The nonlinear dependence of income inequality and carbon emissions: potentials for a sustainable future*

Franziska Dorn† Simone Maxand‡ Thomas Kneib§

August 2023

Abstract

Understanding the interconnected nature of rising carbon emissions and income inequality is crucial to achieve social and ecological sustainability. We contribute to the literature with a systematic analysis of the conditional interdependence by means of a distributional copula model. The model estimates the nonlinear dependence between a country's GINI coefficient and CO2 emissions across and within country income groups. This enables us to uncover complex interdependencies that standard linear regression techniques might hide. Using an unbalanced panel data set of 109 countries from 1960 to 2019, composed of different data sets, we show that dependence is related to the prevailing consumption level, energy sources, the structure of the economy and the political system with heterogeneous effects across country income groups. To estimate the potentials for a sustainable future, we define thresholds of potential social and environmental sustainability. We find that richer countries are furthest away from this, but have the highest potential for realising the defined sustainable space.This further highlights the importance of the service sector and combined policies targeting social and environmental sustainability.

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

JEL: C14, C46, D63, Q56

*Financial support of the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) grant KN 922/9-1 is gratefully acknowledged.

†University of Göttingen, Centre for Statistics, Email: fdorn@uni-goettingen.de

‡Europa-Universität Viadrina, Email: maxand@europa-uni.de

§University of Göttingen, Centre for Statistics, Email: Thomas.Kneib@wiwi.uni-goettingen.de

1 Introduction

For the transition into a socially and environmentally sustainable future, it is crucial to understand what drives the relation between income inequality and carbon emissions. This understanding allows for the development of appropriate policy mixes to make use of occurring synergies and circumvent trade-offs. The correlation between CO2 emissions and the GINI index across time and countries in Figure 1 reveals a positive relation in high- but a negative relation in middle- and low-income countries. The relation seems mostly stable over time, but it is unclear what drives potential differences within and between the country income groups. We expect these differences to arise from specific country settings such as political systems, structural change, the energy mix and income levels. In the first step, we apply bivariate distributional copula models to uncover nonlinear dependence structures between GINI and emissions. We find that the dependence varies across but also within the country groups (low-, middle- and high-income countries) and over the range of the driving factors. In the second step, we estimate thresholds for GINI and CO2 emissions to define an area of sustainability that corresponds to the space below both thresholds. The copula model suggests which potential certain countries have to transition into the sustainable area and which factors are crucial for this transition.

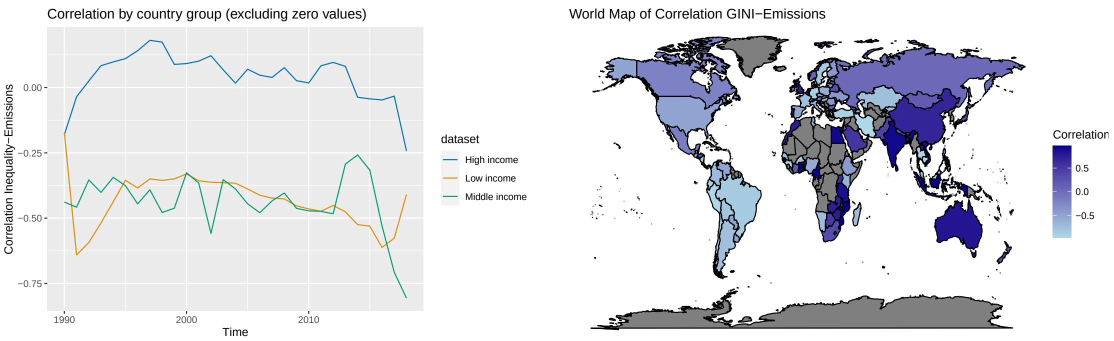

Figure 1: Correlation between GINI and CO2 emissions by country group (low-, middle-, high-imcome countries) over time in 1990–2018 (left) and per country on a map (right) calculated from the 109 countries under study (omitting missing values).

The literature discusses multiple channels implying synergies, trade-offs and decoupling between income inequality and carbon emissions. Political economy arguments centering around systemic structures like political framework or energy mix imply a positive dependence between income inequality and carbon emissions. This is due to the higher political power of the rich in unequal societies or status consumption of carbon-intensive goods to

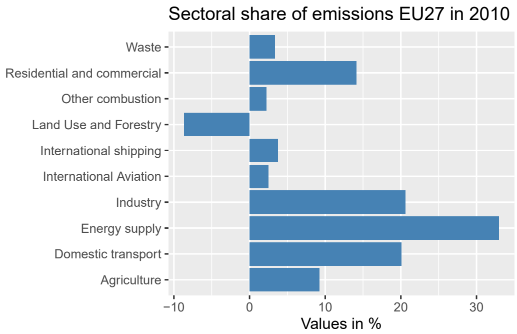

Figure 2: Share of emissions per sector for EU27 countries in 2010, data from "EEA greenhouse gases – data viewer".

demonstrate the social class (Roemer, 1993; Martínez Alier, 2002; Roca, 2003; Boyce, 2018; Scruggs, 1998). Recent studies on the Kuznets and environmental Kuznets (EKC) curve likewise suggest a positive relation as structural change goes along with increasing inequality and carbon emissions (Parrique et al., 2019; Baymul and Sen, 2019). Theories focusing on individual consumption behavior find either positive or negative effects of income inequality on carbon emissions (Veblen, 1899; Wilkinson et al., 2010; Berthe and Elie, 2015; Boyce, 2018; Klasen, 2018; Sager, 2019). In turn, carbon dioxide emissions negatively influence inequality (Heerink et al., 2001; Harlan et al., 2015). Furthermore, empirical studies see the income level as pivotal and show contradicting results (Jorgenson et al., 2016, 2017; Grunewald et al., 2017; Mader, 2018; Wan et al., 2022; Andersson, 2023). We add to the literature by investigating the missing understanding of the nonlinear dependency of the GINI coefficient and carbon emissions while controlling for literature-based transmission channels. A view on the sectoral shares of CO2 emissions, displayed for the EU27 in Figure 2 as an example, provides additional hints for the channels at work and the role different sectors play (e.g., energy supply, transport and industry with largest shares). However, in practice, such channels vary by country groups due to different development paths and current country settings, e.g., related to the strength of certain sectors. This is supported by the worldwide variation visible in the distribution of the correlation in the right-side panel of Figure 1. We therefore study how these instruments differently affect the relationship in high-, middle-, and low-income countries separately.

The nonlinear relationship between the GINI coefficient and carbon emissions has been empirically investigated across income groups or within one country such as the US. These studies mostly use univariate mean regressions. In contrast, we rely on distributional copula regression models to discover complex underlying structures, which are hidden or averaged out by a linear mean analysis. More precisely, mean regression techniques – which usually assume a normal distribution and stable effects over the range of the variables – investigate the transmission channels only in one correlation direction. By contrast, this study analyses the dependence by integrating income inequality and carbon emissions into a bivariate outcome vector. The conditional dependence structure within this vector can then be represented based on a copula specification. The incorporated distributional regression techniques also facilitate the analysis of nonlinear associations between a country's macroeconomic conditions and the relationship between carbon emissions and inequality.

We apply the model to an unbalanced panel data set that comprises 109 countries over the period from 1960 to 2019. We use the widely-applied GINI index as a measure of income inequality and 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). Having established the nonlinear relationship, we are additionally interested in how these two dimensions may define sustainability. For instance, Fanning et al. (2022) theoretically define thresholds in various social and environmental dimensions including a threshold for the GINI index. Given the absence of a broadly established sustainability threshold for GINI, we set our threshold based on the underlying data. For CO2 emissions we use the 1.5 degree threshold calculated by Hausfather (2019). These levels of the GINI index and emissions should not be transgressed for a sustainable society. Our model allows us to go even further and estimate the probabilities that different countries achieve these thresholds. We can thus identify the drivers of a socially and environmentally sustainable future by comparing country conditions concerning their potential for being in the sustainable area.

Our analysis of the relationship between carbon emissions and income inequality reveals four main results: (1) The mean relationship between the two varies across the three country groups (low-, middle-, high-income) showing weak trade-offs in low-, trade-offs in middle- and a decoupled relationship in high-income countries. However, the mean is not necessarily representative as it results from high variations in the strength of dependence within country groups. (2) The structure of the service sector appears to be crucial for the relation between inequality and emissions with diverse effects across the income groups. We find support that reducing the carbon intensity and income inequality of the service sector is crucial for achieving both social and environmental sustainability. (3) Democracy level and fossil energy share have a varying effect on the association between emissions and inequality in the country groups. This implies that decoupling from fossil energy can contribute to greater income equality in high-income countries. The reverse direction in middle- and low-income countries reflects the high dependence on carbon emissions for their development path (Klasen, 2018). Thus, a transformation of the energy system should go along with the implementation of social policies to decouple the dependence and prevent increasing inequalities. (4) In all country groups, this leads to the combined effect of achieving the thresholds of low inequality and emissions which implies that technical as well as structural innovations are necessary for a sustainable future.

The following Section 2 examines 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 results by country groups and Section 5 concludes.

2 Literature review: Relationship between inequality and emissions

The literature provides theoretical background and empirical evidence for three potential directions of the link between carbon emissions and the GINI index. This leads us to review the literature structured by these three directions: synergies, trade-offs and decoupling. In Table 1, we summarize these relationships based on the underlying literature discussed in this section.

2.1 Synergies

A positive relation between inequality and emissions indicates synergy effects, meaning that efforts in reducing one of them would help to reduce the other. For instance, 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 behavior, 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 are at the same time less affected by their adverse effects, 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).

The emulation effect, whereby poor people seek to imitate rich people who have carbon-intensive lifestyles, also suggests synergies. 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-intensive status goods. Consequently, this leads to a positive relation between income inequality and carbon emissions (Veblen, 1899; Klasen, 2018). In turn, 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).

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 (Kahn, 1998). This pattern suggests 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). This negative association is also related to what Heerink et al. (2001) describes as an aggregation effect, i.e., aggregating over the individuals along the Kuznets curve. Especially considering low-income countries, high inequality is coinciding with a higher share of persons without access to electricity inducing lower emissions. Acheampong et al. (2021) find in their study using international data that increasing energy access reduces inequality while access to clean energy worsens income inequality. Effects vary across region and macroeconomic settings such as education and economic growth (Acheampong et al., 2021; Nguyen and Nasir, 2021). Going beyond the U-shaped nature of the relation, Sager (2019) describes the relation between household income and emissions by a concave environmental Engel curve. He finds that redistribution, i.e., steps towards less inequality, induces higher emissions which speaks for an "equity-pollution" dilemma.

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

2.3 Channels for trade-offs or synergies

We can identify further channels that lead to either a positive or negative association depending on, e.g., the state and structure of the economy. Advocates of the Kuznets and environmental Kuznets curve argue that inequality/carbon emissions show a U-shaped association with GDP meaning decreasing inequality/emissions for high levels of GDP. Recent empirical findings contradict both Kuznets curves. On the one side, GDP per capita growth is understood to be positively related to carbon emissions worldwide. In this context the feasibility of green growth and decoupling has been put in the spotlight of recent discussions (see, e.g., Hickel and Kallis, 2020). On the other side, the literature contends that the relation between GDP and income inequality is ambiguously described (Anand and Kanbur, 1993; Milanović, 2000; Weil, 2012; Scholl and Klasen, 2019). We conclude that the association of GDP with the strength of dependence between carbon and inequality can be either positive or negative (such adverse effects of aggregated income are also discussed in, e.g., Drupp et al., 2021). Further empirical literature implicitly conditions the relation between emissions and inequality on GDP by splitting the analysis into different country groups (see, e.g., Jorgenson et al., 2016, 2017; Grunewald et al., 2017). These studies identify a positive or negative relation depending on the country group. Additionally, Mader (2018); Wan et al. (2022); Andersson (2023) contradict their findings. Studies focusing on developing countries suggest a negative relationship between income inequality and environmental degradation Khan et al. (2022); Khan and Yahong (2021) or mixed results over the time span of the study suggesting reverse causality Masud et al. (2020). For China, the relationship depends on the regional economic development Sun (2023), while in Turkey the relationship is negative Demir et al. (2019). Studies investigating different country groups show different results Nguyen and Nasir (2021); Khan et al. (2023) and nonlinear dependence Wang et al. (2023). Table 2 gives an overview on empirical work related to our study.

Empirical evidence on the structural change hypothesis postulates – derived from the Kuznets and environmental Kuznets curve – that a shift to the service sector does not necessarily go along with a reduction in neither carbon emissions nor inequality (Baymul and Sen, 2019; Fix, 2019; Parrique et al., 2019). Both findings are contradicting the argument in the spirit of the environmental Kuznets curve and the Kuznets curve: decoupling of carbon emissions and growth is possible by shifting to the service sector, which is less carbon intensive through direct consumption (Panayotou et al., 2000). A transformation to a more service-based economy does not necessarily go along with a reduction in raw material and energy-use as well as environmental damage, as the service sector depends on material-intensive and polluting infrastructure (Jespersen, 1999; Suh, 2006; Alcántara and Padilla, 2009; Fix, 2019; Parrique et al., 2019). At the same time, recent studies on the growth-inequality relationship opposed to the findings of Kuznets (1955) suggest that structural transformation proceeds from agriculture to services and goes along with an increase in inequality (Baymul and Sen, 2019).[1] We thus expect that the service sector is positively associated with the relation between income inequality and carbon emissions. The direction of the association may be additionally driven by the type of services. Service jobs traditionally in the public sector have a different labor/energy composition (Jespersen, 1999). Based on the above-mentioned reasoning, we expect a positive association in high-income countries and a negative one in middle- and low-income countries, with a smaller magnitude for middle-income countries: similar to the structural change of economies, consumers shift from agricultural products to manufacturing and service goods (Caron and Fally, 2018; Comin et al., 2021).

