.007	0
20	Tanzania	1997	-1	7.69	0.248	0	1	0
21	Tanzania	2008	-1	9.8	0.349	0	0.953	0
22	Tanzania	2009	-1	9.29	0.359	0	0.956	0
23	Tanzania	2014	-1	14.38	0.142	0	0.766	0
23a	Tanzania	2014	-1	80	-0.481	0.128	0.001	0
23b	Tanzania	2014	-1	50	-0.243	0.009	0.037	0
23c	Tanzania	2014	10	14.38	0.072	0	0.85	0
23d	Tanzania	2014	3	14.38	0.118	0	0.796	0

The contour plots in Figure 11 exemplify the shape of the relationship for $GINI$ and *carbon* in Bangladesh and Tanzania, indicating a difference in the variation for changing levels of $fossil$ and *polity*. The illustrated cases represent cases 19, 19a and 19c in the first row of Figure 11 and cases 23, 23a and 23c in the second row of Figure 11. The shape of the relationship largely follows the oval shape of the Frank copula, with only slight asymmetric relations for changing fossil energy shares. Graphic 2 in the first row (case 19a) reveals a stronger dependence for low $GINI$ and *carbon* levels, while the reverse asymmetry is visible in Graphic 2 in the second row (case 23c). The highest density of the relation – the center of the contour lines – varies for reduced fossil energy shares. In Bangladesh, it centers around higher $GINI$ and lower *carbon* values than the real case and in Tanzania it centers around lower $GINI$ but higher *carbon* values.

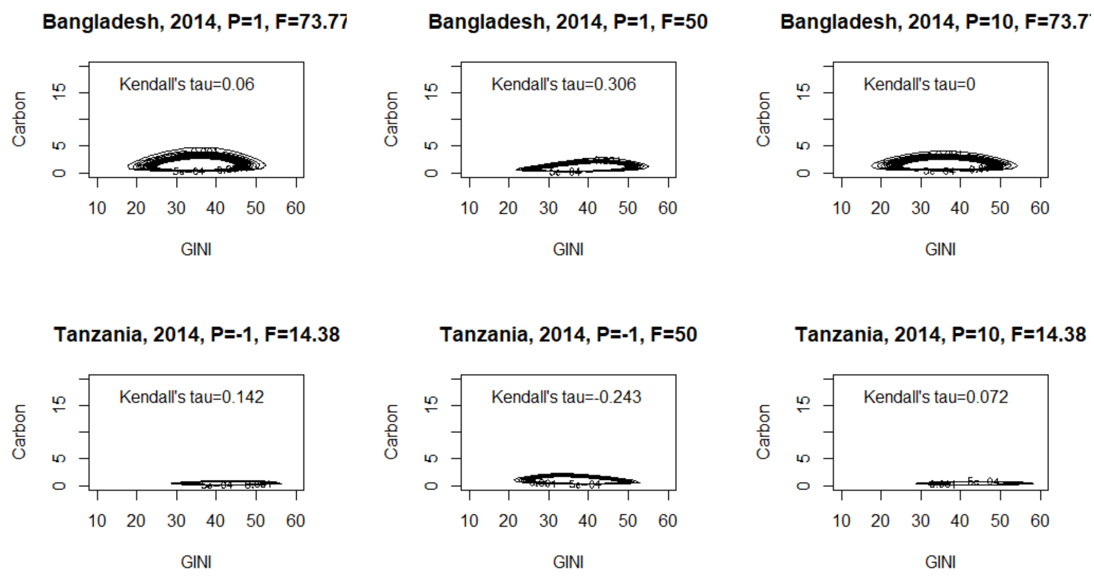

Figure 11: Contour plots for Bangladesh and Tanzania in 2014, different choices of *polity* (P) and *fossil* (F), the remaining covariates are set to their actual value.

Even though polity exhibits no statistically significant impact, it leads to a visible change in Kendall's τ in the cases under investigation, indicating some political economy effect. The negative impact of fossil on the relationship suggests the mechanisms explained in the 'individual Kuznet's curve', namely that rich people live more environmentally-conscious lives while poor people drop out of the carbon economy as they have no direct access to energy other than biofuels. The likelihood of being below the $GINI$ threshold reduces with a decline in fossil energy share. This supports the notion that these countries rely on fossil energy for their development path (Klasen, 2018).

4.4 Summary

The strong variation of dependence structures between $GINI$ and *carbon* in all country groups suggests that according to the country cases, trade-offs, synergies or decoupling can occur. Our analysis shows that the mean prediction is not representative for the full range of the influencing factors, which underlines the use of more complex regression models. We identify that *polity*, *fossil* and GDP are (with large differences) associated with the dependence

Table 10: Summary of the effect of $fossil$, $polity$ and GDP on the relation between inequality and emissions, the related effect on the probability to fall in the socially and environmentally sustainable (SES) area and explaining channels identified in the literature.

Country group	Association range Kendall's τ	Variable's impact	Effect on prob. to be in SES area	Explanation
High-income	$-0.95 - 0.93$	$-fossil^{***}$ $-polity^{***}$ $+/-GDP^{***}$	SES $-$ TH $GINI\uparrow$ TH $carbon$ $-$	Political economy
Middle-income	$-0.89 - 0.75$	$+fossil^{***}$ $+polity^{***}$ $+/-GDP^{***}$	SES $-$ TH $GINI\downarrow$ TH $carbon\uparrow$	Political economy Income effect
Low-income	$-0.93 - 0.67$	$-fossil^{***}$ $-polity$ $+/-GDP^{***}$	SES $\uparrow$(Minimal) TH $GINI\downarrow$ TH $carbon\uparrow$	Individual Kuznet's Curve

structure of $GINI$ and $carbon$. Table 10 summarizes the results for high-, middle- and low-income countries.

