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Abstract

Empirical studies of the relationship between GDP per capita and country-level CO_2 emissions tend to focus on the direct effect of per capita GDP growth, rarely taking political institutions into consideration. This paper introduces theoretical insights from environmental political science research, which suggests that CO_2 emissions models would gain explanatory leverage if moderators gauging political institutions were considered. We test these theories by estimating the potentially moderating effects of democracy, corruption, veto points and players, and civil society activity. Our results suggest a positive and linear per capita GDP-CO_2 relationship, which is barely affected by any variations in political and institutional factors. The only significant moderator in our analysis is bicameralism in democratic, low corrupt countries, which generates a stronger effect of per capita GDP growth at low levels of GDP per capita. Our analysis thus lends rigor to studies in environmental economics that find a positive and linear per capita GDP-CO_2 relationship, and does not provide support for theories common in environmental political science research.

1. Introduction

To address the increasingly tangible threats of climate change, researchers seek to identify factors that can curb greenhouse gas emissions and particularly carbon dioxide (CO_2) emissions, which are the largest anthropogenic contributor to climate change. Economists often propagate the idea that the level of economic development is the strongest driver of CO_2 emissions. The «environmental Kuznets curve» (EKC) is a fundamental, yet controversial, hypothesis in this literature that predicts increased emissions as a consequence of industrialization and intensified production, and decreased emissions resulting from sectoral changes towards service and knowledge production as well as greener technologies (Panayotou, 1997; Stern, 2002; Tsurumi & Managi, 2010). Research in political science, however, claims that the change in countries' emitting behavior can hardly be attributed to economic factors alone. Lowering emissions requires environmental policies and is therefore also dependent on political institutions that shape policy adoption and implementation (Holmberg & Rothstein, 2012; Immergut & Orlowski, 2013; Payne, 1995; Scruggs, 1998, 1999, 2001). The aim of this paper is to test existing theories and examine if political and institutional traits moderate the relationship between economic development and emissions, such that rich well-governed countries emit less.

Theories in environmental political science emphasize a number of factors that affect emissions of greenhouse gases through the adoption and implementation of environmental policies. Democracy entails freedom of speech, opportunities for wide participation and representation, electoral accountability and the active participation of civil society, which it is argued pave the way for environmental policies to be placed on the political agenda (Li and Revenue 2006). The complexity of decision-making structures within government, defined by the number of political actors that have veto power over decision-making, determines how easy it is to adopt environmental laws once issues are present on the political agenda (Immergut, 2010). High corruption and low quality of the public administration responsible for implementation of policies is believed to hamper execution of environmental laws and regulations and disrupt the positive effect that economic growth and democratization might have on the environment (Damania 2002). Environmental political science theories therefore expect that political-institutional factors moderate the relationship between per capita GDP growth and CO_2 emissions by affecting environmental legislation and implementation. However, despite the fact that numerous studies consistently theorize such moderation (e.g., Arvin & Lew 2010, Spilker 2013), they do not model the interaction empirically and do not apply appropriate econometric models to test the relationship.

In this study, we address this research gap and challenge existing environmental political science theories by analyzing the per capita GDP-CO_2 relationship in interaction with a broad spectrum of political-institutional factors using methodologies established in economics. The contribution of our study is two-fold. First, we provide a theoretical framework bridging economics and environmental political science literatures, which can be useful for further research. And, second, our empirical analysis has several methodological advantages compared to previous studies on this subject. We analyze the relationship between GDP per capita and CO_2 emissions using Chudik and Pesaran's (2015) Dynamic Common Correlated Mean Group Estimator (DCCE), which provides a direct estimate of cointegration as well as controls for cross-sectional dependency and parameter heterogeneity. The DCCE estimator furthermore produces country-specific coefficients, which we then use in a cross-sectional analysis to examine linearity and estimate the effect of political and institutional factors on the per capita GDP-CO_2 relationship.

The remainder of the article proceeds as follows. We begin with a presentation of previous research on the relationship between per capita GDP growth, political institutions and CO_2 emissions. Thereafter, we describe our methodological and empirical approach, and proceed with the presentation of results. Lastly, we summarize our main findings in the concluding section, where we also discuss recommendations for policymakers and further research.

2. Theory

2.1. Environmental economics

The environmental economic literature typically describes three mechanisms through which per capita GDP growth is thought to affect environmental outcomes (e.g., CO_2 emissions): changes in the «scales», «compositions» and «technologies» of production. Changed scales refer to the fact that production is a component in GDP, which implies that increased GDP leads to more pollution unless the economy is only progressing in «green» sectors (Blanco et al., 2014; Panayotou, 1994). Compositional change implies that agriculture as well as service and knowledge production are more environmentally friendly than industrial production and manufacturing (Blanco et al., 2014; Panayotou, 1994). Additionally, it is argued that long-term increases in GDP per capita cause economies to develop from the primary sector towards secondary and tertiary forms of production, which contributes to an inverse U-shaped relationship between GDP and environmental degradation (Panayotou, 1994; Syrquin & Chenery, 1989). Lastly, technological change occurs if economic profits are used to build a more energy efficient or pollution-abating infrastructure, which decreases the amount of pollution per unit of production (unless environmental efficiency is already maximized) (Andreoni & Levinson, 2001; Brock & Taylor, 2005).

The relative effects of changes in the scale, composition and technology of production determine how per capita GDP growth relates to environmental outcomes. Increased GDP per capita leads to more pollution if scale change outweighs compositional and technological changes. Meanwhile, per capita GDP growth leads to less pollution if technological changes outweigh changes in the scale and composition of production, and pollution curbs along an inverse U-shaped slope (i.e. an EKC) if the compositional change outweighs changes in the scale and technology of production (or if the latter changes balance each other out). In this context, it is worth noting that the EKC hypothesis predicts environmental improvement as a happy coincidence, or by-product, of economic progress, and therefore does not differentiate between environmental substances. Put differently, economic development should predict global environmental problems like CO_2 emissions equally as well as SO_2 emissions, toxic waste, and other local environmental problems, if the stylized environmental economic theory is correct.