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	Characteristics	Channels
positive ($\rho > 0$)	synergies, reducing both jointly	– emulation effect – political economy, lobbies – environmental degradation
negative ($\rho < 0$)	trade-offs, how to weaken relation	– individual Kuznets curve – concave Environmental Engel curve
positive or negative	synergies or trade-offs	– energy mix – aggregated income level – structural transformation (service sector)
decoupled ($\rho = 0$)	no synergies or trade-offs, independent reduction	– none

Additionally, the energy mix can drive the relationship between income inequality and carbon emissions since 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

[1]The authors do not give any suggestions on why this relationship occurs. The service sector refers to trade, transport, business, government and personal services (Baymul and Sen, 2019).

– like Portugal and the UK – uses more nuclear or renewable energy. In turn, Germany uses more fossil fuel energy, especially from coal plants (Ritchie and Roser, 2021). This may lead to a larger range of carbon emissions in relation to a certain inequality level and specifically places the focus on the role of fossil energy in defining the nonlinear relationship.

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 factors that result in decoupling associations on either a positive or negative relationship between income inequality and carbon emissions.

Table 2: Empirical literature on the relation between income inequality and carbon emissions

Study	Time	Countries	Relationship analysed	Result
Acheampong et al. (2021)	1990 - 2017	166 countries	Energy accessibility on income inequality	Access to electricity reduces global income inequality; Access to modern and clean energy increases global income inequality; Rural and urban electrification reduce global income inequality; Regional differences
Andersson (2023)	1929 - 2019	United States	Relationship between income inequality and carbon emissions	Higher inequality related to lower emissions in the early part of the sample and higher emissions in the end of the sample.
Baloch et al. (2020)	2010 - 2016	40 Sub-Saharan countries	Linkage between income inequality and poverty	Rise in income inequality contributes to increasing CO2 emissions
Demir et al. (2019)	1963 - 2011	Turkey	Income inequality on carbon emissions	Negative association between CO2 emission and income inequality; Confirms EKC
Grunewald et al. (2017)	1980 - 2008	158 countries	CO2 emissions on inequality for different income groups	Direction of association depends on income level, which is positive for high- and negative for low-income countries.
Jorgenson et al. (2016)	1991 - 2008	67 countries	Relationship between consumption-based carbon emissions and domestic income inequality for low-, middle-, and high-income countries	High-income countries: The relationship shifts from negative to positive; Middle-income countries: The relationship is negative, increasing negative relationship in the later years of the study; Low-income countries: No relationship between carbon emissions and domestic income inequality
Jorgenson et al. (2017)	1997 - 2012	United States	CO2 emissions on GINI (top 10%) and controls	Insignificant relation (positive for top 10%)
Kahn (1998)	1993	California vehicle microdata	Poor and rich household pollute most due to vehicles used	Confirm EKC
Khan and Yahong (2021)	1971 - 2015	Pakistan	Income inequality on carbon emissions	No dependence in the short run; negative relation in the long run
Khan et al. (2022)	2006 - 2017	18 Asian developing countries	Income inequality on Ecological Footprint	Negative relation

Continued on next page

Table 2 – continued from previous page

Study	Time	Countries	Relationship analysed	Result
Khan et al. (2023)	2002 - 2019	developing, high-income and Belt Road initiative (BRI) countries	CO2 emissions on income inequality	Negative relation in developing countries, positive relation in high-income and BRI countries
Knight et al. (2017)	2000- 2010	26 high-income countries	Relationship between domestic wealth inequality and consumption-based carbon emissions	Consistently positive and relatively stable over time
Mader (2018)	Repl. of Knight et al. (2017)& Jorgenson et al. (2017)	see Knight et al. (2017), Jorgenson et al. (2017)	Increase in wealth and income inequality on CO2 emissions	No sound empirical evidence for a substantial nexus between social inequality and CO2 emissions
Masud et al. (2020)	1985 - 2015	Indonesia, Malaysia, Philippines, Thailand and Vietnam	Income gap on environmental sustainability and the causality between income inequality and environmental sustainability	Bi-directional causality between income inequality and environmental sustainability exists among the bottom 40%, but mixed causality results for the overall sample
Nguyen and Nasir (2021)	2002 - 2014	51 countries	Nexus between energy poverty and income inequality for low-, middle- and high-income countries	Positive Granger causality between income inequality and energy poverty
Sager (2019)	1996 - 2009	USA	Environmental Engel curves (EEC) which describe the income-CO2-emissions relation across households	Evidence for equity-pollution dilemma: progressive income redistribution may raise the demand for aggregate greenhouse gas emissions.
Sun (2023)	2010 - 2020	205 cities in China	Income inequality on carbon emissions	Continuous improvement of regional economic development leads to increase-decrease-flattening
Wan et al. (2022)	1960 - 2021	217 countries	Causal impact inequality on emissions	Trade-off between income inequality and CO2 emissions
Wang et al. (2023)	1998 - 2018	139 countries	Income inequality on carbon emissions efficiency	Nonlinear dependence

2.4 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 nonlinearly with income, which suggests heterogeneous dependencies between income and carbon emissions. Uddin et al. (2020) find nonlinear effects between income inequality and carbon emissions using non-parametric panel approaches. Thus, for the effect of the influencing factors on both components of the outcome vector, mean regressions do not appropriately account for the dependence and therefore we apply distributional regression techniques instead.

Figure 3 displays schematic examples of a negative, positive (with asymmetric distribution) and no relation between inequality and carbon emissions, illustrated by contour lines. No relation between inequality and emissions means decoupled variables (red), a positive relationship (yellow) implies synergies and a negative relationship (cyan) implies trade-offs. As, for instance, summarized in the sustainable development goals, the efforts for sustainable development aim for low inequality and low emissions which can be evaluated by the location of the contour lines. The intersecting area of the two thresholds for GINI and carbon indicated in Figure 3 defines a socially and environmentally sustainable space. Within this potentially safe and just space any form of the relationship is plausible (see the miniature graphic). However, overall the strength and structure of the relationship are of particular relevance for analysing potential paths towards this area and thus, towards a sustainable future. We discuss the potential thresholds in more detail in Section 3.2.4.

3 Bivariate distributional copula regression

Bivariate distributional copula regression models focus on 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).

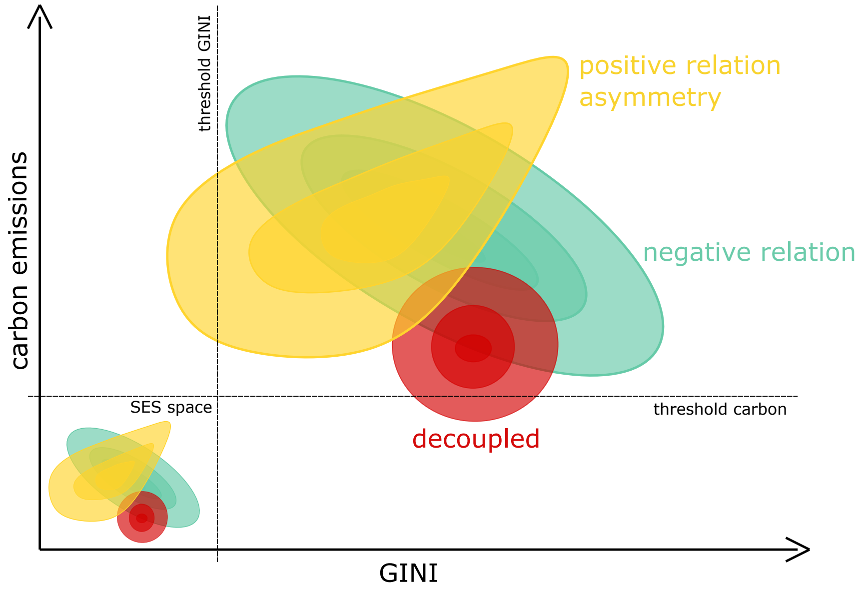

Figure 3: Schematic hypothetical bivariate distribution of GINI and carbon emissions illustrating possible different locations and shapes: positive relation with asymmetric distribution (yellow), negative symmetric relation (cyan) and decoupled (red); socially and environmentally sustainable (SES) space for low values of emissions and GINI (see Section 3.2 for more details).

3.1 Bivariate copula regression

Distributional copula regression for $GINI$ and $carbon$ combines two features: first, it separately specifies the two marginal distributions and subsequently specifies the dependence between income inequality and carbon emissions. The so-called copula regression in the second step incorporates the option to model regression effects on all possible 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 $\theta_{ij} = \theta_j(\boldsymbol{z}_i)$, $j = 1, \ldots, J$ for observations $i = 1, \ldots, n$.

In our application, we consider various types of response distributions for continuous, non-negative responses including *normal*, *log-normal*, *gumbel*, *reverse gumbel*, *dagum* and *singh-maddala* which correspond to the 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 for $k = 1, \dots, K$ covariates 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 nonlinear 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 nonlinearity in the effect estimates.

The covariate effects on the dependence as studied in our model is closest to studying a linear regression model of, e.g., emissions on inequality joint with the interaction of inequality with a further covariate. To our knowledge, this is only done for an interaction with time effects in Jorgenson et al. (2017) and with GDP in Grunewald et al. (2017). Other works use similar covariates to sharpen the relation between inequality and emissions, but the effect on their dependence is hard to see from these mean regression model. Our model fills this gap and applies similar covariates as in the literature and studies their relation with the dependence. These covariates and the applied worldwide data for GINI and consumption-based carbon emissions per capita are introduced in the following. Subsequently, we describe the model specification that allows us to estimate the bivariate distribution in Equation (1).

3.2 Data

The data studied consists of an unbalanced panel data set including 109 countries for the 1960–2019 period, collected from different sources. Our analysis focuses on the relationship between carbon dioxide emissions per capita and the GINI index, which composes the bivariate outcome vector of the 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 variable *carbon* collects this data as Mt-CO2 per capita.

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). While this measure naturally has some shortcomings, it suffices 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 intercountry 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 different control variables.

We place a special focus on the relation 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 relation over the observed time period. The World Development Indicators (World Bank, 2020b) provide the variable GDP per capita in constant 2010 US Dollars. The same data set offers information on 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).

To investigate the political economy hypothesis, we include polity as a measure for the political framework and the share of fossil energy on total energy consumption. Accounting for the relative share of fossil fuel energy can to some extent control for a varying energy mix. The share of fossil fuel consumption $fossil$ is given in percentage of the total energy-use by the aforementioned data set (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-, 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.

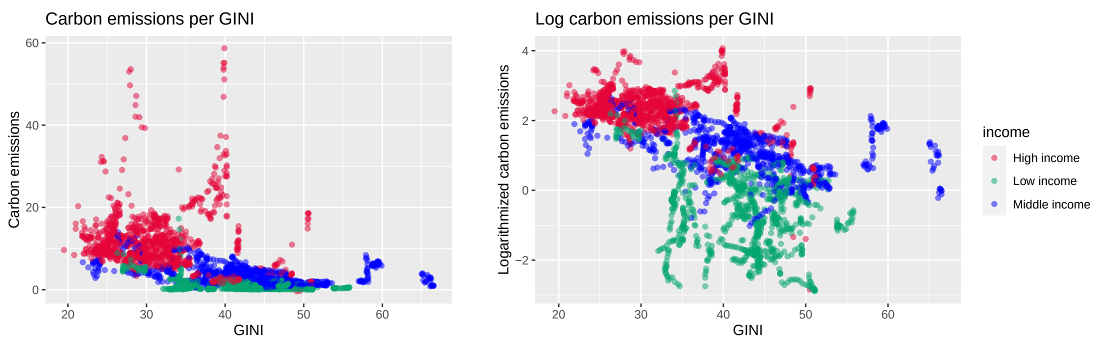

Figure 4: Scatter plot of the variables $GINI$ and $carbon$, pooled over all years and separated into the three income groups of, low- (green), middle- (blue) and high-income countries (red).

Figure 4 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 the use of logarithmized distributions 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 4 indicates that certain countries follow a path of rising emissions with fairly constant $GINI$ indices. It further suggests differences in the strength of the dependence according to the level of income.

The summary statistics in Table 3 support the assumption of heterogeneity over the country groups and increasing emissions from low-income countries with $mean = 1.27$ Mt-CO_2 per capita over middle-income countries with $mean = 3.57$ Mt-CO_2 per capita, to high-income countries with $mean = 12.02$ Mt-CO_2 per capita. The variation in *carbon* is strongest in high-income countries with a standard deviation $sd = 7.17$ Mt-CO_2 per capita compared with middle- and low-income countries, with $sd = 2.18$ and $sd = 1.94$ Mt-CO_2 per capita, respectively. Inequality is highest in middle-income countries with $mean = 42.59$ and lowest in high-income countries with $mean = 30.51$ 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.