The varying significance and impact of $polity$ suggests a particular relevance of the political economy argument. In high- and low-income countries the effect of $polity$ is negative but not statistically significant in low-income countries, while in middle-income countries it is positive. This implies that in middle- as well as high-income countries, a positive change in the democracy score leads to a decoupling of the relationship. At the same time, the likelihood of being below the $GINI$ threshold increases. This is associated to the argument that more democratic societies are more equal, leading to a decoupling or positive effect on the dependence structure of $GINI$ and $carbon$. Less powerful elites and democratic mechanisms may enable better environmental and social policies, potentially leading to a socially and environmentally sustainable society.

The varying effect direction of the impact of $fossil$ indicates an association between fossil fuels and the development path of countries. A falling share of fossil energy is associated with a stronger positive association in the high- and low-income country cases, suggesting synergies between $GINI$ and $carbon$. In middle-income countries, a decreasing share of fossil energy is associated with a negative effect on the relationship, indicating stronger negative dependencies. Further, in high-income countries a reduction in $fossil$ increases while in middle- and low-income countries it reduces the likelihood of being below the $GINI$ threshold. While in high-income countries we find no visible impact on the carbon threshold nor on the joint area, in middle- and low-income countries a falling fossil share has a positive impact on the likelihood of falling below the carbon threshold. Only in certain low-income countries (e.g. Bangladesh) is a small change in the likelihood of being in the socially and environmentally sustainable area visible. These results indicate that a reduction of the share of fossil fuel energy in high-income countries even supports more income equality. This suggests that decoupling from fossil fuels is not hampering equality but is even favorable for a more equal society. On the other hand, it affirms the arguments that middle- and low-income countries depend on fossil fuels for their development path and a reduction in income inequality. The findings are also in line with the argument that poor people drop out of the carbon economy (as suggested by the individual Kuznets curve) (Klasen, 2018).

5 Conclusions

The analysis of the dependence between income inequality and carbon emissions clearly shows their heterogeneous dependency. To study the association in detail, we have used distributional copula models stratified with respect to high-, middle- and low-income countries. We find heterogeneous effects indicating that synergies, decoupling and trade-offs occur depending on the influencing factors.

Democracy score and fossil energy share have a varying influence in the different income groups. This highlights that the development path and sustainability of societies depend on energy mix and political systems. For all studied cases, it is unlikely to fall into the environmentally and socially sustainable area, indicating the challenge of achieving both goals together. Further investigations are necessary to identify the channels that enable a joint transition into an environmentally and socially sustainable area. Specifically, in high- and middle-income countries, a positive change in the democracy score leads to a decoupling of the dependency between GINI and carbon emissions and an increasing likelihood of being in a potentially socially sustainable space. A reduced fossil energy share is associated with an increasing positive dependency between carbon emissions and income inequality in high- and low-income countries, thus suggesting synergies, while the reverse holds for middle-income countries suggesting trade-offs. In high- (low- and middle-) income countries, a reduction in fossil energy increases (reduces) the likelihood of being potentially socially sustainable. Unlike high-income countries, low- and middle-income countries have an increasing likelihood of being environmentally sustainable with a decreasing fossil energy share.

These findings support the argument that rich elites exploit the environment, as in the short term the rich benefit from environmental degradation. In turn, more democratic societies are more environmentally-cautious, as environmentally-friendly policies may be implemented. In high-income countries, a reduction in the fossil fuel energy share increases the likelihood of falling below the GINI threshold. Reducing the share of fossil fuel energy in high-income countries leads to more income equality. Consequently, decoupling from fossil fuels is not hampering equality but favorable for a more equal society. On the other hand, the results indicate a trade-off between income equality and carbon emissions in low- and middle-income countries, underpinning the dependence on fossil energy for their development path.

The effect differences among the country groups enable drawing conclusions on global structures. The recorded fossil energy share does not necessarily indicate the consumption of that country due to traded goods. Thus, some countries rely on higher fossil energy to realize income, while others – especially in the group of high-income countries – rather consume carbon-intensive goods. Different within-country findings for the effect of fossil energy share and democracy sore likely reflect international dynamics, whereby poor countries disproportionately bear the costs of climate change, while rich countries disproportionately benefit from environmental exploitation. This requires further investigations into the driving factors to find global solutions to transition into a socially and environmentally sustainable future.

Furthermore, the model precision can be improved by taking the dependencies over the development paths (e.g. by cointegrating relations) into account. This requires a theoretical extension of the present copula modeling framework. The consideration of alternative measures of environmental pollution is an interesting economic model variation. Countries might be more easily convinced to target reducing emission variables such as SO2 or NOx due to a higher immediacy of the results (Iwata et al., 2010). We suspect similar dependence patterns for these alternative measures. Thus, social and environmental dimension need to be addressed jointly by considering their heterogeneous interdependence for the transition into a sustainable future.

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A Appendix

The Appendix comprises a detailed country list in Table A1 and regression results for high, middle- and low-income countries in Sections A.1, A.2 and A.3, respectively.

Table A1: Country groups by level of income; number of countries.