Although this stylized environmental economic theory does not address the role of government, it is common to argue that economic progress and environmental quality are linked through environmental policy decisions (Arrow et al., 1995; Kijima, Nishide, & Ohyama, 2010; Panayotou, 1997; Pasten & Figueroa, 2012). In this perspective, economic progress leads to an increased demand for environmental protection, and it provides resources that are necessary to feed this demand. There are two main reasons why economic progress is expected to increase the demand for environmental protection: First, because economic progress leads to increased environmental degradation unless the economy is regulated, and the extent of degradation causes more concern about the environment; second, high income generates a sense of material satisfaction, which leads to broadened and more altruistic political preferences (this development is sometimes labeled as «post-materialistic», see for example Inglehart & Welzel 2005). Politicians are consequently more inclined to pursue environmental policies after a period of economic progress, and it is policies that stimulate compositional- and technological change. If the effect of GDP per capita on emissions is indeed mediated by policy initiatives, political institutions that shape policy adoption and implementation are likely to moderate this effect.[1]

[1] Data limitations prevent us from examining the potentially mediating effect of environmental policies, but we examine if political-institutional features, which are likely to affect policy decisions and implementation, have an impact on the per capita GDP-CO_2 relationship. This moderation can only be explained if a sizable portion of the relationship is mediated by policy initiatives, and absence of moderation is only plausible if the effect of GDP per capita on CO_2 emissions is mainly direct.

The following section discusses how the per capita GDP-CO_2 relationship might be affected by specific political and institutional traits. Before we proceed with this discussion, it is however useful to notice that the empirical findings in environmental economic research are somewhat inconsistent. Several recent studies report a positive and linear effect of per capita GDP growth on CO_2 emissions (Berenguer-Rico, 2011; Liddle, 2015; Stern, 2010; Wagner, 2008, 2015), but a number of studies also find a negative relationship, or that emission levels curb along a U-shaped, N-shaped or inverse U-shaped slope as GDP per capita increases (Al-Mulali, Saboori, & Ozturk, 2015; Apergis, 2016; Kaika & Zervas, 2013a; Liao & Cao, 2013; Zapata & Pandel, 2009). Among the studies that find a positive and linear relationship between GDP per capita and CO_2 emissions, there is also a considerable variation in the reported effect size. Lack of empirical consistency is thus a part of this article's impetus, and we seek to provide more accurate estimates of CO_2 emissions by taking political-institutional conditions into account.

2.2. Environmental politics

The environmental politics literature discusses a large number of factors that may affect environmental policy adoption and implementation, and in this article we focus on the most prominent ones in the existing research: regime type, quality of institutions, policy implementation, complexity of decision-making structures, and the extent of civil society participation.[2]

Regime type shapes preference aggregation within a polity and is argued to affect the appearance of environmental policies on the political agenda (Li and Revenue 2006). Democracy, in particular, opens up opportunities for a wide representation of interests in power structures through free and fair elections and enables people to manifest their environmental preferences through political initiatives and to demand adoption of environmental policies (Dahl, 1973; O'donnell et al., 2004). This regime type furthermore entails free media, which spreads awareness about environmental issues among the population and allows citizens to make environmentally informed decisions. It also implies freedom of association, allowing civil society groups, including environmental non-governmental organizations, to organize and participate in public life, lobby their interests, and thus bring environmental issues onto the political agenda. Without these liberties, it is implausible that post-material value changes would lead to improved environmental outcomes through increasingly stringent environmental policies (Bättig &

[2] We acknowledge that other political institutions relating to policy diffusion (Holzinger, Knill, & Sommerer, 2008; Meseguer, 2004; Simmons & Elkins, 2004; Volden, 2006) and regulatory competitiveness (Holzinger, 2003; Holzinger & Sommerer, 2011; Lazer, 2001; Wheeler, 2001) can add to the theoretical framework. Data availability, however, prevents us from testing these theories and therefore we do not explicitly address them in this paper.

Bernauer, 2009; Li & Reuveny, 2006; Payne, 1995). Additionally, democracy safeguards a minimum level of economic redistribution, which facilitates development of post-material values through GDP growth (Acemoglu, Naidu, Restrepo, & Robinson, 2013; Inglehart & Welzel, 2005; Reuveny & Li, 2003; Welzel, 2013). Consequently, environmental political science theories imply a moderating effect of democracy on the relationship between economic development and emissions (Arvin & Lew, 2009; Spilker, 2013).

Although decisions to protect the environment and the presence of appropriate environmental policies are necessary for reaching desirable environmental outcomes, they are not necessarily sufficient. This brings us to the discussion of the second mechanism through which political institutions may impact environmental outcomes. The causation between policy decisions and intended outcomes requires a government that is capable of implementing such decisions. One of the most disruptive impediments towards higher government ability to implement environmental goals is corruption. Corruption opens up opportunities for public officials to enrich themselves instead of pursuing policy goals (Lewis, 2007), which can lead to inadequate environmental inspections, underreporting of actual emission levels and stimulate incompliance by polluters (Damania, 2002; Wilson & Damania, 2005). Clientelism and nepotism in hiring practices lead to lower competence levels among bureaucrats, as well as decreased commitments to policy objectives (Lewis, 2007). Thus it is reasonable to expect that incorrupt governments facilitate implementation of policy initiatives and help deliver desirable environmental outcomes. Existing research suggests that increased corruption is indeed associated with higher emissions, even when the level of economic development is accounted for (Cole, 2007; Pellegrini & Gerlagh, 2006; Welsch, 2004). However, corruption in itself does not generate emissions and we therefore argue that it is more accurate to consider whether corruption levels moderate the effect of per capita GDP on CO_2 emissions.

Existing studies seem to imply that democratic institutions and corruption-free public administration provide conditions that are necessary for the adoption and implementation of emission reduction policies, arguably constituting the ground pillars for GDP per capita's potential effect on emissions. We therefore expect that higher levels of democracy and freedom from corruption will help to transform economic progress into environmental improvement, and we examine the following hypothesis to test this claim:

H_1: The effect of economic development on CO_2 emissions is moderated by levels of democracy and corruption.

In addition to having a democratic and incorrupt government, it is also argued that increased participation of civil society moderates the relationship between economic development and the environment because environmental groups put additional pressure on politicians to adopt environmental policies (Duit, Hall, Mikusinski, & Angelstam, 2009; Fukuyama, 2001; Pretty & Ward, 2001; Putnam, Leonardi, & Nanetti, 1994). Citizens are also more likely to adopt egalitarian or altruistic values if they participate in civil society organizations (Duit et al., 2009; Inglehart & Welzel, 2005; Putnam, 2001; Putnam et al., 1994; Welzel, 2013), and it is therefore plausible that post-material value creation accelerates faster in highly active societies, as per capita GDP grows. The second hypothesis we examine is therefore the following:

H_2: The effect of economic development on CO_2 emissions is moderated by the extent of civil society participation.