3.2.4 Socially and environmentally sustainable space

To postulate a potential socially and environmentally sustainable (SES) space, we specify thresholds for $GINI$ and *carbon*. 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 Mt-CO_2 per capita per year[2], whereas the current global av-

[2]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 for the lifespan (Hausfather, 2019).

Table 3: Summary statistics of the outcome variables *GINI* and *carbon* (CO_2 emissions per capita in Mt-CO_2) 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

erage emissions are at 4.9 Mt-CO_2 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.

It is more challenging to establish a threshold for GINI as an indicator for social sustainability. Income inequality relates to individual and societal well-being, by having harmful effects on health and social problems, such as crime, mental illness and drug misuse and better explains these outcomes compared to average income (Wilkinson and Pickett, 2009; Wilkinson et al., 2010; Wilkinson and Pickett, 2017; Pickett and Wilkinson, 2010, 2015). These damages are not limited to the poor but affect most segments of society (Wilkinson and Pickett, 2009). Due to these linkages, we argue that measures of income inequality matter for social sustainability, an often vaguely defined category (Eizenberg and Jabareen, 2017). As far as we know, previous research has not explored the sustainable level of income inequality. For the purpose of our exercise, we propose the following threshold: for a socially sustainable future, we estimate the optimal GINI coefficient as the lowest quantile of the GINI distribution of countries with the highest democracy level (polity score of 10). The resulting GINI threshold is 25.7%.

Jointly, the limit of 0.5 Mt-CO_2 annual carbon emissions per capita and a GINI of 25.7% define the potential socially and environmentally sustainable space, which is schematized in Figure 3. 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) and Fanning et al. (2022). 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 Akaike information criterion (AIC) and the Bayesian information criterion (BIC) and quantile-quantile-plots (QQ-plots) of the model residuals for different choices of the distribution. The selected marginal distributions and copula specifications for the three country groups are as follows: $carbon$ 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.[3] 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.[4]

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 dependence parameter for the copula. These five parameters specify the bivariate distribution for each income group $g = 1, 2, 3$, i.e.

$$\begin{pmatrix} GINI \\ Carbon \end{pmatrix} \sim D_g(\theta_1, \theta_2, \theta_3, \theta_4, \theta_5). \tag{4}$$

[3]The parameters in (5) are estimated using the R package *GJRM* (Marra and Radice, 2020).

[4]We do not consider specifications where the estimation procedure does 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 full list of AIC and BIC values for all model specifications is displayed in Tables A2-A4, A11-A13 and A20-A22 for high-, middle- and low-income countries, respectively.

The specific marginals and copulas are described by the set of parameters $\theta_j, j = 1, \ldots, 5$, where 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 $g = 1, 2, 3$, we obtain a predictor for observation $i = 1, \ldots, n_g$,

$$\begin{aligned}\eta_{g,i}^{\theta_j} = \beta_{0g}^{\theta_j} + s_g(GDP_i)^{\theta_j} + \beta_{3g}^{\theta_j} manu_i + \beta_{4g}^{\theta_j} serv_i + \beta_{5g}^{\theta_j} agri_i + \beta_{6g}^{\theta_j} urban_i \\ + \beta_{7g}^{\theta_j} fossil_i + \beta_{8g}^{\theta_j} polity_i + s_g(year_i)^{\theta_j}.\end{aligned} \tag{5}$$

The intertemporal variation of the GINI index is small within countries and varies more across countries (see Figure 4). Therefore, we apply a fixed grouping for the countries following the income classes and control for nonlinear 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_g with ten inner knots for year effects. Likewise, we model GDP by using a penalized splines with ten inner knots to account for nonlinear effects.[5] According to the distribution of the resulting model residuals (see Figures A9, A15 and A21), the explanatory variables seem to sufficiently control for heterogeneity between the countries, which was equally observable as country-specific paths in Figure 4.

In Equation (5), the first four parameters $\theta_1, \ldots, \theta_4$ determine the marginal distributions of $GINI$ and *carbon*. We are primarily interested in the effect of the covariates on the dependence which is described by the copula parameter θ_5 in Equation (5). To allow an economic interpretation, we convert the copula parameter into an association measure. Kendall's τ is a measure of association, which is similar to the rank correlation estimates for mean statistical analysis. However, it is not limited to linear dependence and only uses the ordinal scale of variables. Kendall's τ is particularly prominent when using copulas since it allows to compare dependencies across different models irrespective of the marginal distributions and the copula. Thus, Kendall's τ, which takes values between -1 and 1, allows us to measure the dependence structure between inequality and carbon emissions. To study how the dependence varies with different covariates, we estimate average marginal effects of the covariates on Kendall's τ. The average marginal effect (AME) of covariate z corresponds to

$$AME(z) = \frac{1}{n} \sum_{i=1}^{n} \tau(z_i + 1) - \tau(z_i), \tag{6}$$

where z_i+1 is the covariate at observation i plus one unit, and $\tau(z)$ is calculated

[5]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).

as Kendall's τ of the distribution which is linked to the predictor from (5).

4 Results

For each country group, we consider the mean copula prediction in Section 4.1, identify potential channels of the dependence by the average marginal covariate effects of associated factors in Section 4.2 and compare these to a selection of country-specific predictions in Section 4.3.[6] Our analysis specifically focuses on the covariates *polity*, $fossil$, *service* and *GDP* as factors of the relationship. This allows us to deduce potential policy implications in line with a sustainable future.

4.1 The average dependence between inequality and emissions

The average strength and direction of the dependence between $GINI$ and *carbon* shows large differences among the country groups. The left column of Figure 5 displays the mean dependence structure as an average over all predictions of the parameters $\theta_j, j = 1, \ldots, 5$ calculated from the estimated regression coefficients and the covariate value of each observation. The right column shows a histogram of the Kendall's τ values for each observation separately. The first row represents high-income countries, the second row middle-income countries and the bottom row low-income countries.

The mean copula prediction for high-income countries suggests hardly any dependence between carbon emissions and inequality with Kendall's τ of -0.08 and a confidence interval containing zero, $(-0.23, 0.08)$. This is in line with other empirical results for high-income countries, as, e.g., in Jorgenson et al. (2017); Mader (2018) (see Table 2). In contrast, the mean copula for middle- and low-income countries exhibits a negative relation. We observe the strongest mean dependence in middle-income countries. More specifically, in middle-income countries Kendall's τ is -0.39 joint with a confidence interval of $(-0.55, -0.21)$ (a negative relation is also found by, e.g., Grunewald et al., 2017; Demir et al., 2019). In low-income countries, the Frank copula suggests an oval shape, which – due to the marginal distributions – implies higher dependence at higher $GINI$ values, and hence a lower variation in emissions. A Kendall's τ of -0.097 joint with a confidence interval of -0.27 to 0.08 suggests

[6] 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 A9, A15 and A21) support the grouping by income. In this sense, the grouping results in effect homogeneity on the dependence but heterogeneity in the dependence structures.

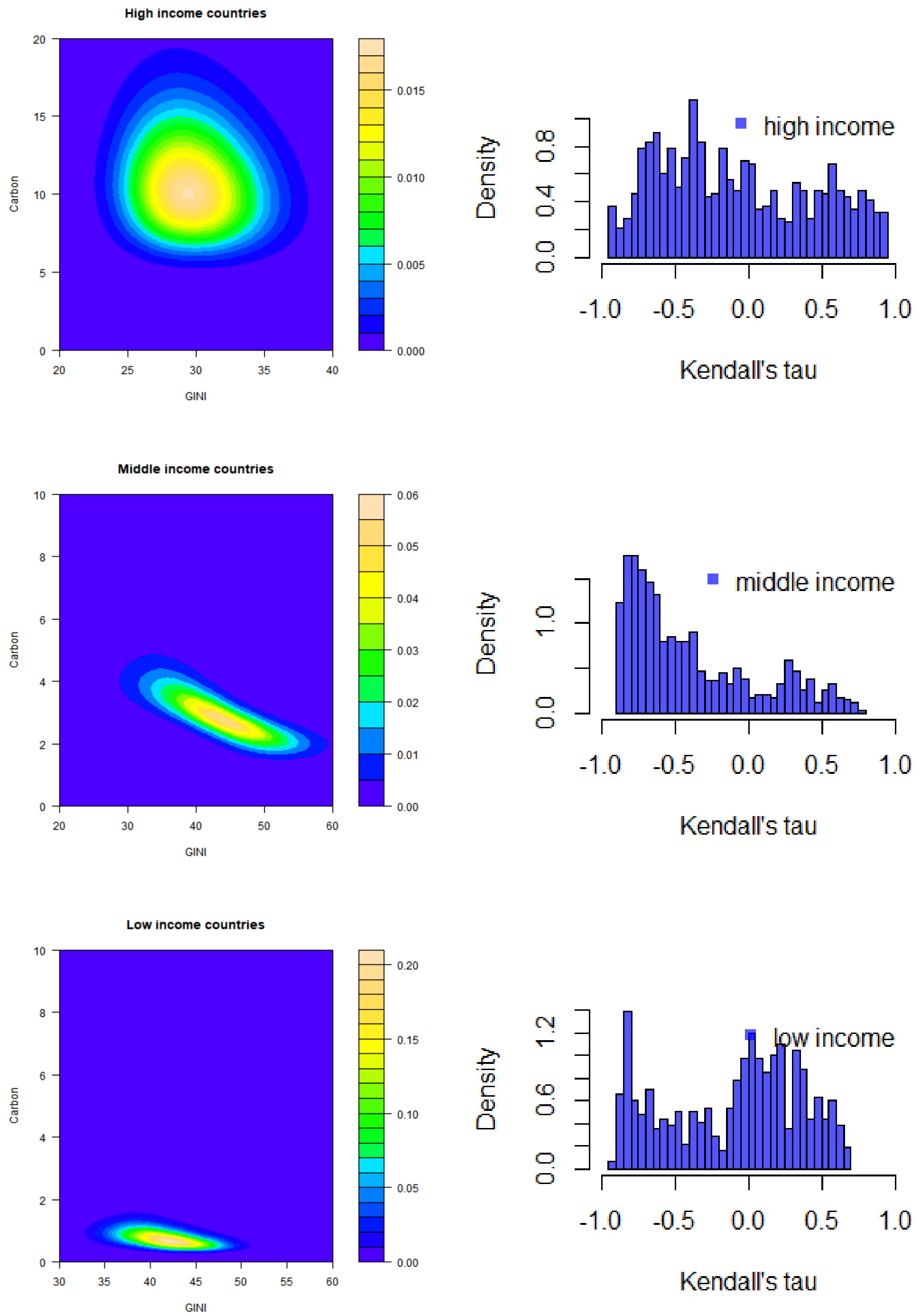

Figure 5: Average contour plots and Kendall's tau distribution. Note that the scaling differs by graphic due to illustrational reasons.

that there is only a weak relation (analogue to the results found by Grunewald et al., 2017; Khan and Yahong, 2021; Khan et al., 2022, 2023, which mostly confirm a negative relation in low-income countries).

The dependence structures widely differ from the mean prediction in all country groups (see the variation of Kendall's τ in Figure 5) as the mean is not necessarily representative for the dependence over the full range of the influencing factors. This nonlinearity has been found in prior empirical works which study the relation over time (Andersson, 2023) and for different countries and income groups (see, e.g. Jorgenson et al., 2016; Grunewald et al., 2017; Khan et al., 2023; Wang et al., 2023). Thus, instead of providing an average view on the income groups, our method rather distinguishes the dependence conditional on the levels of the included covariates.

4.2 Identifying the channels of the dependence

We estimate average marginal effects of the covariates on the strength of the dependence measured by Kendall's τ. The results are displayed in Table 4 where significance levels are based on the estimates in Tables A9, A18 and A27 for high-, middle- and low-income countries, respectively.

The polity level has a varying association with Kendall's τ in the different country groups supporting the political economy argument in high- and middle-income countries.[7] This finding is supported by Grunewald et al. (2017) who also find a varying effect of the polity indicator. However, their study is not providing full results to calculate average effects. In our study, for high- and middle-income countries the association is highly statistically significant, but it is statistically insignificant for low-income countries. In high-income countries the magnitude of the association of the polity level is the largest with -0.069 units. The association in middle-income countries amounts to 0.038 units, having the reverse sign compared to high-income countries. In low-income countries the association is not only statistically insignificant but the magnitude is also relatively small, suggesting a neither statistical nor economic relevance. Thus in middle- as well as high-income countries, a positive change in the democracy score goes along with a decoupling of the relationship. Our results support several theoretical studies (Veblen, 1899; Boyce, 1994, 2018; Klasen, 2018) which argue 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 $fossil$ indicates an association between fossil fuels and the development path of countries. The share of fossil fuels in the

[7]In general, positive and negative relations have to be placed in relation to the initial predictor, which depends on the intercept and level of the other variables, and thus, can lead to strengthening or weakening effects at the same time. More specifically, if the predictor for a given country is initially negative, an increase in polity consequently induces an even stronger negative relationship, while if the predictor is initially positive, such an increase leads to a weaker positive relation and can even result in a negative or decoupling scenario.

energy mix of countries exhibits a significantly negative association with the dependence between inequality and carbon emissions in high- (-0.014) and low-income (-0.007) countries, while the association is positive in middle-income countries (0.014). The magnitude is similar in high- and middle-income countries with a reverse sign. These results differ from those of, e.g., Dunlap and Brulle (2015), who find a positive effect of the share of fossil fuels on emissions. The deviations of our study are likely driven by the fact that our model studies the effect of fossil fuels on the relation between inequality and emissions rather than emissions only. Our 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 (Klasen, 2018). 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).