High-income	Middle-income	Low-income	
Australia	Albania	Afghanistan	Papua New Guinea
Austria	Algeria	Angola	Philippines
Bahrain	Argentina	Bangladesh	Rwanda
Belgium	Armenia	Benin	Senegal
Canada	Azerbaijan	Bhutan	Sierra Leone
Chile	Belarus	Bolivia	Solomon Island
Croatia	Bosnia and Herzegovina	Burkina Faso	Somalia
Cyprus	Botswana	Burundi	Sudan
Czech Republic	Brazil	Cambodia	Syria
Denmark	Bulgaria	Cameroon	Tajikistan
Estonia	China	Cape Verde	Tanzania
Finland	Colombia	Central African Republic	Togo
France	Costa Rica	Chad	Tunisia
Germany	Dominican Republic	Comoros	
Greece	Ecuador	Djibouti	Uganda
Hungary	Equatorial Guinea	Egypt	Ukraine
Ireland	Fiji	El Salvador	Uzbekistan
Israel	Gabon	Ethiopia	Vietnam
Italy	Georgia	Gambia	Yemen
Japan	Guatemala	Ghana	Zambia
Kuwait	Guyana	Guinea	Zimbabwe
Latvia	Iran	Guinea-Bissau	
Lithuania	Iraq	Haiti	
Luxembourg	Jamaica	Honduras	
Netherlands	Jordan	India	
New Zealand	Kazakhstan	Indonesia	
Norway	Kosovo	Kenya	
Oman	Lebanon	Kyrgyzstan	
	Libya	Laos	
Poland	Malaysia	Lesotho	
Portugal	Mauritius	Liberia	
Qatar	Mexico	Madagascar	
Saudi Arabia	Montenegro	Malawi	
Singapore	Namibia	Mali	
Slovakia	Paraguay	Mauritania	
Slovenia	Peru	Moldova	
Spain	Romania	Mongolia	
	Russia		
Sweden	Serbia	Morocco	
Switzerland	South Africa	Mozambique	
Trinidad and Tobago	Sri Lanka	Myanmar	
United Arab Emirates	Suriname	Nepal	
United Kingdom	Thailand	Nicaragua	
United States of America	Turkey	Niger	
Uruguay	Turkmenistan	Nigeria	
	Venezuela	Pakistan	
43	46	65	

A.1 Specifications for high-income countries

This section displays the AIC and BIC levels for different choices of the marginals and copula in Table A2-A4, plot of the model residuals for selected setting in Figure A12, the respective parameter estimates (Table A5-A8) and splines (Figure A13-A16) for the distribution parameter of the marginals $\theta_1 - \theta_4$ and several alternative country cases in Table A9.

Table A2: AIC and BIC values for alternative choices of the marginal distribution: variable $GINI$, high-income countries. We only include marginal distributions that converge.

	AIC	BIC
Normal	4292.75	4485.35
Gumbel	4341.96	4541.87
rotated Gumbel	4327.22	4522.37
Log Normal	4285.79	4477.27
Dagum	62881.91	63239.01

Table A3: AIC and BIC values for alternative choices of the marginal distribution: variable *carbon*, high-income countries. We only include marginal distributions that converge.

	AIC	BIC
Normal	4070.38	4262.20
Gumbel	4247.25	4440.75
rotated Gumbel	3999.47	4185.55
Log Normal	3958.81	4150.05

Table A4: AIC and BIC values for alternative copula specifications; high-income countries. We only include marginal distributions that converge.

	AIC	BIC
N	7643.95	8152.33
F	7655.84	8142.45
AMH	8096.28	8519.15
FGM	8051.36	8472.11

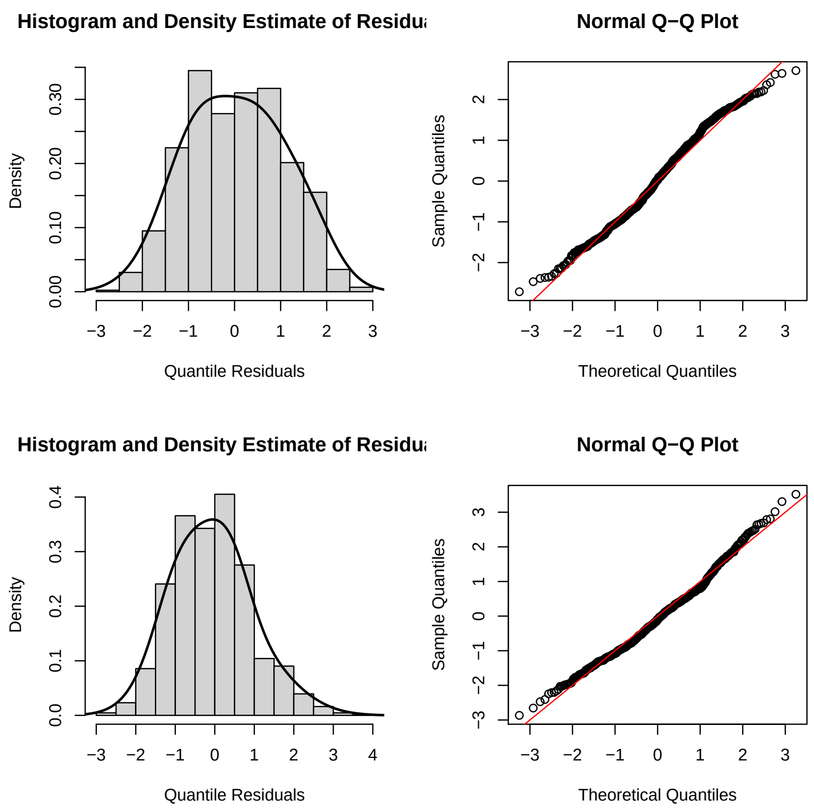

Figure A12: Histogram and Q-Q Plot for model residuals for high-income countries

Table A5: High-income countries: equation for parameter θ_1 of the marginal distribution of $GINI$