A fourth, potential, mechanism goes though the structural organization of governments, which is likely to affect environmental decision-making and policy setting within a polity (Immergut, 2010; Lijphart, 1999; Tsebelis, 2002). In particular, it is often argued that policy outcomes depend upon the number of institutions that can obstruct the enactment or implementation of legislation; namely, the number of veto points and players, such as the executive and legislative houses, independent central banks and constitutional courts. Studies in environmental politics mention several reasons why increased veto points and players might have desirable implications (Jänicke, 2005; Jörgens, Weidner, & Jänicke, 2013; Lijphart, 1999; Scruggs, 2001): It paves the way for smaller (i.e. «green») political parties, it increases the likelihood of coalition government (i.e. involving smaller parties), and it increases the time horizon of policymakers because accountability mechanisms become ambiguous.

Yet, some researchers claim that a large number of veto points and players indicates a complex and potentially heterogeneous government, which is less likely to reach consensus in policy matters (Immergut, 2010; Tsebelis, 2002). Increased numbers of veto points and players may therefore deflate the relationship between per capita GDP growth and CO_2 emissions, given the assumption that much of the GDP-CO_2 relationship is mediated by the stringency and extent of policy initiatives (Immergut & Orlowski, 2013; Neumayer, 2003). The relationship between veto points (and players) and environmental outcomes is, however, yet to be explored with appropriate methodologies or in interaction with GDP per capita, and we address this gap by examining the following hypothesis:

H_3: The effect of economic development on CO_2 emissions is moderated by the number of veto points and players in the structural organization of decision-making.

3. Methods and data

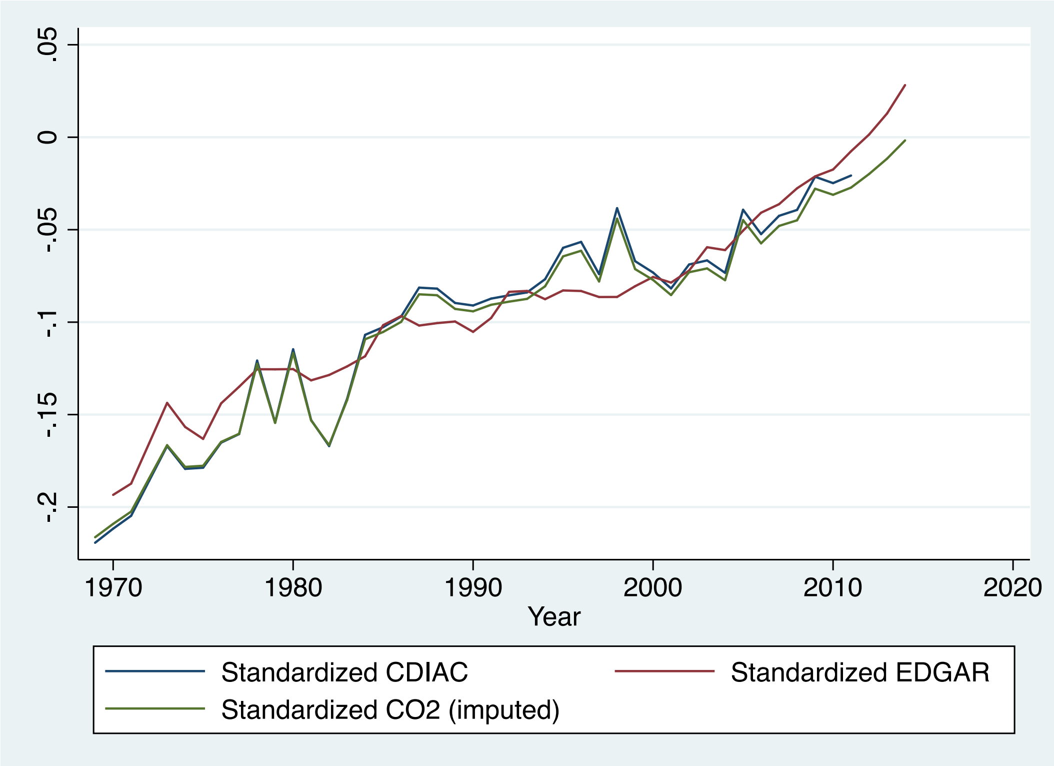
Our analysis consists of two parts. First, we perform a panel analysis with annual observations of 128 countries over the time-period 1972-2014, where CO_2 emissions is the dependent variable and GDP per capita is one of the independent variables.[3] Second, we use the country-specific coefficients of GDP per capita, obtained in the previous stage, as the dependent variable in a cross-country analysis. We avoid using interaction terms in the panel regression because traditional solutions to non-stationarity (i.e. differentiation and/or controlling for cross-sectional averages) do not apply to interaction terms (Liddle, 2015; Wagner, 2008, 2015). This strategy allows us to examine if the per capita GDP-CO_2 relationship is non-linear, moderated by political-institutional factors or if it is non-linear under specific political-institutional conditions. The sample size is limited to 104 countries in the second (cross-sectional) part of the analysis after we remove six outlying countries that have a disproportionate impact on the estimates. Another eighteen countries drop out due to data availability. Table 3 in the supplementary materials presents an overview of the countries, where bold and underlined names respectively denote outliers and dropouts in the cross-sectional analysis.

3.1. Data

To measure GDP per capita, we apply data from the Institute for Health Metrics and Evaluation (IHME) (James, Gubbins, Murray, & Gakidou, 2012). IHME have merged six of the most used measures of GDP per capita to create an indicator that covers 210 countries from 1950 to 2015, without gaps. None of the original measures cover all countries and time-points, but most observations are covered by one or more of the measures. Consequently, it is possible to impute most missing values based on growth-rates in the existing time-series. Some observations are nevertheless missing in all the original time-series, and IHME relies on «mixed effects models» (MEM) to impute missing values in these cases. We, however, exclude all MEM imputations and there are three main reasons for this decision: First, we are skeptical of MEM imputations; second, our analysis does not require balanced data; and third, we only gain a handful of observations by including the MEM imputations.