Among the country groups not only the significance but also the association size of GDP per capita varies. While in high-income countries an increase in GDP per capita by 1000$ per year is slightly positively associated with Kendall's τ by 0.03 units, it shows a positive association of 0.084 units in middle-income countries. In low-income countries it is significantly higher and negatively associated with 0.54 units. This is mostly in line with, e.g., Jorgenson et al. (2016); Grunewald et al. (2017), but with an effect difference in low-income countries. These differences might be due to the fact that our averaged effects result from a non-parametric effect estimation via splines, c.f. Figure A26 [8]

The structure of the economy, displayed by the share of the separate economic sectors, influences the relationship. Manufacturing is positively associated with the dependence between income inequality and carbon emissions in high- and low-income countries while the association is negative in middle-income countries. The service sector positively associates to the relationship

[8] For different levels of GDP, we can identify a varying relation with 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 splines for GDP and *year* for high-income countries are displayed in Figure A14. The spline indicates that GDP per capita has a nonlinear effect on the dependence, which is statistically significant, as indicated in Table A9. By contrast, the spline for the year effect (right-hand graphic in Figure A14) does not strongly vary over the time period, suggesting no variation in the dependence due to year effects. Figure A20 displays the centered splines for GDP and year effects for middle-income countries and Figure A26 for low-income countries.

Table 4: Average marginal effects on Kendall's tau

	High	Middle	Low
GDP	0.030***	0.084***	-0.540***
Manu	0.010**	-0.030***	0.031***
Serv	0.034***	-0.009**	-0.103***
Agri	0.084***	0.000	0.002
Urban	0.000***	-0.019	0.010***
Fossil	-0.014***	0.014***	-0.007***
Polity	-0.069***	0.038***	-0.004
Year	0.004***	-0.021***	-0.005

$^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.
One unit GDP is equivalent to 1000$. All other units for the corresponding variables are set to 1.

in high-income countries and negatively in middle- and low-income countries exhibiting a relative high magnitude of -0.103 units compared to 0.034 units (high-income) and -0.009 units (middle-income).[9] In contrast, the share of the agricultural sector has only an economic and statistically significant association with the dependence between GINI and carbon emissions in high-income countries, suggesting that the agricultural sector is unrelated to that relationship in middle- and low-income countries. We analyse the association of the sectors separately instead of an averaged effect (joint with the urban population) as displayed in the sensitivity analysis of Grunewald et al. (2017). Even though they also find varying effects, our results allow for a more detailed effect analysis.

Results on the urban population suggest that there are no differences in high- and middle-income countries on the relationship, while it is positive in low-income countries. In high-income countries, the magnitude of urban is irrelevant with 0 units. The year effect varies among country groups being on average the highest in middle-income countries, with a negative association of -0.021 units.

4.3 Country-specific cases and their potential for a sustainable future

For diverse covariate settings, we report the related change in Kendall's τ (i.e., the strength and direction/rotation of the resulting copula), the shape of the copula and the probabilities for falling below the thresholds for $GINI$ (25.7%)

[9] We infer that the relationship might depend on the type of service predominantly present in the country groups. Less polluting care services have a lower income than other service sector jobs (Folbre et al., 2021).

Table 5: Covariate values to analyse the potentials to fall in the SES. We use the same adjustments for all country groups, only case c varies for high- and low-/middle-income countries due to varying base categories.

Case	*polity* (high/ low&middle)	*fossil*	*service*
a	–	50	–
b	–	10	–
c	9/10	–	–
d	3	–	–
e	–	–	20
f	–	10	20

and *carbon* (0.5 Mt-CO_2 per capita), specified as a potential socially and environmentally sustainable space in Section 3.2.4. For instance, if increasing a covariate leads to a shift or stretch of the copula towards lower (higher) levels of $GINI$ and *carbon*, this covariate can be interpreted to likely have a positive (negative) effect on the achievement of a sustainable future in terms of the SES space sketched in Figure 3. Table 5 shows the potential cases we study for all country groups, i.e., we analyse whether specific changes in the polity level, fossil energy share and the share of the service sector are influential. More specifically, we reduce the share of fossil energy to a level of 10 which relates to policy decisions, e.g., subsidies, into the direction of renewable energy or technical innovations. Additionally, we consider a shrunken service sector. We assume a high diversity and inequality within the service sector in most countries (see, e.g., Baymul and Sen, 2019; Fix, 2019; Parrique et al., 2019; Folbre et al., 2021). By reducing its share we study the importance of the service sector and can suspect various transmission channels coupled to it. Case f in Table 5 relates to the joint change in the fossil energy share and the service sector (e.g., Jespersen, 1999; Suh, 2006; Alcántara and Padilla, 2009, describe the varying carbon intensity in the service sector). The interpretation of varying effects over the covariates is sometimes difficult to relate to prior studies applying mean regressions (cf. Section 3.1). Thus, we base on them, but mainly relate our results to different theoretical channels from the literature.

4.3.1 High-income countries

The results of exemplary copula predictions for Germany and the US displayed in Table 6 support the analysis of the covariate effects from the pooled estimation 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*, $fossil$ and *service*. The variation in the strength of the dependence underpins the economic relevance, as, for instance, a lower polity score is associated with a higher positive dependence of $GINI$ and *carbon*. Specifically, cases 4c and 4d as well as 8c and 8d show changes in the strength of the dependence 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 shares 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. Cases 4e and 8e show results for a lower share in services (all other sectors remain unchanged) indicating a strong influence on the relationship which turns negative in both cases.

Table 6: 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 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 A10.

Case	Country	*year*	*polity*	$fossil$	*service*	K's τ	TH $GINI$	TH *carbon*	SES Area
1	Germany	1997	10	84.63	61.11	-0.302	0.079	0	0
2	Germany	2008	10	80.8	62.22	0.052	0.027	0	0
3	Germany	2009	10	79.97	64.23	-0.187	0.005	0	0
4	Germany	2015	10	78.86	62.21	0.428	0.101	0	0
4a	Germany	2015	10	50	62.21	0.749	0.168	0	0
4b	Germany	2015	10	10	62.21	0.925	0.436	0	0
4c	Germany	2015	9	78.86	62.21	0.502	0.068	0	0
4d	Germany	2015	3	78.86	62.21	0.797	0.001	0	0
4e	Germany	2015	10	78.86	20	-0.892	0.626	0	0
4f	Germany	2015	10	10	20	-0.226	0.739	0.021	0.009
5	USA	1997	10	86.46	71.81	0.311	0	0	0
6	USA	2008	10	84.97	74.53	0.827	0	0	0
7	USA	2009	10	84.15	76.44	0.775	0	0	0
8	USA	2015	10	82.43	76.82	0.877	0	0	0
8a	USA	2015	10	50	76.82	0.954	0	0	0
8b	USA	2015	10	10	76.82	0.986	0	0	0
8c	USA	2015	9	82.43	76.82	0.895	0	0	0
8d	USA	2015	3	82.43	76.82	0.959	0	0	0
8e	USA	2015	10	82.43	20	-0.823	0.584	0	0
8f	USA	2015	10	10	20	0.154	0.665	0.056	0.046

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 GDP fell in Germany and the US due to the financial crisis. 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 6, 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 fossil energy share the likelihood increases. Cases 4f and 8f refer to joint changes of two covariates, $fossil$ and $services$. Only in these cases we can observe an increase in the likelihood of being in the socially and environmentally sustainable space. In the remaining settings, Germany and the US have a zero likelihood of falling below the carbon threshold or in the socially and environmentally sustainable area. Furthermore, the US only shows a positive likelihood to fall below the GINI threshold for a decrease in the service sector.

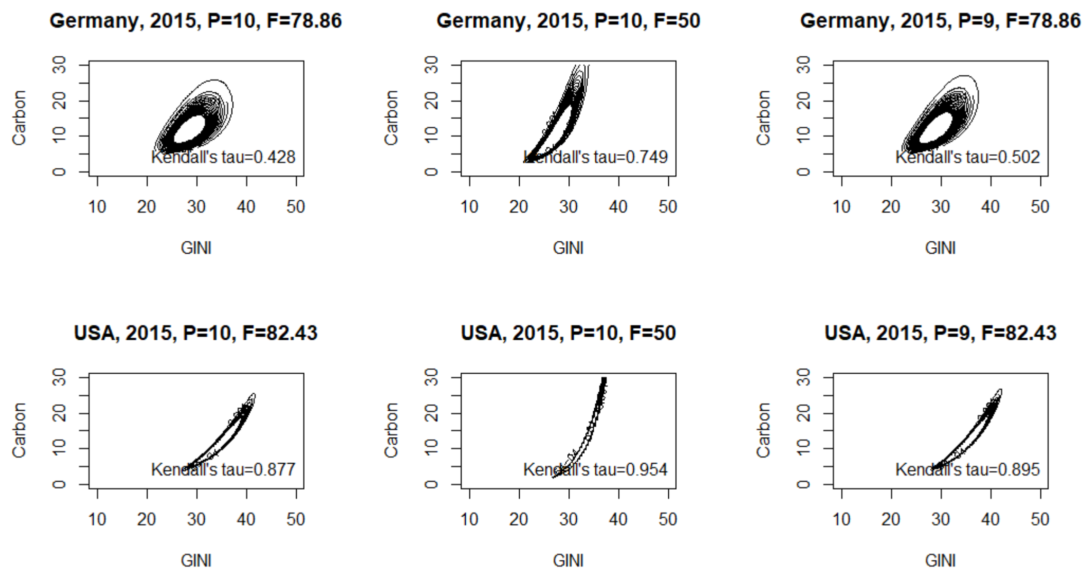

Figure 6: Contour plots for Germany and the US in 2015. The first column shows the original setting, the second column refers to changes in $fossil$ and the third column to changes in *polity*, the remaining covariates are set to their actual value.

Figure 6 illustrates the changes in the shape of the copula prediction, i.e. of the contour lines, for changing covariates, showing a higher dependence for lower polity scores and fossil share. For instance, we compare the real situation of Germany in 2015 (in the first column, first row) to a fictive situation with a different polity score (in the third column). 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. With a decrease in the fossil energy share in the same setting (third column), the variation is also lower. The contour plots for the US (second row) present a similar direction but the shape of the contour lines differ, 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.

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 suggest 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). Other empirical findings for high income countries such as (Jorgenson et al., 2016; Grunewald et al., 2017; Knight et al., 2017) support our results. Specifically, the US show an increasing and steadily high relation between income inequality and carbon emissions which coincides with other empirical studies on the US by Jorgenson et al. (2017); Andersson (2023) and contradicts the finding by Mader (2018), which argues for no evident relation between carbon emissions and income inequality. 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 6) have a positive Kendall's τ, whereby lower fossil energy shares strengthen the relation between *carbon* and $GINI$. This implies that reducing the fossil energy share likely leads to synergy effects between social and environmental sustainability.

The positive association between the variable *service* and the strength of dependence between income and carbon emissions points to a particular relevance of the structural change argument in high-income countries. Transforming the economy to a larger service sector has a strengthening effect on the relationship and decreases the probability of achieving a social and environmental sustainable future. In this sense, a transformation to a largely service-based economy can not be seen as a straightforward solution for lower emissions and more just societies. However, maybe not a reduction in services but a change in the structure of services towards more care-related services (often public sector with less inequality and carbon emissions) can lead to a simultaneous decline in inequality and carbon emissions (Jespersen, 1999; Folbre et al., 2021). This would require further investigations, with more disaggregated data on the industry level.

4.3.2 Middle-income countries

The specific cases of interest – China and South Africa – expose the economic relevance of the relation of *polity*, $fossil$, *service* 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*, $fossil$ and *service*. 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 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. Similar to high-income countries, the change in the relationship between 2008 and 2009 ranges between a positive relation of 0.1 for China and 0.02 for South Africa. In difference, a decrease in the share of the service sector is associated to a decrease in the negative dependence for China and an increase of the positive dependence in South Africa underlining the positive relation of this variable. These changes support the economic relevance of the variables.

For both countries, the probability for falling below the threshold of $GINI$ changes with the macroeconomic setting. It slightly decreases with an increasing level of democracy (comparing cases 11 and 11c, 15 and 15c), 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 (alone or in combination with a small share of services). Considering the likelihood of falling in the socially and environmentally sustainable space,

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 A19.