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	2.211	0.057	38.519	0.000
Manu	0.009	0.001	12.051	0.000
Serv	0.016	0.001	19.763	0.000
Agri	0.027	0.003	10.754	0.000
Urban	-0.000	0.000	-0.963	0.336
fossil	0.002	0.000	10.984	0.000
polity	-0.016	0.001	-17.007	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	8.198	8.744	350.3	<2e-16
s(Year)	7.640	8.440	192.7	<2e-16

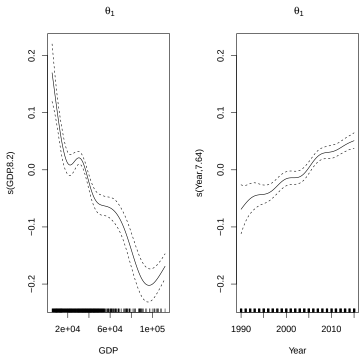

Figure A13: Spline for *GDP* and *year* for parameter θ_1 for high-income countries

Table A6: High-income-countries: equation for parameter θ_2 of the marginal distribution of *carbon*

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	2.447	0.173	14.183	0.000
Manu	0.002	0.002	0.989	0.323
Serv	-0.010	0.002	-4.774	0.000
Agri	-0.052	0.007	-7.651	0.000
Urban	0.008	0.001	12.191	0.000
fossil	0.004	0.001	6.972	0.000
polity	-0.027	0.003	-8.325	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
s(GDP)	8.825	8.981	613.6	<2e-16
s(Year)	2.430	3.063	172.8	<2e-16

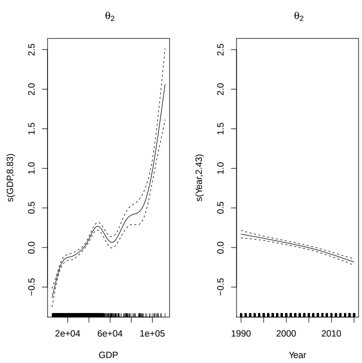

Figure A14: Spline for *GDP* and *year* for θ_2 for high-income countries

Table A7: High-income countries: equation for parameter θ_3 of the marginal distribution of *carbon*

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	1.577	0.462	3.413	0.001
Manu	-0.063	0.008	-8.217	0.000
Serv	-0.068	0.005	-12.323	0.000
Agri	-0.102	0.022	-4.563	0.000
Urban	0.008	0.003	3.138	0.002
fossil	0.007	0.002	4.135	0.000
polity	0.035	0.008	4.201	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	8.498	8.918	141.37	$<$ 2e-16
s(Year)	3.564	4.442	60.07	1.04e-11

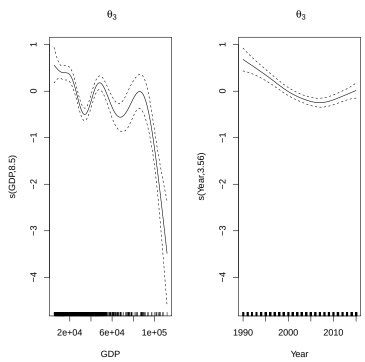

Figure A15: Spline for GDP and $year$ for θ_3 for high-income countries

Table A8: High-income countries: equation for parameter θ_4 of the marginal distribution of $GINI$

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.697	0.482	-1.447	0.148
Manu	-0.006	0.007	-0.896	0.370
Serv	-0.018	0.005	-3.274	0.001
Agri	0.053	0.030	1.742	0.081
Urban	0.020	0.002	8.304	0.000
fossil	-0.014	0.002	-8.953	0.000
polity	-0.021	0.008	-2.547	0.011
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	8.785	8.975	154.47	$< 2e-16$
s(Year)	7.620	8.466	53.84	1.46e-08

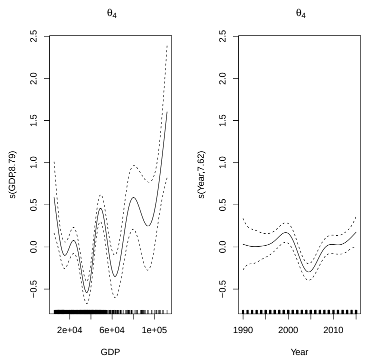

Figure A16: Spline for GDP and $year$ for θ_4 for high-income countries

Table A9: Additional country cases: high-income countries, with the respective choices of the variables $year$, $polity$ and $fossil$ (the remaining covariates are set to their actual value). In the last four columns: Kendall's τ (K's τ) and the probability of being below the threshold for $GINI$ and $carbon$ and in the socially and environmentally sustainable (SES) area in the specific setting.