[3] The sample size is as large as data availability allows.

Figure 1. Illustration of original and imputed CO_2-measures, using Algeria as example



Note: IMPUTED is a version of the CDIAC measure, where missing values are filled with an imputation procedure that is based on the EDGAR measure's exponential growth rate (see text for further details). We illustrate the data with standardized values because CDIAC and EDGAR have different scales.
Abbreviations: EDGAR= Emission Database for Global Atmospheric Research; CDIAC= Center for Carbon Dioxide Emission Analysis

Table 1. Correlation matrix with different measures of CO_2 emissions

	EDGAR	CDIAC	IMPUTED
EDGAR	1.0000		
CDIAC	0.9850	1.0000	
IMPUTED	0.9850	1.0000	1.0000

Note: IMPUTED is a version of the CDIAC measure, where missing values are filled with an imputation procedure based on the EDGAR measure's exponential growth rate (see text for further details). The correlation tests are performed with the extended sample (see explanation in the text).
Abbreviations: EDGAR= Emission Database for Global Atmospheric Research; CDIAC= Center for Carbon Dioxide Emission Analysis

We construct our dependent variable, CO_2 emissions, with data from the Center for Carbon Dioxide Emission Analysis (CDIAC) (Boden, Marland, & Andres, 2015) and the Emission Database for Global Atmospheric Research (EDGAR) (Oliver, Jansens-Maenhout, Muntean, & Peters, 2015). We merge these measures with the same initial procedure as the IHME uses on GDP per capita: First, we use the EDGAR measure's exponential growth rate to predict the exponential growth rate of the CDIAC measure and second, we use the predicted values to forecast and backcast the CDIAC measure. Table 1 presents a correlation matrix between different measures of CO_2 emissions. Figure 1 illustrates the difference between the values in the original and imputed measures of CO_2 per capita using the example of Algeria. As one can tell, CDIAC has missing values at the end of the time-series, and EDGAR has missing values at the beginning. This is the case in all countries and it is the reason why we create an imputed measure.

To measure the level of democracy, corruption and the extent of civil society participation, we use data from the Varieties of Democracy (V-Dem) project (Coppedge et al., 2016, Pemstein et al. 2015). V-Dem's index of democracy measures freedom of association and expression, the extent to which elections in countries are free and fair, whether suffrage is universal, and whether the executive is elected through popular elections or through a popularly elected legislature. Their corruption index captures how pervasive political corruption is in the public sector, legislature, judiciary, and among the members of the executive. V-Dem's civil society index reports on the "participatory environment for the civil society organizations", which accounts for the number and diversity of civil society organizations present in countries and whether it is common for citizens to participate actively in them.

We examine institutional arrangements that constitute veto points (i.e. bicameralism) and generate veto players (i.e. proportional representation), as well as contexts where veto players are "absorbed" (i.e. legislative fractionalization) separately, rather than using a composite measure of veto points and players. This allows us to derive a more straightforward interpretation of the results and reach more policy relevant conclusions. Proportional representation and bicameralism are coded dichotomously, based on legal documents and expert judgment (Cruz, Keefer, & Scartascini, 2016; Henisz, 2013). Legislative fractionalization is approximated with a formula that calculates the probability that two members in the legislative chamber(s) represent different political parties (Henisz, 2013).

According to theories in environmental politics and political science, it is very likely that the per capita GDP-CO_2 relationship is moderated by political-institutional factors. However, it is rather problematic to model all political-institutional interactions simultaneously (using the cross-sectional design that amends stationarity issues). One would face large problems with collinearity and limited degrees of freedom if all variables were included in their original form. We therefore model political-institutional moderation with a number of dichotomous constructs as follows:

- First, we recode the measures of democracy and civil society participation by setting above-medium values equal to 1 and below-medium values equal to 0 (by medium, we mean the middle of the scale, e.g., 2/4). We demonstrate in the appendix that our results are not very sensitive to the «medium-threshold».
- Second, we recode the corruption-measure by setting below-medium values equal to 1 and above-mean values equal to 0.
- Third, we generate country-specific means for each dichotomous variable (i.e. the three constructs above, as well as the measures of bicameralism and proportional representation). The time range of mean values is restricted to 1972-2014 and each mean value is based on 25 or more observations in each country.
- Fourth, we recode the new, country-specific means by setting values below .75 equal to 0, and values above .75 equal to 1 (if the original country-specific mean value is above medium). Said differently, a "1" indicates that the country has above-medium values of (e.g., democracy) in 75% or more of the observations, and that the mean value over the whole time period is higher than medium. The measure, therefore, captures experience with democracy rather than current democracy level.
- Fifth, we generate composite government indicators by coding countries with a "1" if they have a "1" on democracy and corruption, as well as bicameralism, proportional representation or civil society.
- Additionally, to tease out the effect that extraction of oil has on national CO_2 emissions, we account for the extent of oil production by countries. The measure is taken from the Ross Oil and Gas Dataset (2014) and we divide it by population size to derive oil production per capita. We also control for the extent of merchandise imports to account for the potential impacts of pollution intensive trade. The measure calculates the value of goods received on c.i.f. terms from other countries in current US dollars and it is taken from the World Bank (2015). We also divide the import measure by population. Lastly, to model the effect of different weather conditions and account for some of the unit heterogeneity, we control for countries' geographical position using the data on latitude from La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1999) and fill in the missing values using Atlas data. Descriptive statistics are presented in Table 4 in the supplementary materials.

3.2. Methods

In our panel analysis, we use DCCE methodology as suggested by Chudik and Pesaran (2015) to estimate error correction (EC) model (see Eq. 1). The DCCE model augments an ordinary EC model by including cross-sectional averages (CAs) and lagged CAs on the right side of the equation, and by utilizing a mean group estimator (Eberhardt & Presbitero, 2015). The CAs help to account for cross-sectional dependency, while the mean group estimator addresses parameter heterogeneity. We examine if our data is marked by cross-sectional dependency, stationarity and parameter heterogeneity in the supplementary materials.