Case	Country	*year*	*polity*	*fossil*	*service*	K's τ	TH *GINI*	TH *carbon*	SES Space
9	China	2008	-7	87.22	42.86	-0.87	0.213	0	0
10	China	2009	-7	87.64	44.41	-0.869	0.21	0	0
11	China	2014	-7	87.67	48.27	-0.747	0.303	0	0
11a	China	2014	-7	50	48.27	-0.848	0.091	0	0
11b	China	2014	-7	10	48.27	-0.893	0.001	0.032	0
11c	China	2014	10	87.67	48.27	-0.088	0.229	0	0
11d	China	2014	3	87.67	48.27	-0.522	0.261	0	0
11e	China	2014	-7	87.67	20	-0.625	0.475	0	0
11f	China	2014	-7	10	20	-0.875	0.257	0.067	0
12	South Africa	1997	9	84.91	57.84	0.338	0.036	0	0
13	South Africa	2008	9	88.15	59.07	0.196	0.047	0	0
14	South Africa	2009	9	87.68	60.51	0.216	0.065	0	0
15	South Africa	2014	9	86.79	61.02	0.327	0.089	0	0
15a	South Africa	2014	9	50	61.02	-0.562	0.001	0	0
15b	South Africa	2014	9	10	61.02	-0.799	0	0.057	0
15c	South Africa	2014	10	86.79	61.02	0.385	0.085	0	0
15d	South Africa	2014	3	86.79	61.02	-0.15	0.115	0	0
15e	South Africa	2014	9	86.79	20	0.689	0.466	0	0
15f	South Africa	2014	9	10	20	-0.676	0.231	0.109	0

none of the country settings in Table 7 show a non-zero probability. Cases 11e and 15e show that reducing the share of the service sector increases the likelihood of falling below the GINI threshold to the highest level on all cases for both countries.

The contour plots for the copula predictions in Figure 7 illustrate the varying dependence structures with changing fossil share and polity score (cases 11a and 11c for China and 15a and 15c for South Africa). The contour plots illustrate a stronger dependence for a falling fossil energy share and decoupling for an increase in *polity* in China. For South Africa, the contour plots 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.

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*. Although the direction of the relation 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 soci-

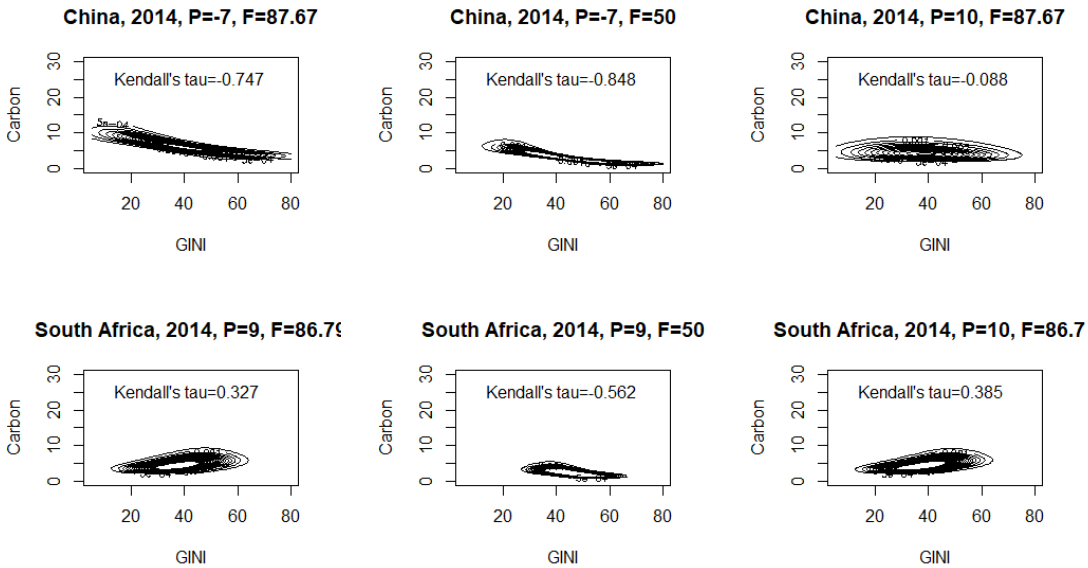

Figure 7: Contour plots for China and South Africa in 2014. The first column shows the original setting, second column refers to changes in *fossil* and the third column to changes in *polity* the remaining covariates are set to their actual value.

eties 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. Further, with an increasing level of democracy, the likelihood of being below the GINI threshold increases.

Additionally, falling fossil shares lead to stronger 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 (Sager, 2019). Further, middle-income countries strongly rely on fossil energy to realize their development path (Klasen, 2018).

A decrease in the service sector has the opposite effect as in high-income countries. It decreases the negative dependence in China and increases the positive dependence in South Africa which is in line with the previously identified negative relation of this variable. As a decrease largely increases the probability of falling below the GINI threshold and (jointly with a change in fossil energy) the carbon threshold, we conclude that a structural transformation towards a larger share of the service sector would likewise decrease these probabilities. In the first place, this is in line with arguments which relate a structural transformation towards a service-based economy to an increase of inequalities (Baymul and Sen, 2019). The separate effect of the share of services on the environment is not visible when studying the carbon threshold. Thus, we infer that the relationship is interlinked with the share of fossil fuels used in the service sector. As pointed out above, these findings suggest a deeper study of the structure of the service sector.

4.3.3 Low-income countries

The results for the specific cases of Bangladesh and Tanzania underpin the economic relevance of the relation of $fossil$ and *service*. 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*, $fossil$ and *service*. Even though *polity* is insignificant in the parameter estimation in Table A27, 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 from a Kendall's τ of 0.06 for $fossil = 73.77$ to a Kendall's τ of 0.567 for $fossil = 10$, holding all other variables fixed. For Tanzania, the relationship even turns negative for an increasing share of fossil energy which accords to the strengthening effect of lower fossil energy shares. In difference to the other country groups, a relation to GDP can not be directly followed from the change between 2008 and 2009 as, specifically in Bangladesh, any changes between 2008 and 2009 might be dominated by the strong shift from a negative to positive polity score.

Over the years under consideration, the likelihood of Bangladesh being below the GINI threshold increases and of being below the carbon threshold decreases. A strong decrease in $fossil$ is counteracting here and increases the likelihood of being below the carbon threshold. Bangladesh exhibits a small likelihood of 0.1 to 0.4 percent of falling into the socially and environmentally sustainable space in 2008–2014 with decreasing probability over time. Reducing the share of the service sector and fossil energy share results in a high likelihood of falling below the carbon threshold but a low likelihood of falling into the potentially socially and environmentally safe space. The considered cases for Tanzania exhibit no probability of being in the socially and environmentally sustainable area. Also the likelihood of Tanzania to be below the GINI threshold is close to zero. However, a rise in the share of fossil energy increases this likelihood. Similar to Bangladesh, the likelihood of being below the carbon threshold decreases with the increase of $fossil$.

Table 8: 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 A28.

Case	Country	*year*	*polity*	$fossil$	$Service$	K's τ	TH $GINI$	TH *carbon*	SES Space
16	Bangladesh	1997	6	56.57	49.93	0.359	0	0.543	0
17	Bangladesh	2008	-6	67.58	52.93	0.328	0.014	0.114	0.004
18	Bangladesh	2009	5	69.01	53.32	0.244	0.016	0.049	0.002
19	Bangladesh	2014	1	73.77	53.64	0.06	0.051	0.009	0.001
19a	Bangladesh	2014	1	50	53.64	0.306	0.004	0.057	0.001
19b	Bangladesh	2014	1	10	53.64	0.567	0	0.774	0
19c	Bangladesh	2014	10	73.77	53.64	0	0.045	0.003	0
19d	Bangladesh	2014	3	73.77	53.64	0.046	0.05	0.007	0
19e	Bangladesh	2014	1	73.77	20	-0.589	0.168	0	0
19f	Bangladesh	2014	1	10	20	-0.124	0.004	0.809	0.003
20	Tanzania	1997	-1	7.69	35.43	0.248	0	1	0
21	Tanzania	2008	-1	9.8	43.72	0.349	0	0.953	0
22	Tanzania	2009	-1	9.29	44.55	0.359	0	0.956	0
23	Tanzania	2014	-1	14.38	41.3	0.142	0	0.766	0
23a	Tanzania	2014	-1	80	41.3	-0.481	0.128	0.001	0
23b	Tanzania	2014	-1	50	41.3	-0.243	0.009	0.037	0
23c	Tanzania	2014	10	14.38	41.3	0.072	0	0.85	0
23d	Tanzania	2014	3	14.38	41.3	0.118	0	0.796	0
23e	Tanzania	2014	-1	14.38	20	-0.375	0.001	0.778	0
23f	Tanzania	2014	-1	10	20	-0.342	0.001	0.907	0

The contour plots in Figure 8 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 8 and cases 23, 23a and 23c in the second row of Figure 8. 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.

A reduction of the service sector leads to a negative relation between carbon emissions and income inequality in Bangladesh and Tanzania. The negative relation is accompanied by a reduction in income inequality and an increase in carbon emissions. Thus, the service sector is causing inequality, that leads to less carbon emissions, probably driven by the concave environmental Engel curve (Sager, 2019) or the individual Kuznets curve, where the poor drop out the carbon economy and only a few rich can afford carbon consumption (Acheampong et al., 2021). The negative relation to $fossil$ is in line with these observations and also suggests the mechanisms explained in the individual Kuznets curve. 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). Even though polity exhibits no statistically significant relation, an artificial increase in $polity$ (and the changes in Bangladesh in 2008-2009) leads to a visible change in Kendall's τ in the cases under investigation, indicating some political economy effect.

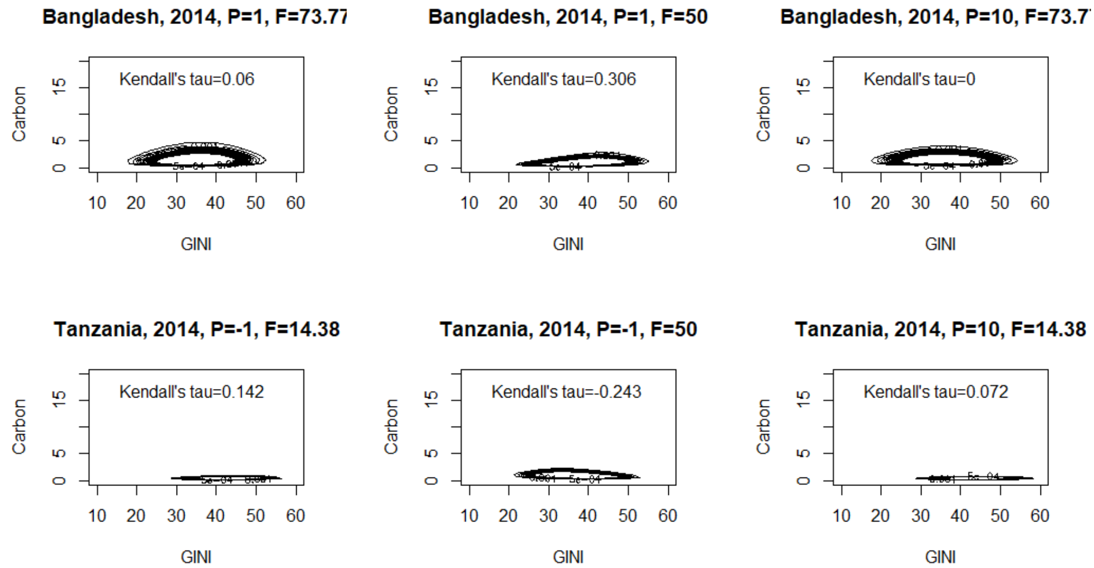

Figure 8: Contour plots for Bangladesh and Tanzania in 2014. Contour plots for China and South Africa in 2014. The first column shows the original setting, second column refers to changes in $fossil$ and the third column to changes in $polity$ the remaining covariates are set to their actual value.

5 Conclusions

Heterogeneous dependence between income inequality and carbon emissions reveals multiple channels for a potential sustainable future. Along these lines, there is no straightforward solution for the world. Rather we need varying strategies as unique country settings imply synergies, decoupling or trade-offs between inequality and emissions. To disentangle the complexity, we use novel distributional copula models stratified with respect to high-, middle- and low-income countries. Our analysis supports multiple previous studies in finding differing relationships between income inequality and carbon emissions for these country groups (Grunewald et al., 2017; Jorgenson et al., 2016; Knight et al., 2017). We advance their findings by studying influencing factors on the relationship and the likelihood that a country achieves inequality and emissions thresholds for potential sustainability. We expect the transmission channels to vary by country setting, which our distributional copula approach makes apparent.

The potential for a sustainable future differs between country groups and across related factors. We find the potential for social sustainability to be the highest in high-income countries. In the US, this goal is largely coupled to the service sector. In difference, the threshold for low emissions is likely to be achieved in low-income countries. In high-income countries there is only potential when two channels are addressed: a fossil energy and service sector share reduction or rather transformation. This implies that technical as well as structural innovations are needed. The structure within the service sector seems to play a crucial role, especially related to its inequality and carbon intensity. This contradicts the implications from both the Kuznets and the environmental Kuznets curve. To understand this relationship in depth, further studies on the disaggregated level – especially differentiating between public and private sector services – are necessary. This is not only relevant for the relation between income inequality and carbon emissions, but particularly for the creation of more resilient economic structures in light of crises, for example, induced by environmental or pandemic events.