Country	$year$	$polity$	$fossil$	K's τ	TH $GINI$	TH $carbon$	SES Space
France	1997	10	52.9	0.483	0.021	0	0
France	2008	9	50.84	0.714	0.001	0	0
France	2009	9	50.85	0.617	0	0	0
France	2015	9	46.49	0.753	0.003	0	0
France	2015	9	80	0.362	0.002	0	0
France	2015	9	10	0.918	0.01	0	0

France	2015	10	46.49	0.712	0.007	0	0
France	2015	3	46.49	0.902	0	0	0
Australia	1997	10	93.51	-0.237	0.18	0	0
Australia	2008	10	94.35	0.597	0.215	0	0
Australia	2009	10	95.51	0.5	0.261	0	0
Australia	2015	10	89.63	0.606	0.16	0	0
Australia	2015	10	50	0.879	0.251	0	0
Australia	2015	10	10	0.964	0.491	0.001	0.001
Australia	2015	9	89.63	0.66	0.125	0	0
Australia	2015	3	89.63	0.865	0.01	0	0
United Kingdom	1997	10	86.72	-0.433	0.036	0	0
United Kingdom	2008	10	90.18	-0.152	0.013	0	0
United Kingdom	2009	10	87.37	-0.253	0	0	0
United Kingdom	2015	10	80.35	0.106	0.037	0	0
United Kingdom	2015	10	50	0.589	0.056	0	0
United Kingdom	2015	10	10	0.875	0.161	0	0
United Kingdom	2015	9	80.35	0.203	0.022	0	0
United Kingdom	2015	3	80.35	0.65	0	0	0
Switzerland	1997	10	57.21	0.556	0.009	0	0
Switzerland	2008	10	52.51	-0.651	0	0	0
Switzerland	2009	10	53.24	-0.609	0	0	0
Switzerland	2015	10	50.17	-0.621	0	0	0
Norway	1997	10	54.57	-0.892	0.912	0	0
Norway	2008	10	61.67	-0.929	0.915	0	0
Norway	2009	10	63.11	-0.936	0.891	0	0
Sweden	1997	10	35.64	0.588	0.52	0	0
Sweden	2008	10	33.11	0.925	0.487	0	0
Sweden	2009	10	31.98	0.918	0.431	0	0
Sweden	2015	10	25.12	0.916	0.309	0	0
Chile	1997	8	74.66	-0.62	0.274	0	0
Chile	2008	10	75.18	-0.74	0.381	0	0
Chile	2009	10	73.47	-0.758	0.363	0	0
Chile	2015	10	74.65	-0.646	0.267	0	0
Canada	1997	10	74.74	-0.073	0.093	0	0
Canada	2008	10	75.08	0.67	0.386	0	0
Canada	2009	10	75.07	0.583	0.172	0	0
Canada	2015	10	74.09	0.811	0.155	0	0
Canada	1997	10	74.74	-0.073	0.093	0	0
Canada	2008	10	75.08	0.67	0.386	0	0

Canada	2009	10	75.07	0.583	0.172	0	0
Canada	2015	10	74.09	0.811	0.155	0	0
Oman	2010	-8	100	-0.513	0	0	0
Bahrain	2014	-10	99.37	-0.331	0.05	0	0
Qatar	2013	-10	100	-0.888	0.62	0	0
United Arab Emirates	2008	-8	99.93	0.167	0.493	0	0
Saudi Arabia	2013	-10	99.57	-0.613	0.435	0	0

A.2 Specifications for middle-income countries

This section displays the AIC and BIC levels for different choices of the marginals and copula in Table A10-A12, plot of the model residuals for the selected setting in Figure A17, the respective parameter estimates (Table A13-A16) and splines (Figure A18-A21) for the distribution parameter of the marginals $\theta_1 - \theta_4$ and several alternative country cases in Table A17.

Table A10: AIC and BIC values for alternative choices of the marginal distribution: variable $GINI$, middle-income countries. We only include marginal distributions that converge.

	AIC	BIC
Normal	4248.93	4414.47
Gumbel	4264.29	4449.05
rotated Gumbel	4271.37	4427.94
Log Normal	4254.86	4420.91

Table A11: AIC and BIC values for alternative choices of the marginal distribution: variable *carbon*, middle-income countries. We only include marginal distributions that converge.

	AIC	BIC
Normal	4248.93	4414.47
Gumbel	4264.29	4449.05
rotated Gumbel	4271.37	4427.94
Log Normal	4254.86	4420.91

Table A12: AIC and BIC values for alternative copula specifications; middle-income countries. We only include marginal distributions that converge.

	AIC	BIC
N	5362.75	5763.16
G90	154799.67	155218.74
G270	5428.51	5895.59
F	5357.09	5771.30
AMH	5669.03	5988.71
FGM	5631.33	5946.47

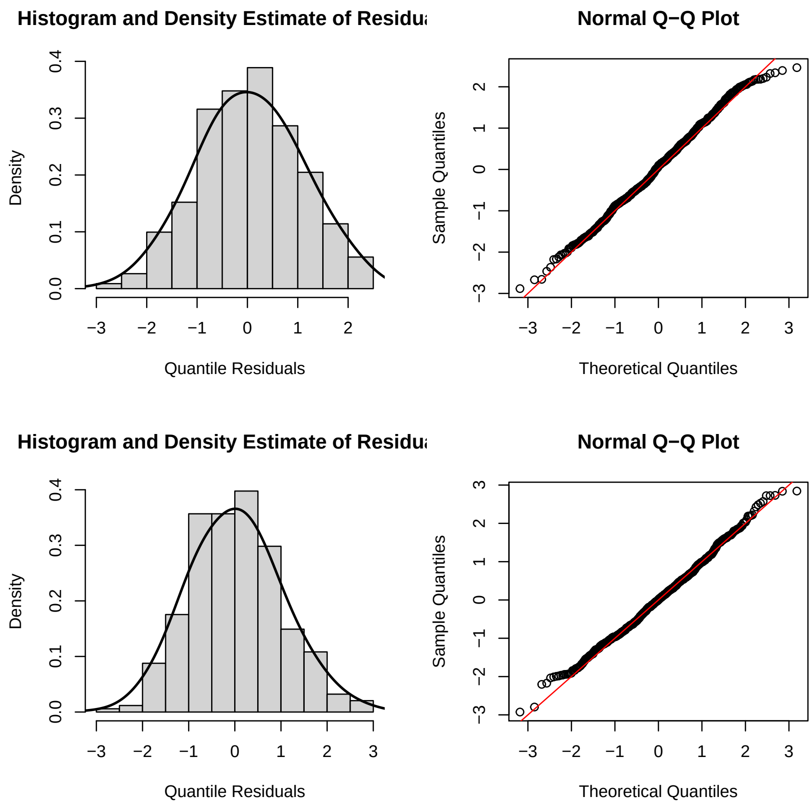

Figure A17: Histogram and Q-Q Plot for model residuals for middle-income countries