Eq. 1

$$\begin{aligned}\Delta CO2_t = {} & \alpha + \beta_1 CO2_{t-1} + \beta_2 \Delta GDPpc_t + \beta_3 GDPpc_{t-1} + \beta_4 \Delta MIMPpc_t \\ & + \beta_5 MIMPpc_{t-1} + \beta_6 \Delta POP_t + \beta_7 POP_{t-1} + \beta_8 \mathrm{YEAR}_t + \beta_9 \overline{\Delta CO2_{\iota,t}} \\ & + \beta_{10} \overline{\Delta CO2_{\iota,t-1}} + \beta_{11} \overline{\Delta CO2_{\iota,t-2}} + \beta_{12} \overline{CO2_{\iota,t-1}} + \beta_{13} \overline{\Delta GDPpc_{\iota,t}} \\ & + \beta_{14} \overline{\Delta GDPpc_{\iota,t-1}} + \beta_{15} \overline{\Delta GDPpc_{\iota,t-2}} + \beta_{16} \overline{GDPpc_{\iota,t-1}} + \beta_{17} \overline{\Delta MIMPpc_{\iota,t}} \\ & + \beta_{18} \overline{\Delta MIMPpc_{\iota,t-1}} + \beta_{19} \overline{\Delta MIMPpc_{\iota,t-2}} + \beta_{20} \overline{MIMPpc_{\iota,t-1}} + \beta_{21} \overline{\Delta POP_{\iota,t}} \\ & + \beta_{22} \overline{\Delta POP_{\iota,t-1}} + \beta_{23} \overline{\Delta POP_{\iota,t-2}} + \beta_{24} \overline{POP_{\iota,t-1}} + \varepsilon\end{aligned}$$

The EC specifications constrain all coefficients of level-variables to equal zero, and therefore drop out of the equation, unless they are co-integrated with the dependent variable (Söderbom, Teal, Eberhardt, Quinn, & Zeitlin, 2014). This property implies that we can include level-variables in the equation without producing spurious regression, which is beneficial because it enables us to distinguish between short-term and long-term effects (De Boef & Keele, 2008; Eberhardt & Presbitero, 2015). More specifically, we calculate the long-term effect (i.e. «long-run multiplier» (LRM)) by dividing the respective lagged-level variable-coefficients with the negative value of the error correction term (e.g., $\beta_8/-\beta_1$, Eq. 1), while the coefficients of differenced variables (e.g., β_7, Eq. 1) are interpreted as short-run effects.

The LRM calculation can be performed with country-specific coefficients, which produces an average long-run (ALR) coefficient, but it can also be calculated with panel-average coefficients, in which case the LRM is called the long-run average (LRA) coefficient. We calculate the standard errors and corresponding significance statistics of LRAs with the delta method, and use Pesaran's (1995) non-parametric method for the ALRs. These coefficients can differ, and we present them both to assemble a complete picture.

Since the DCCE estimator is heterogeneous, we can calculate panel-average LRMs in two ways (Eberhardt & Presbitero, 2015). On the one hand, we can calculate the LRM in each respective country and then take the average of country-specific LRMs, in which case the panel-average LRM is labeled as an «average long-run» (ALR) coefficient. On the other hand, we can take the average of country-specific EC terms and lagged level coefficients, and use these averages to generate a so-called «long-run average» (LRA) coefficient. It is theoretically possible to get significantly different ALR and LRA coefficients, which is why we present both variants in our analysis. Moreover, we calculate ALR and LRA coefficients with robust means to weigh down outliers.

Kapetanios, Pesaran, and Yamagata (2011) argue that CAs account for non-stationarity, and therefore, as the model already includes CAs, it is not necessary to apply EC specifications to avoid spurious regression. Chudik and Pesaran (2015), however, point out that the DCCE estimator has a more relaxed exogeneity assumption than the CCE estimator. More specifically, the DCCE estimator allows for feedback effects between the independent variables, whereas the CCE estimator requires strict exogeneity. The DCCE model also enables us to make direct inferences about individual time series and panel-average cointegration, by examining the significance of the EC term, and there are consequently both methodological and practical reasons to add dynamic specifications (and lagged CAs) to the CCE model.

The heterogeneous aspect of the DCCE model enables us to examine non-linearity and conditionality with an alternative approach. Non-linearity is usually examined with a polynomial equation, in which the relevant variable is raised to a number of powers (i.e. $GDPpc^2$, $GDPpc^3$ etc.), but this practice is problematic since differencing does not make higher power-variables stationary (Liddle, 2015; Wagner, 2008). To get around this issue, we examine the potential non-linearity of GDPpc's effect on CO_2 emissions by regressing country-specific LRM coefficients of GDPpc against country-specific mean values of GDPpc. We also use this approach to examine if political-institutional features moderate the GDPpc-CO2 relationship, and tests of linearity and moderation constitute the second stage of our analysis.

We divide the cross-sectional analysis into a series of models due to multicollinearity. First, we study how the mean level of GDP per capita and each of the political-institutional indicators affect the GDP-CO_2 relationship, and then we examine if the mean value of GDP per capita and political-institutional indicators affect the GDP-CO_2 relationship in conjunction. To provide reliable cross-sectional estimates, we use robust regression to identify outliers (we consider observations with lower weights than 0.1 outliers), and apply Huber and White's (1967) method to calculate heteroscedasticity robust standard errors. To examine if the residuals possess skewness and/or kurtosis, we apply D'Agostino, Belanger and D'Agostino Jr.'s (1980) test, and complement our main findings with graphical illustrations of residual distributions (see Figure 3 in the Supplementary materials).

Eq. 2

$$LRM(GDPpc) = \alpha + \beta_1(GDPpc) + \beta_2(GOV\_DC) + \beta_3(GDPpc * GOV\_DC) + \beta_4(LAT) + \beta_5(OPRODpc) + \varepsilon$$

Equation 3 presents an example of the models in our cross-sectional analysis. The equation has two control variables, oil production per capita (OPRODpc) and latitude (LAT), as well as the product and constituent variables of GDP per capita (GDPpc) and incorrupt democracy (GOV_DC). By estimating this model, we examine if the extent of non-linearity in the GDPpc-CO_2 relationship depends on the presence of an incorrupt and democratic government.

4. Results

Table 2 presents panel-average coefficients, confidence intervals and regression diagnostics from four models, which are arranged from left to right according to efficiency.