Furthermore, reducing the share of fossil fuel energy in high-income countries leads to more income equality, resulting in a higher likelihood of being below the GINI threshold. Consequently, reducing fossil fuels is not hampering equality but is favorable for a more equal society. In middle-income countries reducing the share of fossil energy already leads to the achievement of emission targets. However, in this scenario inequality likely increases. Additionally, the results indicate a trade-off between income equality and low carbon emissions in low- and middle-income countries, underpinning the dependence on fossil energy for the development path of these countries. Thus, when targeting a reduction of fossil energy shares, further supporting social policies are needed to dissolve the dependence and prevent increasing inequality.

Additionally, the effect heterogeneities among the country groups enable us to draw conclusions on global structures. Different within-country findings for the effect of fossil energy share and democracy score likely reflect international dynamics, whereby poor countries disproportionately bear the costs of climate change, while rich countries disproportionately benefit from environmental exploitation. Further research needs to understand the complex systems and to suggest efficient pathways and global solutions for the transition into a socially and environmentally sustainable future.

Our results show the importance of deeper understanding the relationship between ecologically and social sustainability. Future research should study specific channels in more detail. To provide more precise estimates one can extend the present copula modeling framework, for instance by taking dependencies over the development paths (e.g. by cointegrating relations) into account. Such models should consider alternative measures of environmental pollution. Due to a higher immediacy of the results, countries might be more easily convinced to reduce emission variables such as SO_2 or NO_x (Iwata et al., 2010). We suspect similar dependence patterns for these measures. Thus, social and environmental dimension need to be addressed jointly by considering their heterogeneous interdependence for the transition into a sustainable future.

Abbreviations

AIC	Akaike Information Criterion
AME	Average marginal effects
BIC	Bayesian Information Criterion
BRI	Belt Road Initiative
CDF	Cumulative distribution function
CO2	Carbon Dioxide
EKC	Environmental Kuznets curve
EEC	Environmental Engel curves
GAMLSS	Generalized additive models for location scale and shape
GDP	Gross Domestic Product
Mt	Mega Tonnes
NO_x	Nitrogen dioxide
QQ-plots	Quantile-quantile-plots
SES	Socially and environmentally sustainable area
SO_2	Sulphur dioxide
US	United States

References

Acheampong, A. O., J. Dzator, and M. Shahbaz (2021). Empowering the powerless: Does access to energy improve income inequality? *Energy Eco-*

nomics 99, 105288.

Alcántara, V. and E. Padilla (2009). Input–output subsystems and pollution: an application to the service sector and CO2 emissions in Spain. *Ecological Economics 68*(3), 905–914.

Anand, S. and S. R. Kanbur (1993). The Kuznets process and the inequality-development relationship. *Journal of Development Economics 40*(1), 25–52.

Andersson, F. N. (2023). Income inequality and carbon emissions in the united states 1929–2019. *Ecological Economics 204*, 107633.

Baloch, M. A., S. U.-D. Khan, Z. Ş. Ulucak, A. Ahmad, et al. (2020). Analyzing the relationship between poverty, income inequality, and co2 emission in sub-saharan african countries. *Science of the Total Environment 740*, 139867.

Baymul, C. and K. Sen (2019). Kuznets revisited: what do we know about the relationship between structural transformation and inequality? *Asian Development Review 36*(1), 136–167.

Berthe, A. and L. Elie (2015). Mechanisms explaining the impact of economic inequality on environmental deterioration. *Ecological Economics 116*, 191 – 200.

Boyce, J. K. (1994). Inequality as a cause of environmental degradation. *Ecological Economics 11*(3), 169–178.

Boyce, J. K. (2018). The environmental cost of inequality. *Scientific American 319(5)*, 72–77.

Caron, J. and T. Fally (2018). Per capita income, consumption patterns, and CO2 emissions. *National Bureau of Economic Research Working Paper 24923*.

Center for Systemic Peace (2020). INSCR data page. `http://www.systemicpeace.org/inscrdata.html`, retrieved: 23.8.2020.

Comin, D., D. Lashkari, and M. Mestieri (2021). Structural change with long-run income and price effects. *Econometrica 89*(1), 311–374.

Demir, C., R. Cergibozan, and A. Gök (2019). Income inequality and co2 emissions: Empirical evidence from turkey. *Energy & Environment 30*(3), 444–461.

Drupp, M. A., U. Kornek, J. N. Meya, and L. Sager (2021). Inequality and the environment: The economics of a two-headed hydra. *CESifo Working Paper No 9447*.

Dunlap, R. E. and R. J. Brulle (Eds.) (2015). *Climate Change and Society: Sociological Perspectives*. New York: Oxford University Press.

Eizenberg, E. and Y. Jabareen (2017). Social sustainability: a new conceptual framework. *Sustainability 9*(1), 68.

Fahrmeir, L., T. Kneib, S. Lang, and B. Marx (2013). *Regression: Models, Methods and Applications*. Berlin: Springer.

Fanning, A. L., D. W. O'Neill, J. Hickel, and N. Roux (2022). The social shortfall and ecological overshoot of nations. *Nature Sustainability 5*, 26–26.

Fix, B. (2019). Dematerialization through services: evaluating the evidence. *BioPhysical Economics and Resource Quality 4*(2), 1–17.

Folbre, N., L. Gautham, and K. Smith (2021). Essential workers and care penalties in the United States. *Feminist Economics 27*(1-2), 173–187.

Global Carbon Project (2020). Global carbon atlas. `http://www.globalcarbonatlas.org/en/CO2-emissions`, retrieved: 1.9.2020.

Grunewald, N., S. Klasen, I. Martínez-Zarzoso, and C. Muris (2017). The trade-off between income inequality and carbon dioxide emissions. *Ecological Economics 142*, 249–256.

Harlan, S. L., Pellow, David N., Roberts, J. Timmons, S. E. Bell, W. G. Holt, and J. Nagel (2015). Climate Justice and Inequality. In R. E. Dunlap and R. J. Brulle (Eds.), *Climate Change and Society: Sociological Perspectives*, pp. 127–163. New York: Oxford University Press.

Hausfather, Z. (2019). Analysis: Why children must emit eight times less CO2 than their grandparents. `https://www.carbonbrief.org/analysis-why-children-must-emit-eight-times-less-co2-than-their-grandparents`, retrieved: 27.01.2021.

Heerink, N., A. Mulatu, and E. Bulte (2001). Income inequality and the environment: aggregation bias in environmental kuznets curves. *Ecological Economics 38*(3), 359–367.

Hickel, J. and G. Kallis (2020). Is green growth possible? *New Political Economy 25*(4), 469–486.

Iwata, H., K. Okada, and S. Samreth (2010). Empirical study on the environmental Kuznets curve for CO2 in France: the role of nuclear energy. *Energy Policy 38*(8), 4057–4063.

Jespersen, J. (1999). Reconciling environment and employment by switching from goods to services? A review of Danish experience. *European Environment 9*(1), 17–23.

Jorgenson, A., J. Schor, and X. Huang (2017). Income inequality and carbon emissions in the United States: a state-level analysis, 1997–2012. *Ecological Economics 134*, 40–48.

Jorgenson, A. K., J. B. Schor, K. W. Knight, and X. Huang (2016). Domestic inequality and carbon emissions in comparative perspective. *Sociological Forum 31*(1), 770–786.

Kahn, M. E. (1998). A household level environmental Kuznets curve. *Economics Letters 59*(2), 269–273.

Kasperson, R. E. and J. X. Kasperson (2001). *Climate Change, Vulnerability, and Social Justice.* Stockholm: Stockholm Environment Institute.

Khan, H., L. Weili, and I. Khan (2023). The effect of political stability, carbon dioxide emission and economic growth on income inequality: evidence from developing, high income and belt road initiative countries. *Environmental Science and Pollution Research 30*(3), 6758–6785.

Khan, S. and W. Yahong (2021). Symmetric and asymmetric impact of poverty, income inequality, and population on carbon emission in pakistan: new evidence from ardl and nardl co-integration. *Frontiers in Environmental Science 9*, 666362.

Khan, S., W. Yahong, and A. Zeeshan (2022). Impact of poverty and income inequality on the ecological footprint in asian developing economies: Assessment of sustainable development goals. *Energy Reports 8*, 670–679.

Klasen, S. (2018). Inequality and greenhouse gas emissions. *Journal of Income Distribution 26*(3), 1–14.

Klein, N., T. Kneib, G. Marra, R. Radice, S. Rokicki, and M. E. McGovern (2019). Mixed binary-continuous copula regression models with application to adverse birth outcomes. *Statistics in Medicine 38*(3), 413–436.

Knight, K. W., J. B. Schor, and A. K. Jorgenson (2017). Wealth inequality and carbon emissions in high-income countries. *Social Currents 4*(5), 403–412.

Kuznets, S. (1955). Economic growth and income inequality. *The American Economic Review 45*(1), 1–28.

Mader, S. (2018). The nexus between social inequality and co2 emissions revisited: Challenging its empirical validity. *Environmental Science & Policy 89*, 322–329.

Marra, G. and R. Radice (2017). Bivariate copula additive models for location, scale and shape. *Computational Statistics & Data Analysis 112*, 99–113.

Marra, G. and R. Radice (2020). GJRM: Generalised Joint Regression Modelling. R package version 0.2-2. `https://cran.r-project.org/web/packages/GJRM/`, retrieved: 20.10.2020.

Martínez Alier, J. (2002). *The Environmentalism of the Poor: A Study of Ecological Conflicts and Valuation*. Cheltenham: Edward Elgar.

Masud, M. M., F. Kari, H. Banna, and M. K. Saifullah (2020). Does income inequality affect environmental sustainability? evidence from the asean-5. In *Climate Change Mitigation and Sustainable Development*, pp. 27–42. Routledge.

Milanović, B. (2000). Determinants of Cross-Country Income Inequality: An 'Augmented' Kuznets Hypothesis. In V. Franičević and M. Uvalić (Eds.), *Equality, Participation, Transition*, pp. 48–79. London: Palgrave Macmillan.

Mileti, D. S. (1999). *Disasters by Design: a Reassessment of Natural Hazards in the United States*. Washington, DC: Joseph Henry Press.

Nguyen, C. P. and M. A. Nasir (2021). An inquiry into the nexus between energy poverty and income inequality in the light of global evidence. *Energy Economics 99*, 105289.

O'Neill, D., A. L. Fanning, W. F. Lamb, and J. Steinberger (2018). A good life for all within planetary boundaries. *Nature Sustainability 1*(2), 88–95.

Oswald, Y., A. Owen, and J. K. Steinberger (2020). Large inequality in international and intranational energy footprints between income groups and across consumption categories. *Nature Energy 5*(3), 231–239.

Panayotou, T., A. Peterson, and J. D. Sachs (2000). Is the environmental Kuznets curve driven by structural change? What extended time series may imply for developing countries. *Consulting Assistance on Economic Reform II CAER II Discussion Paper No. 80.*

Parrique, T., J. Barth, F. Briens, C. Kerschner, A. Kraus-Polk, A. Kuokkanen, and J. Spangenberg (2019). *Decoupling debunked. Evidence and arguments against green growth as a sole strategy for sustainability.* European Environment Bureau.

Peters, G. P., J. C. Minx, C. L. Weber, and O. Edenhofer (2011). Growth in emission transfers via international trade from 1990 to 2008. *National Academy of Sciences 108*(21), 8903–8908.

Pickett, K. E. and R. G. Wilkinson (2010). Inequality: an underacknowledged source of mental illness and distress. *The British Journal of Psychiatry 197*(6), 426–428.

Pickett, K. E. and R. G. Wilkinson (2015). Income inequality and health: a causal review. *Social Science & Medicine 128*, 316–326.

Ritchie, H. and M. Roser (2021). CO2 Emissions. Our World in Data. `https://ourworldindata.org/co2-emissions`, retrieved: 27.01.2021.

Roca, J. (2003). Do individual preferences explain the environmental Kuznets curve? *Ecological Economics 45*(1), 3–10.

Roemer, J. E. (1993). Would economic democracy decrease the amount of public bads? *The Scandinavian Journal of Economics 95*(2), 227–238.

Sager, L. (2019). Income inequality and carbon consumption: Evidence from environmental engel curves. *Energy Economics 84*, 104507.

Scholl, N. and S. Klasen (2019). Re-estimating the relationship between inequality and growth. *Oxford Economic Papers 71*(4), 824–847.

Scruggs, L. A. (1998). Political and economic inequality and the environment. *Ecological Economics 26*(3), 259–275.

Solt, F. (2016). The standardized world income inequality database: SWIID version 6.0, July 2017. *Social Science Quarterly 97*(5), 1267–1281.

Solt, F. (2020). Measuring income inequality across countries and over time: the standardized world income inequality database. *Social Science Quarterly 101*(3), 1183–1199.

Suh, S. (2006). Are services better for climate change? *Environmental Science & Technology 40*(21), 6555–6560.

Sun, Y. (2023). Income inequality, carbon emissions, and green development efficiency. *Environmental Science and Pollution Research 30*(8), 21081–21091.

Torras, M. and J. K. Boyce (1998). Income, inequality, and pollution: a reassessment of the environmental Kuznets curve. *Ecological Economics 25*(2), 147 – 160.