Table A13: Middle-income countries: equation for parameter θ_1 of the marginal distribution of $GINI$

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	44.684	2.711	16.485	0.000
Manu	0.127	0.034	3.749	0.000
Serv	0.199	0.035	5.641	0.000
Agri	-0.030	0.043	-0.693	0.488
Urban	-0.014	0.015	-0.928	0.353
fossil	-0.181	0.008	-22.081	0.000
polity	0.118	0.026	4.476	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	8.348	8.788	190.4	<2e-16
s(Year)	5.136	6.192	137.9	<2e-16

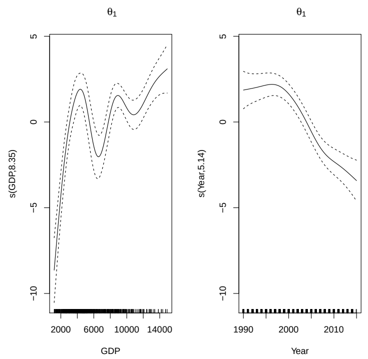

Figure A18: Spline for GDP and $year$ for θ_1 for middle-income countries

Table A14: Middle-income countries: equation for parameter θ_2 of the marginal distribution of *carbon*

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.137	0.137	0.998	0.318
Manu	-0.000	0.002	-0.148	0.883
Serv	-0.003	0.002	-1.677	0.093
Agri	0.001	0.003	0.390	0.696
Urban	-0.007	0.001	-7.179	0.000
fossil	0.021	0.001	27.247	0.000
polity	-0.021	0.003	-8.107	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	8.769	8.953	473.88	$<$ 2e-16
s(Year)	3.215	4.017	22.42	0.000172

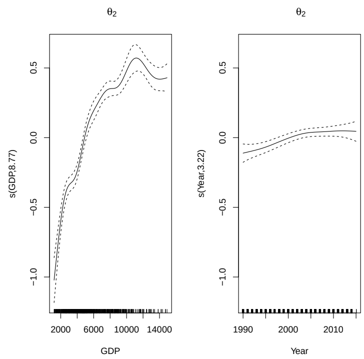

Figure A19: Spline for GDP and $year$ for θ_2 for middle-income-countries

Table A15: Middle-income countries: equation for parameter θ_3 of the marginal distribution of $GINI$

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	5.363	0.466	11.507	0.000
Manu	-0.008	0.007	-1.206	0.228
Serv	-0.045	0.005	-8.181	0.000
Agri	-0.077	0.010	-8.065	0.000
Urban	-0.021	0.002	-8.667	0.000
fossil	0.011	0.003	4.318	0.000
polity	-0.010	0.008	-1.349	0.177
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	5.881	7.027	266.39	$<$ 2e-16
s(Year)	2.578	3.239	25.64	1.87e-05

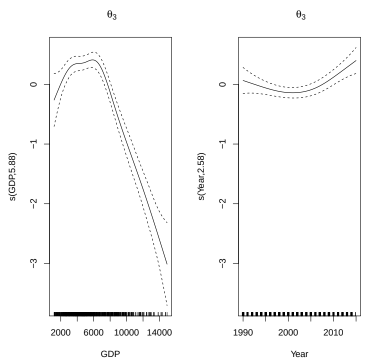

Figure A20: Spline for GDP and $year$ for θ_3 for middle-income countries

Table A16: Middle-income countries: equation for parameter θ_4 of the marginal distribution of *carbon*

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.221	0.378	-0.584	0.559
Manu	0.003	0.007	0.408	0.683
Serv	-0.011	0.004	-2.352	0.019
Agri	-0.031	0.009	-3.510	0.000
Urban	0.000	0.003	0.043	0.966
fossil	-0.003	0.002	-1.332	0.183
polity	-0.006	0.009	-0.638	0.524
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	7.956	8.673	79.615	1.12e-13
s(Year)	2.343	2.929	2.117	0.58

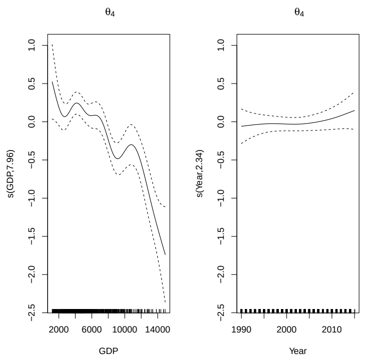

Figure A21: Spline for *GDP* and *year* for θ_4 for middle-income countries

Table A17: Additional country cases: middle-income countries, with the respective choices of the variables *year*, *polity* and *possil* (the remaining covariates are set to their actual value). In the last four columns: Kendall's τ (K's τ) and the probability of being below the threshold for $GINI$ and *carbon* and in the socially and environmentally sustainable (SES) area in the specific setting.