Table 2. Panel-average estimates

	[1] MG	[2] DMG	[3] CCE	[4] DCCE
EC		-.456***		-.902***
		[-.493 -.420]		[-.951 -.852]
GDPpc	.552***	.620***	.483***	.480***
	[.406 .698]	[.414 .827]	[.369 .597]	[.294 .666]
POP	1.148***	1.237***	1.357***	1.053**
	[.619 .677]	[.679 1.795]	[.756 1.957]	[.190 1.917]
MIMPpc	.046***	.007	.077***	.059***
	[.020 .071]	[-.033 .047]	[.050 .104]	[.016 .101]
Trend	-.0053954	-.009	-.022***	-.024***
	[-.015 .004]	[-.021 .002]	[-.036 -.007]	[-.041 -.006]
Constant	-14.841***	-15.771***	-21.903***	-12.509
	[-23.690 -5.991]	[-25.187 -6.355]	[-34.586 -9.219]	[-28.428 3.409]
CD	34.49***	21.94***	0.41	-0.14
PUR	-23.869***	-63.059***	-40.946***	-75.309***
RMSE	.110	.075	.084	.043
Countries	128	128	128	128
Time-range	1972-2014	1972-2014	1972-2014	1972-2014
N	5422	5422	5422	5422

* p<0.1, ** p<0.05, *** p<0.01

Note: A) The dependent variable is CO_2-emissions; B) 95% confidence intervals in parentheses (calculated with non-parametric standard errors, following Pesaran and Smith (1995)); C) Other variables from the analysis are included in the estimating equations but omitted from the table (i.e. cross-sectional averages (all models) and first-differenced and lagged level variables (Model 2 and 4)).

Abbreviations: MG= Mean group estimator; MG-ECM= Dynamic mean group estimator; CCE= Common correlated effects estimator; DCCE= Dynamic common correlated effects estimator; EC= Error correction term; POP= Population; MIMPpc= Merchandise imports per capita; PUR= Panel unit root test; CD= Cross-sectional dependency test; RMSE= Root mean squared error.

Model 4 is the DCCE model that we discuss in the methods section, and the remaining models are included to illustrate the necessity of DCCE estimation. The results show that different models do not produce significantly different GDPpc coefficients. This finding is somewhat unexpected, as Models 1 and 2 fail to produce cross-sectional independent residuals. The residuals in each model are, furthermore, stationary, which implies panel-average cointegration, and there are consequently no great differences in the panel-average results. However, since we use the country-specific coefficients in the second stage of our analysis, it is useful to consider if they are also unaffected by changes in the model specifications and choice of estimator (we only consider the country-specific coefficients in Models 3 and 4 as Models 1 and 2 fail to produce independent residuals).

Table 3. Description of country-specific LRM coefficients for GDP per capita (from Model 3 and 4)

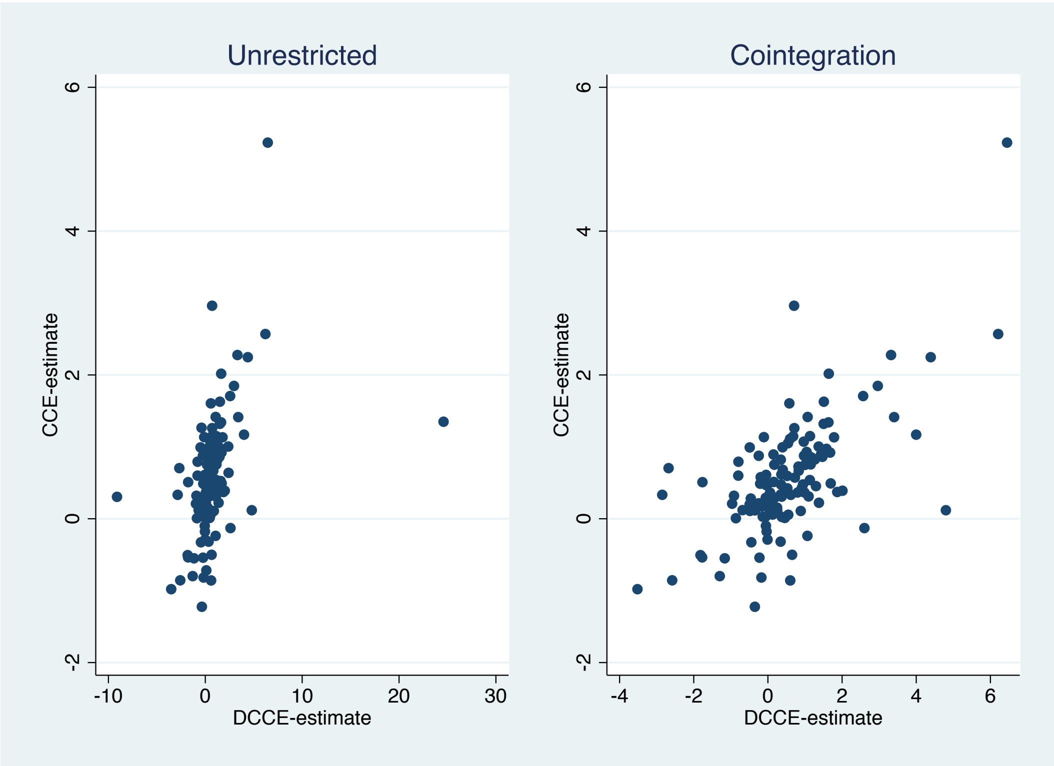
	Unrestricted		**Cointegration**	
	CCE	DCCE	CCE	DCCE
Lowest value	-1.224	-9.111	-1.224	-3.517
Highest value	5.230	24.596	5.230	6.449
Mean	.555***	.719***	.552***	.578***
Std. Err	.072	.240	.075	.135
95% CI (lower)	.412	.243	.402	.309
95% CI (upper)	.698	1.195	.702	.847
Robust mean	.483***	.480***	.471***	.444***
Std. Err	.058	.094	.059	.093
95% CI (lower)	.368	.292	.353	.258
95% CI (upper)	.598	.668	.590	.629
Correlation	0.4190		0.6550	
N	128		120	

* p<0.1, ** p<0.05, *** p<0.01

Note: A) The CCE columns describe country-specific beta coefficients, which are estimated with Model 3; B) The DCCE columns describe country-specific LRM coefficients, which are calculated with estimates from Model 4; C) The cointegration columns represent a subsample of countries where there the error correction term in Model 4 has a lower t-score than 2 (i.e. 120 countries where there is significant evidence of cointegration); D) The unrestricted columns represent the full sample; E) The correlation coefficients represent the correlation between country-specific GDPpc coefficients that are estimated with the CCE and DCCE.