Uddin, M. M., V. Mishra, and R. Smyth (2020). Income inequality and CO2 emissions in the G7, 1870–2014: Evidence from non-parametric modelling. *Energy Economics 88*, 104780.

Veblen, T. (1899). *The Theory of the Leisure Class: An Economic Study of Institutions*. London: Macmillan.

Wan, G., C. Wang, J. Wang, and X. Zhang (2022). The income inequality-CO2 emissions nexus: Transmission mechanisms. *Ecological Economics 195*, 107360.

Wang, Q., L. Li, and R. Li (2023). Uncovering the impact of income inequality and population aging on carbon emission efficiency: an empirical analysis of 139 countries. *Science of The Total Environment 857*, 159508.

Weil, D. N. (2012). *Economic Growth*. Boston: Pearson Addison Wesley.

Wilkinson, R. G. and K. E. Pickett (2009). Income inequality and social dysfunction. *Annual Review of Sociology 35*, 493–511.

Wilkinson, R. G. and K. E. Pickett (2017). The enemy between us: the psychological and social costs of inequality. *European Journal of Social Psychology 47*(1), 11–24.

Wilkinson, R. G., K. E. Pickett, and R. De Vogli (2010). Equality, sustainability, and quality of life. *British Medical Journal 341*, 1138–1140.

World Bank (2020a). World bank country and lending groups. `https://datahelpdesk.worldbank.org/knowledgebase/articles/906519`, retrieved: 08.10.2020.

World Bank (2020b). World development indicators. `https://data.worldbank.org/data-catalog/world-development-indicators`, retrieved: 10.08.2020.

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		Papua New Guinea
Austria			Philippines
	Argentina	Bangladesh	Rwanda
Belgium	Armenia	Benin	Senegal
Canada	Azerbaijan		
Chile	Belarus	Bolivia	
Croatia		Burkina Faso	
Cyprus	Botswana		
Czech Republic	Brazil	Cambodia	
Denmark	Bulgaria	Cameroon	
Estonia	China		Tanzania
Finland	Colombia		Togo
France	Costa Rica		Tunisia
Germany	Dominican Republic		
Greece	Ecuador		Uganda
Hungary		Egypt	Ukraine
Ireland		El Salvador	
Israel		Ethiopia	Vietnam
Italy	Georgia		
Japan	Guatemala	Ghana	Zambia
		Guinea	Zimbabwe
Latvia	Iran		
Lithuania			
Luxembourg	Jamaica	Honduras	
Netherlands	Jordan	India	
New Zealand	Kazakhstan	Indonesia	
Norway		Kenya	
		Kyrgyzstan	
		Laos	
Poland	Malaysia		
Portugal	Mauritius		
Qatar	Mexico	Madagascar	
Saudi Arabia		Malawi	
Singapore	Namibia		
Slovakia	Paraguay		
Slovenia	Peru		
Spain	Romania	Mongolia	
	Russia		
Sweden		Morocco	
Switzerland	South Africa	Mozambique	
Trinidad and Tobago	Sri Lanka		
		Nepal	
United Kingdom	Thailand	Nicaragua	
United States of America	Turkey		
Uruguay		Nigeria	
	Venezuela	Pakistan	
39	32	38	

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 A9, the respective parameter estimates (Table A5-A8) and splines (Figure A10-A13) for the distribution parameter of the marginals $\theta_1 - \theta_4$ and several alternative country cases in Table A10.

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

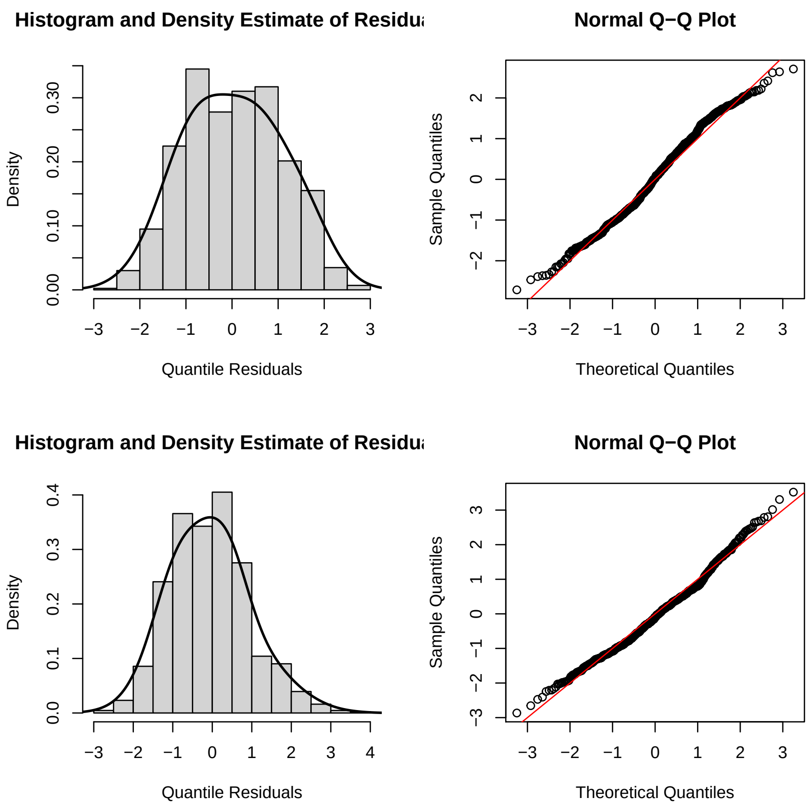

Figure A9: Histogram and QQ-plot for model residuals for high-income countries
Note: The first row shows the histogram and normal Q-Q Plot of the log-normal margin of the variable $GINI$. The second row shows the histogram and normal Q-Q Plot of the log-normal margin of the variable *carbon* for the final copula model of 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

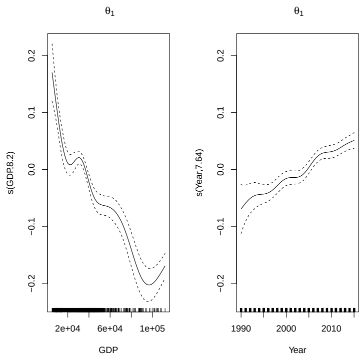

Figure A10: Spline for GDP and $year$ for parameter θ_1 for high-income countries

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

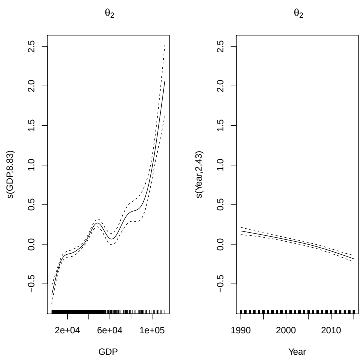

Figure A11: Spline for GDP and $year$ for θ_2 for high-income countries

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

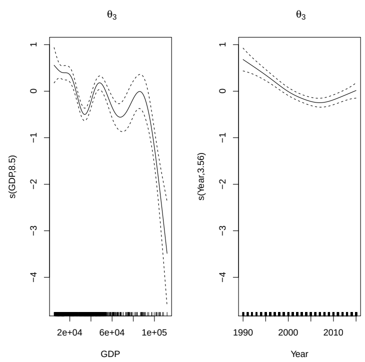

Figure A12: Spline for GDP and $year$ for θ_3 for high-income countries

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

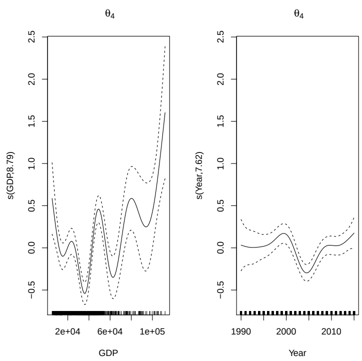

Figure A13: Spline for GDP and $year$ for θ_4 for high-income countries

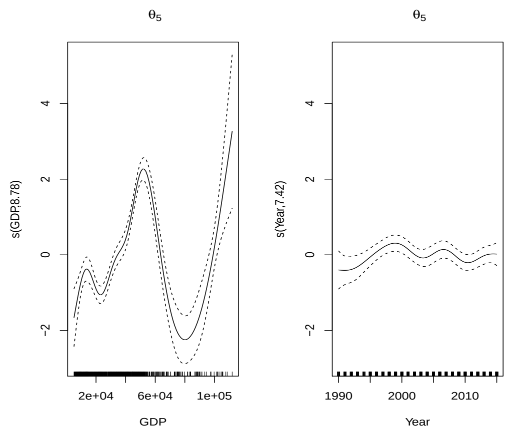

Figure A14: High-income countries: splines for GDP and $year$ for the copula parameter. The splines for the other model equations are in Figures A10-A13.

Table A9: 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

Table A10: 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*	$fossil$	$Service$	K's τ	TH $GINI$	TH *carbon*	SES Space
France	1997	10	52.9	65.4	0.483	0.021	0	0
France	2008	9	50.84	69.65	0.714	0.001	0	0
France	2009	9	50.85	70.75	0.617	0	0	0
France	2015	9	46.49	70.21	0.753	0.003	0	0
France	2015	9	80	70.21	0.362	0.002	0	0
France	2015	9	10	70.21	0.918	0.01	0	0
France	2015	10	46.49	70.21	0.712	0.007	0	0
France	2015	3	46.49	70.21	0.902	0	0	0
France	2015	9	46.49	20	-0.856	0.634	0	0
France	2015	9	10	20	-0.575	0.688	0.007	0
Australia	1997	10	93.51	63.33	-0.237	0.18	0	0
Australia	2008	10	94.35	64.49	0.597	0.215	0	0
Australia	2009	10	95.51	64.14	0.5	0.261	0	0
Australia	2015	10	89.63	67.29	0.606	0.16	0	0
Australia	2015	10	50	67.29	0.879	0.251	0	0
Australia	2015	10	10	67.29	0.964	0.491	0.001	0.001
Australia	2015	9	89.63	67.29	0.66	0.125	0	0
Australia	2015	3	89.63	67.29	0.865	0.01	0	0

Australia	2015	10	89.63	20	-0.889	0.573	0	0
Australia	2015	10	10	20	-0.004	0.655	0.05	0.033
United Kingdom	1997	10	86.72	65.29	-0.433	0.036	0	0
United Kingdom	2008	10	90.18	69.79	-0.152	0.013	0	0
United Kingdom	2009	10	87.37	71.61	-0.253	0	0	0
United Kingdom	2015	10	80.35	70.41	0.106	0.037	0	0
United Kingdom	2015	10	50	70.41	0.589	0.056	0	0
United Kingdom	2015	10	10	70.41	0.875	0.161	0	0
United Kingdom	2015	9	80.35	70.41	0.203	0.022	0	0
United Kingdom	2015	3	80.35	70.41	0.65	0	0	0
United Kingdom	2015	10	80.35	20	-0.967	0.583	0	0
United Kingdom	2015	10	10	20	-0.72	0.66	0.007	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 A11-A13, plot of the model residuals for the selected setting in Figure A15, the respective parameter estimates (Table A14-A17) and splines (Figure A16-A19) for the distribution parameter of the marginals $\theta_1 - \theta_4$ and several alternative country cases in Table A19.

Table A11: 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 A12: 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 A13: 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

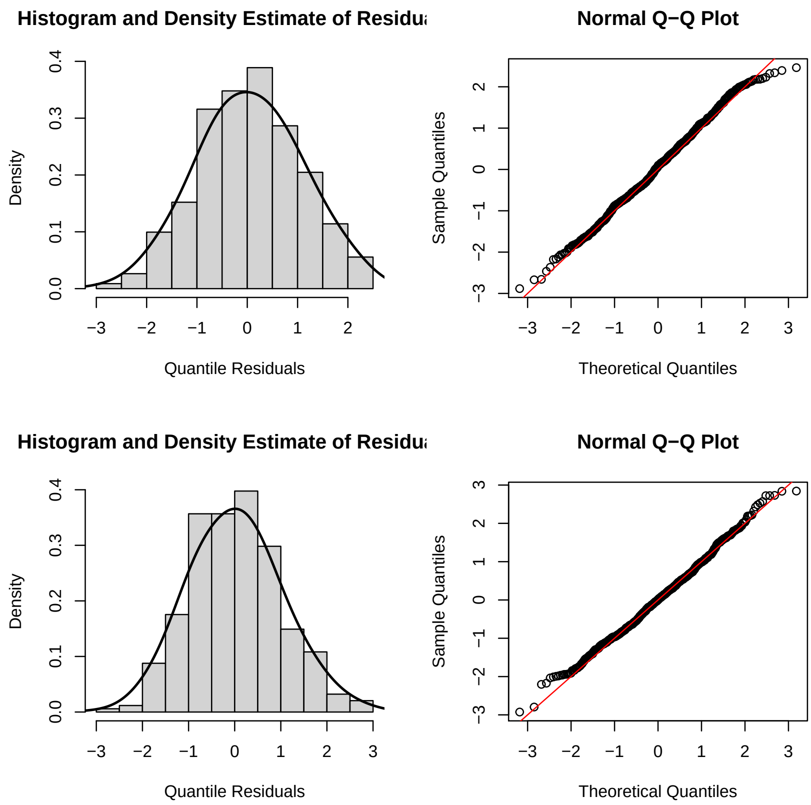

Figure A15: Histogram and QQ-plot for model residuals for middle-income countries

Note: The first row shows the histogram and normal Q-Q Plot of the normal margin of the variable $GINI$. The second row shows the histogram and normal Q-Q Plot of the log-normal margin of the variable *carbon* for the final copula model of middle income countries.