Country	*year*	*polity*	$fossil$	K's τ	TH $GINI$	TH *carbon*	SES Space
Argentina	1997	7	86.9	-0.673	0	0	0
Argentina	2008	8	90.65	-0.626	0	0	0
Argentina	2009	8	89.61	-0.644	0	0	0
Argentina	2014	8	87.72	-0.584	0	0	0
Argentina	2014	8	50	-0.799	0	0	0
Argentina	2014	8	10	-0.871	0	0.012	0
Argentina	2014	10	87.72	-0.51	0	0	0
Argentina	2014	3	87.72	-0.7	0	0	0
Brazil	1997	8	56.68	-0.685	0	0	0
Brazil	2008	8	52.57	-0.796	0	0	0
Brazil	2009	8	51.32	-0.795	0	0	0
Brazil	2014	8	59.11	-0.828	0	0	0
Brazil	2014	8	80	-0.772	0	0	0
Brazil	2014	8	10	-0.892	0	0.002	0
Brazil	2014	10	59.11	-0.816	0	0	0
Brazil	2014	3	59.11	-0.853	0	0	0
Russia	2008	4	90.95	-0.593	0	0	0
Russia	2009	4	90.16	-0.372	0	0	0
Russia	2014	4	92.14	-0.595	0	0	0
Russia	2014	4	50	-0.813	0	0	0
Russia	2014	4	10	-0.877	0	0.001	0
Russia	2014	10	92.14	-0.323	0	0	0
Russia	2014	8	92.14	-0.438	0	0	0

A.3 Specification for low-income countries

This section displays the AIC and BIC levels for different choices of the marginals and copula in Table A18-A20, plot of the model residuals for the chosen setting in Figure A22, the respective parameter estimates (Table A21-A24) and splines (Figure A23-A26) for the distribution parameter of the marginals $\theta_1 - \theta_4$ and several alternative country cases in Table A25.

Table A18: AIC and BIC values for alternative choices of the marginal distribution: variable $GINI$, low-income countries. We only include marginal distributions that converge.

	AIC	BIC
Normal	5067.89	5243.94
Gumbel	5090.19	5276.19
rotated Gumbel	5187.36	5365.09
Log Normal	5092.13	5267.62

Table A19: AIC and BIC values for alternative choices of the marginal distribution: variable *carbon*, low-income countries. We only include marginal distributions that converge.

	AIC	BIC
Normal	131.31	297.84
Gumbel	366.67	547.76
rotated Gumbel	-15.09	155.12
Log Normal	-52.12	101.75
Dagum	46077.65	46340.50

Table A20: AIC and BIC values for alternative copula specifications; low-income countries. We only include marginal distributions that converge.

	AIC	BIC
F	3156.32	3570.82
AMH	3269.06	3644.73

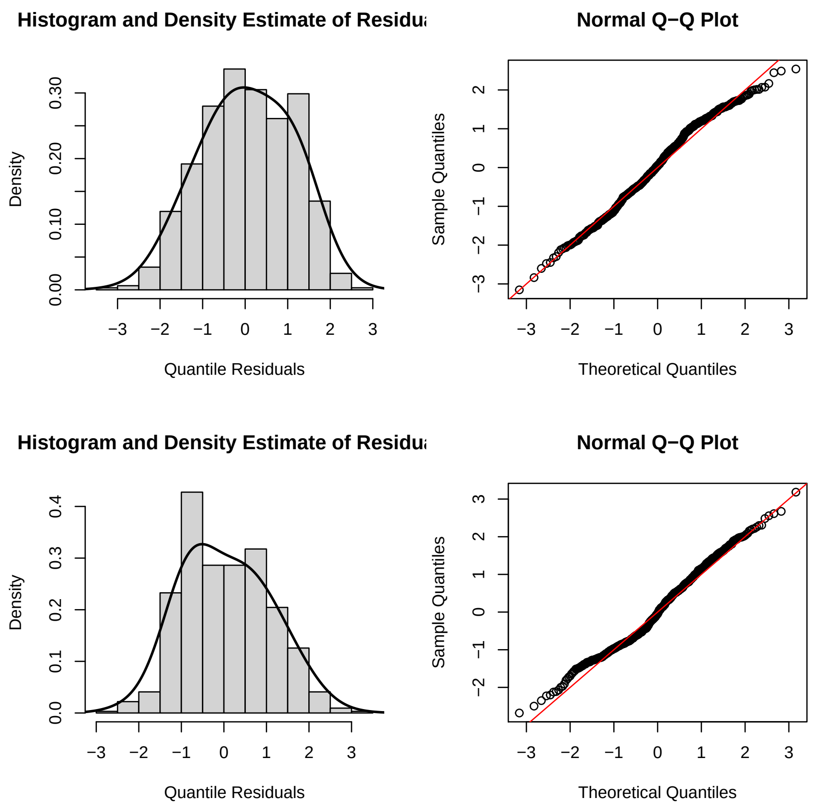

Figure A22: Histogram and Q-Q Plot for model residuals for low-income countries

Table A21: Low-income countries: equation for parameter θ_1 of the marginal distribution of $GINI$

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	57.667	2.533	22.768	0.000
Manu	-0.198	0.040	-4.938	0.000
Serv	-0.055	0.021	-2.585	0.010
Agri	-0.322	0.032	-10.020	0.000
Urban	0.087	0.025	3.532	0.000
fossil	-0.160	0.007	-22.650	0.000
polity	0.085	0.019	4.496	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	8.393	8.871	334.91	<2e-16
s(Year)	3.165	4.017	95.11	<2e-16