Table 3 and Figure 2 show that the underlying country-specific coefficients in Models 3 and 4 are dissimilar, even though their mean values cannot be distinguished with statistical confidence. If the coefficients were identical, we should see a diagonal line of dots from the bottom left corner to the top right corner in Figure 2, as well as a 1.0-correlation in Table 3. Instead, the scatter-plot looks more like a vertical line and the correlation is 0.42. Another indication of dissimilarity is the difference between the lowest CCE coefficient (-1.224) and the lowest DCCE coefficient (-9.111), as well as the difference between the highest CCE coefficient (5.230) and the highest DCCE coefficient (24.596).

Figure 2. Scatter plot of country-specific LRM coefficients for GDP per capita (from Model 3 and 4)



Note: A) The DCCE estimates represent beta coefficients that are estimated with Model 4, and the CCE estimates represent LRM coefficients that are estimated with Model 3; B) The right-hand panel only includes countries where the error correction term in Model 4 has a lower t-score than 2 (i.e. 120 countries where there is significant evidence of cointegration); C) The left-hand panel includes all 128 countries.

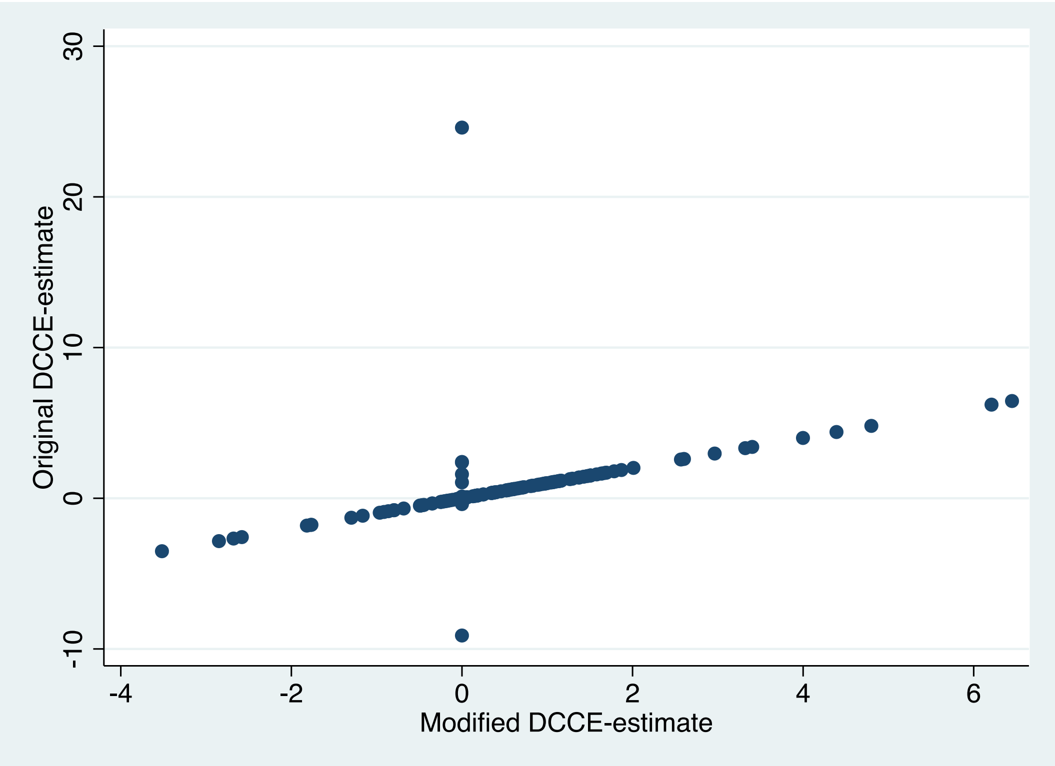
One reason why the country-specific coefficients differ is that the EC term is non-significant in eight countries (i.e. there is no evidence of cointegration), and the DCCE coefficient is therefore invalid in these countries. These countries are removed from the sample that we use to calculate the statistics of the two far-right columns in Table 3, as well as the right-hand panel in Figure 2. As a consequence, the correlation between CCE and DCCE coefficients increases and the scatter plot becomes more diagonal, but it is still far from perfect. The remaining lack of correlation is likely due to the fact that the CCE and DCCE estimators have different exogeneity assumptions.

Table 4. Description of modified country-specific LRM coefficients for GDP per capita (based on Model 4)

Mean	.542***	Robust mean	.403***	Lowest value	-3.517
Std. Err	.127	Std. Err	.085	Highest value	6.449
95% CI (lower)	.289	95% CI (lower)	.234	N	128
95% CI (upper)	.795	95% CI (upper)	.572		

* p<0.1, ** p<0.05, *** p<0.01

Figure 3. Scatter-plot of original and modified, country-specific, LRM coefficients for GDP per capita (based on Model 4)



Note: A) The estimates represent country-specific LRM coefficients that are calculated with estimates from Model 4; B) The «modification» is explained in the text.

We base the second stage of our analysis on the DCCE coefficients because they are estimated with more realistic exogeneity assumptions than the CCE coefficients. The DCCE coefficients are replaced with zero in the eight countries where there is no evidence of cointegration. The dependent variable in our next analyses is thus a modified set of DCCE coefficients. Descriptive statistics and a comparison with the original DCCE coefficients are displayed in Table 4 and Figure 3 respectively.