Table A14: 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

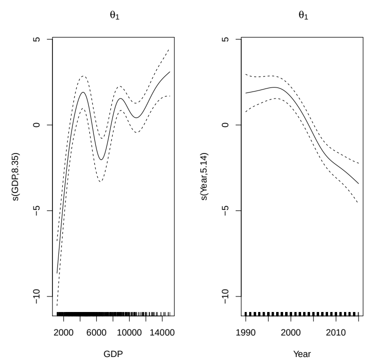

Figure A16: Spline for GDP and $year$ for θ_1 for middle-income countries

Table A15: 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

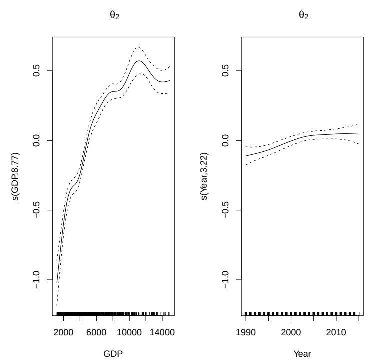

Figure A17: Spline for GDP and $year$ for θ_2 for middle-income-countries

Table A16: 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

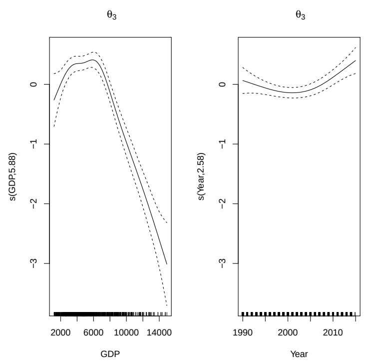

Figure A18: Spline for GDP and $year$ for θ_3 for middle-income countries

Table A17: 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

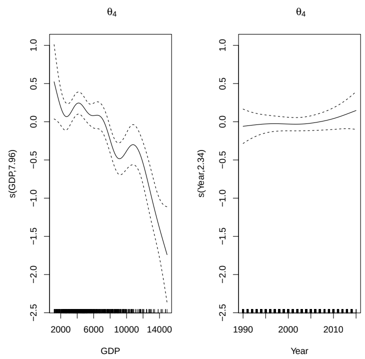

Figure A19: Spline for *GDP* and *year* for θ_4 for middle-income countries

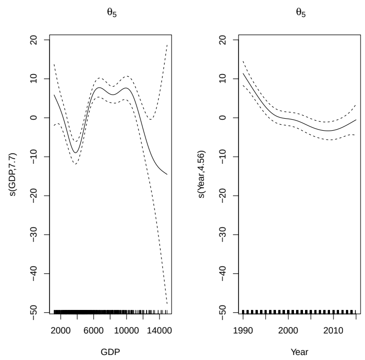

Figure A20: Middle-income countries: splines for *GDP* and *year* for the copula parameter. The splines for the other model equations are in Figure A16-A19.

Table A18: Middle-income countries, $n = 636$: equation for the copula parameter θ_5. Tables A14 -A17 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

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 A20-A22, plot of the model residuals for the chosen setting in Figure A21, the respective parameter estimates (Table A23-A26) and splines (Figure A22-A25) for the distribution parameter of the marginals $\theta_1 - \theta_4$ and several alternative country cases in Table A28.

Table A20: 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: 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*	*Service*	K's τ	TH $GINI$	TH *carbon*	SES Space
Argentina	1997	7	86.9	60.85	-0.673	0	0	0
Argentina	2008	8	90.65	50.26	-0.626	0	0	0
Argentina	2009	8	89.61	53.31	-0.644	0	0	0
Argentina	2014	8	87.72	52.94	-0.584	0	0	0
Argentina	2014	8	50	52.94	-0.799	0	0	0
Argentina	2014	8	10	52.94	-0.871	0	0.012	0
Argentina	2014	10	87.72	52.94	-0.51	0	0	0
Argentina	2014	3	87.72	52.94	-0.7	0	0	0
Argentina	2014	8	87.72	20	-0.147	0.226	0	0
Argentina	2014	8	10	20	-0.839	0	0.034	0
Brazil	1997	8	56.68	60.61	-0.685	0	0	0
Brazil	2008	8	52.57	56.8	-0.796	0	0	0
Brazil	2009	8	51.32	59.15	-0.795	0	0	0
Brazil	2014	8	59.11	61.25	-0.828	0	0	0
Brazil	2014	8	80	61.25	-0.772	0	0	0
Brazil	2014	8	10	61.25	-0.892	0	0.002	0
Brazil	2014	10	59.11	61.25	-0.816	0	0	0
Brazil	2014	3	59.11	61.25	-0.853	0	0	0
Brazil	2014	8	59.11	20	-0.744	0.005	0	0
Brazil	2014	8	10	20	-0.863	0	0.013	0
Russia	2008	4	90.95	50.7	-0.593	0	0	0
Russia	2009	4	90.16	53.77	-0.372	0	0	0
Russia	2014	4	92.14	55.68	-0.595	0	0	0
Russia	2014	4	50	55.68	-0.813	0	0	0
Russia	2014	4	10	55.68	-0.877	0	0.001	0
Russia	2014	10	92.14	55.68	-0.323	0	0	0
Russia	2014	8	92.14	55.68	-0.438	0	0	0
Russia	2014	4	92.14	20	-0.126	0.323	0	0
Russia	2014	4	10	20	-0.845	0	0.01	0

Table A21: 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 A22: 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

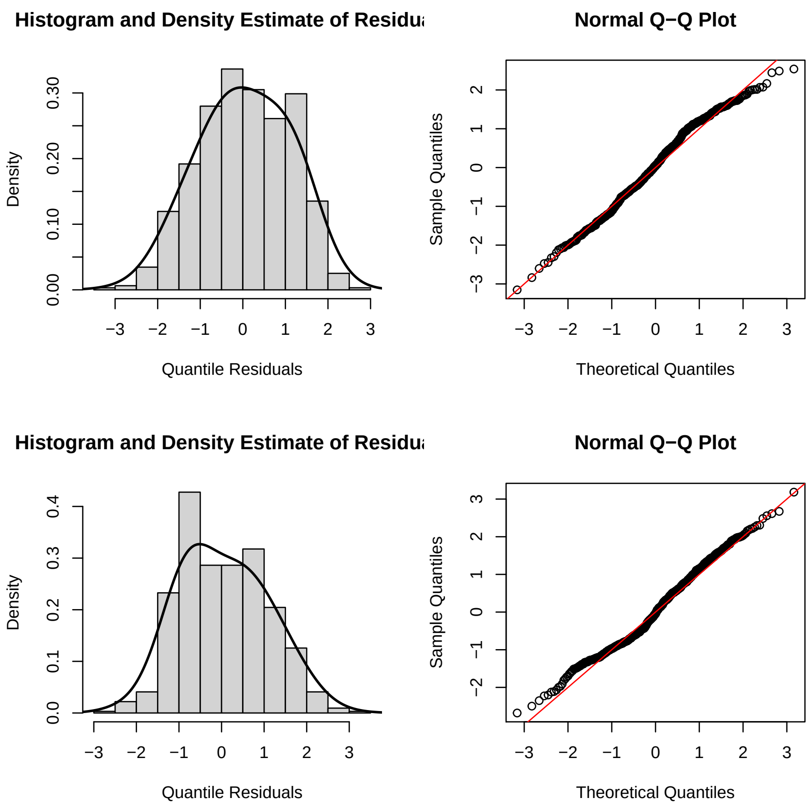

Figure A21: Histogram and QQ-plot for model residuals for low-income countries

Note: The first row shows the histogram and normal Q-Q Plot of the normal margin of the variable $GINI$. The second row shows the histogram and normal Q-Q Plot of the log-normal margin of the variable *carbon* for the final copula model of low income countries.

Table A23: 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

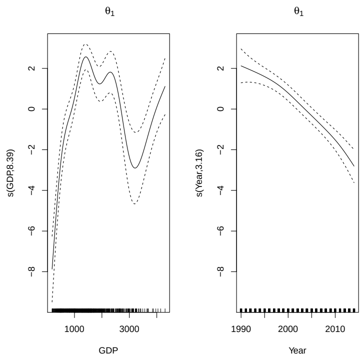

Figure A22: Spline for *GDP* and *year* for θ_1 for low-income countries

Table A24: 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

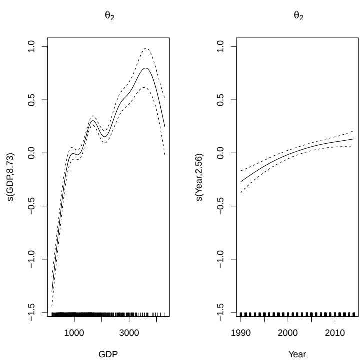

Figure A23: Spline for *GDP* and *year* for θ_2 for low-income countries

Table A25: 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

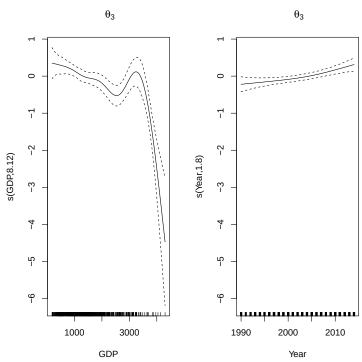

Figure A24: Spline for GDP and $year$ for θ_3 for low-income countries

Table A26: 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

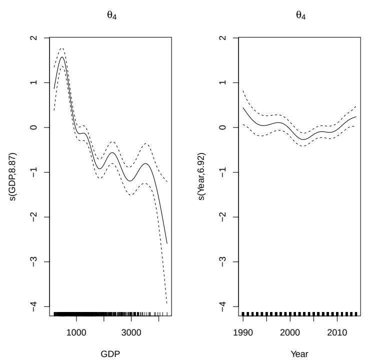

Figure A25: Spline for *GDP* and *year* for θ_4 for low-income countries

Table A27: Low-income countries: equation for the copula parameter, n = 898. All results for the model parameters are in Table A23-A26.

	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

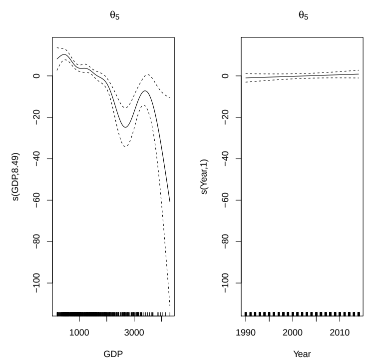

Figure A26: Low-income countries: splines for *GDP* and *year* for the copula parameter. The splines for the other model equations are in Figures A22-A25.

Table A28: 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*	$fossil$	*Service*	K's τ	TH $GINI$	TH *carbon*	SES Space
Bolivia	1997	9	78.35	49.22	-0.3	0	0.026	0
Bolivia	2008	8	82.6	40.5	-0.599	0.008	0	0
Bolivia	2009	7	80.96	43.51	-0.562	0.007	0.001	0
Bolivia	2014	7	84.15	41.47	-0.811	0.007	0.063	0
Bolivia	2014	7	50	41.47	-0.773	0	0.156	0
Bolivia	2014	7	10	41.47	-0.706	0	0.577	0
Bolivia	2014	10	84.15	41.47	-0.813	0.007	0.054	0
Bolivia	2014	3	84.15	41.47	-0.809	0.007	0.076	0
Bolivia	2014	7	84.15	20	-0.848	0.048	0.017	0
Bolivia	2014	7	10	20	-0.787	0	0.566	0
India	1997	8	61.77	39.08	-0.137	0.001	0.11	0
India	2008	9	69.01	45.88	-0.232	0.002	0	0
India	2009	9	71.14	45.98	-0.251	0.002	0	0
India	2012	9	72.42	46.3	-0.406	0.004	0	0
India	2012	9	50	46.3	-0.211	0	0	0
India	2012	9	10	46.3	0.218	0	0.615	0
India	2012	10	72.42	46.3	-0.411	0.004	0	0
India	2012	3	72.42	46.3	-0.38	0.004	0	0
India	2012	9	72.42	20	-0.684	0.044	0	0
India	2012	9	10	20	-0.408	0	0.455	0
Egypt	1997	-6	94.16	48.15	-0.572	0.001	0	0
Egypt	2008	-3	96.16	46.67	-0.868	0.001	0	0
Egypt	2009	-3	96.4	46.57	-0.875	0.004	0	0
Egypt	2014	-4	97.93	52.32	-0.871	0.039	0	0
Egypt	2014	-4	50	52.32	-0.847	0	0	0
Egypt	2014	-4	10	52.32	-0.818	0	0.094	0
Egypt	2014	10	97.93	52.32	-0.874	0.028	0	0
Egypt	2014	3	97.93	52.32	-0.873	0.033	0	0
Egypt	2014	-4	97.93	20	-0.897	0.135	0	0
Egypt	2014	-4	10	20	-0.866	0	0.006	0