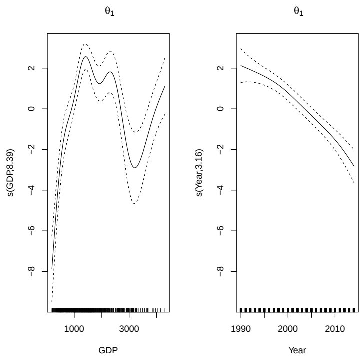

Figure A23: Spline for *GDP* and *year* for θ_1 for low-income countries

Table A22: Low-income countries: equation for parameter θ_2 of the marginal distribution of *carbon*

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.020	0.183	-5.570	0.000
Manu	0.003	0.002	1.078	0.281
Serv	-0.002	0.002	-0.839	0.401
Agri	-0.004	0.002	-1.592	0.111
Urban	-0.003	0.002	-1.628	0.103
fossil	0.020	0.001	36.995	0.000
polity	-0.003	0.002	-1.114	0.265
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	8.734	8.968	800.1	$<$ 2e-16
s(Year)	2.555	3.234	50.9	1.4e-10

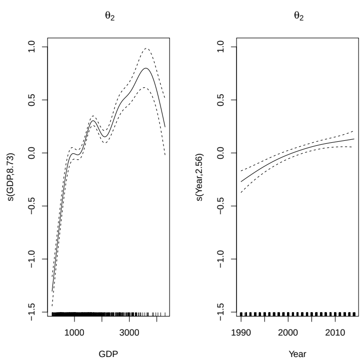

Figure A24: Spline for *GDP* and *year* for θ_2 for low-income countries

Table A23: Low-income countries: equation for parameter θ_3 of the marginal distribution of $GINI$

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	1.597	0.578	2.763	0.006
Manu	0.017	0.008	2.210	0.027
Serv	-0.021	0.007	-3.219	0.001
Agri	-0.020	0.008	-2.369	0.018
Urban	0.012	0.004	2.774	0.006
fossil	0.006	0.002	3.519	0.000
polity	0.005	0.007	0.703	0.482
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	8.124	8.756	56.03	9.66e-09
s(Year)	1.797	2.264	16.27	0.000636

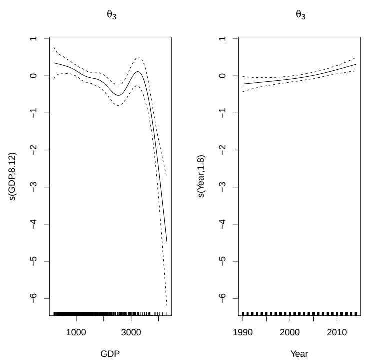

Figure A25: Spline for GDP and $year$ for θ_3 for low-income countries

Table A24: Low-income countries: equation for parameter θ_4 of the marginal distribution of *carbon*

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-3.883	0.489	-7.943	0.000
Manu	0.018	0.008	2.342	0.019
Serv	0.014	0.006	2.387	0.017
Agri	-0.015	0.007	-2.199	0.028
Urban	0.044	0.004	9.928	0.000
fossil	0.008	0.002	4.365	0.000
polity	-0.019	0.007	-2.621	0.009
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	
s(GDP)	8.867	8.988	260.67	$<$ 2e-16
s(Year)	6.918	8.000	32.22	8.53e-05

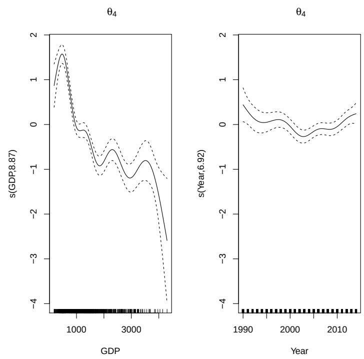

Figure A26: Spline for *GDP* and *year* for θ_4 for low-income countries

Table A25: Additional country cases: low-income countries, with the respective choices of the variables *year*, *polity* and *fossil* (the remaining covariates are set to their actual value). In the last four columns: Kendall's τ (K's τ) and the probability of being below the threshold for $GINI$ and *carbon* and in the socially and environmentally sustainable (SES) area in the specific setting.

Country	*year*	*polity*	*fossil*	K's τ	TH $GINI$	TH *carbon*	SES Space
India	1997	8	61.77	-0.137	0.001	0.11	0
India	2008	9	69.01	-0.232	0.002	0	0
India	2009	9	71.14	-0.251	0.002	0	0
India	2012	9	72.42	-0.406	0.004	0	0
India	2012	9	50	-0.211	0	0	0
India	2012	9	10	0.218	0	0.615	0
India	2012	10	72.42	-0.411	0.004	0	0
India	2012	3	72.42	-0.38	0.004	0	0
Egypt	2008	-3	96.16	-0.868	0.001	0	0
Egypt	2009	-3	96.4	-0.875	0.004	0	0
Egypt	2014	-4	97.93	-0.871	0.039	0	0
Egypt	2014	-4	50	-0.847	0	0	0
Egypt	2014	-4	10	-0.818	0	0.094	0
Egypt	2014	10	97.93	-0.874	0.028	0	0
Egypt	2014	3	97.93	-0.873	0.033	0	0
Bolivia	2008	8	82.6	-0.599	0.008	0	0
Bolivia	2009	7	80.96	-0.562	0.007	0.001	0
Bolivia	2014	7	84.15	-0.811	0.007	0.063	0
Bolivia	2014	7	50	-0.773	0	0.156	0
Bolivia	2014	7	10	-0.706	0	0.577	0
Bolivia	2014	10	84.15	-0.813	0.007	0.054	0
Bolivia	2014	3	84.15	-0.809	0.007	0.076	0