Table 5. Cross-sectional estimates

	[1]	[2]	[3]	[4]	[5]	[6]
GDPpc	-0.000899	0.0165	-0.0181	-0.00407	-0.0199	-0.0184
	[-0.0230,0.0212]	[-0.0275,0.0605]	[-0.0500,0.0138]	[-0.0308,0.0226]	[-0.0494,0.00960]	[-0.0463,0.00950]
$GDPpc^2$		-0.000471				
		[-0.00162,0.000676]				
GOV_DC			0.580			
			[-0.194,1.354]			
GOV_DCP				0.154		
				[-0.402,0.710]		
GOV_DCB					0.883***	
					[0.297,1.468]	
GOV_DCC						0.629*
						[-0.118,1.375]
LEGFRAC					0.151	
					[-0.821,1.124]	
OPRODpc	-0.0100	-0.000534	0.00526	-0.00743	0.0181	-0.00101
	[-0.0500,0.0299]	[-0.0495,0.0484]	[-0.0370,0.0476]	[-0.0490,0.0341]	[-0.0283,0.0645]	[-0.0405,0.0385]
LATITUDE	-0.00449	-0.00558	-0.00587	-0.00499	-0.00179	-0.00381
	[-0.0180,0.00901]	[-0.0186,0.00741]	[-0.0195,0.00776]	[-0.0185,0.00852]	[-0.0161,0.0126]	[-0.0172,0.00959]
Constant	0.543***	0.521***	0.557***	0.550***	0.437	0.546***
	[0.222,0.864]	[0.183,0.860]	[0.234,0.880]	[0.227,0.872]	[-0.158,1.031]	[0.225,0.868]
N	103	103	103	103	103	103
R^2	0.0110	0.0153	0.0353	0.0134	0.0813	0.0382
RMSE	.84983	.85232	.84361	.85312	.82747	.84234
SK-test	3.05	3.18	2.53	3.28	3.54	1.99

* p<0.1, ** p<0.05, *** p<0.01

Note: A) The dependent variable is a modified set of DCCE coefficients. The coefficients are estimated with Model 4 (Table 2), and the modification is explained in the text; B) 95%-confidence intervals in brackets.

Abbreviations: GOV_DC= Democratic and incorrupt government; GOV_DCP= Democratic incorrupt government with proportional representation; GOV_DCB= Democratic, incorrupt and bicameral government; GOV_DCC= Democratic and incorrupt government with a vibrant civil society; OPRODpc= oil production per capita; LEGFRAC= legislative fractionalization; SK-test= Skewness and kurtosis-test for normality.

In Table 5, we examine if the GDPpc-CO_2 relationship depends on how rich a country is or the type of government characteristics it has. Results from Models 1 and 2 suggest that the GDPpc-CO_2 relationship is linear, while results from Model 3 imply that the GDPpc-CO_2 relationship is not moderated by the presence of incorrupt and democratic government. Model 4 adds proportional representation to the list of political-institutional indicators, and it does not report significant moderation. Model 5 suggests that an increase in GDP per capita is associated with higher CO_2 emissions in countries that have incorrupt, democratic and bicameral government institutions. Lastly, findings in Model 6 show that the GDPpc-CO_2 relationship is not significantly different in countries with incorrupt, democratic government and a vibrant civil society, compared to other states.

The supplementary materials include robustness tests where we respectively modify the analyses in Table 5 in five different ways: 1) Include outliers in the sample; 2) Use lower threshold in the coding of institutional dummies; 3) Use higher threshold in the coding of institutional dummies; 4) Use CCE estimates as the dependent variable; 5) Use the original DCCE estimates as the dependent variable. The robustness tests find a weaker evidence of non-linearity under incorrupt, democratic and bicameral government, and some evidence of non-linearity under incorrupt and democratic regime with a vibrant civil society. It is also clear that the alternative operationalization of the dependent variable with CCE estimates impacts the results.

Table 6. Cross-sectional estimates, continued

	[1]	[2]	[3]	[4]
GDPpc	0.0161	0.00446	-0.00515	0.000974
	[-0.0465,0.0786]	[-0.0266,0.0355]	[-0.0357,0.0254]	[-0.0216,0.0235]
GOV_DC	0.781*			
	[-0.106,1.669]			
GOV_DC*GDPpc	-0.0371			
	[-0.103,0.0284]			
GOV_DCP		0.446		
		[-0.332,1.225]		
GOV_DCP*GDPpc		-0.0178		
		[-0.0561,0.0205]		
GOV_DCB			1.786***	
			[0.891,2.681]	
GOV_DCB*GDPpc			-0.0431**	
			[-0.0815,-0.00466]	
GOV_DCC				1.228**
				[0.174,2.282]
GOV_DCC*GDPpc				-0.0371*
				[-0.0755,0.00135]
LEGFRAC			-0.0183	
			[-1.030,0.993]	
OPRODpc	0.00251	-0.00208	0.00115	0.0111
	[-0.0375,0.0425]	[-0.0433,0.0391]	[-0.0427,0.0450]	[-0.0292,0.0513]
LATITUDE	-0.00798	-0.00628	-0.00539	-0.00580
	[-0.0213,0.00537]	[-0.0197,0.00714]	[-0.0202,0.00943]	[-0.0189,0.00726]
Constant	0.523***	0.539***	0.523*	0.514***
	[0.185,0.861]	[0.213,0.866]	[-0.0866,1.132]	[0.189,0.840]
N	103	103	103	103
R2	0.0439	0.0204	0.113	0.0593
RMSE	.84415	.85445	.8173	.83731
SK-test	2.53	3.39	3.90	2.49

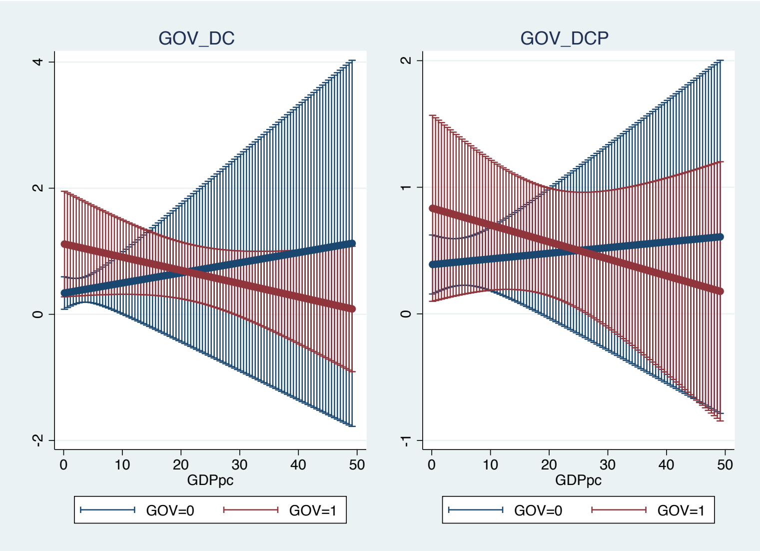
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: A) The dependent variable is a modified set of DCCE coefficients. The coefficients are estimated with Model 4 (Table 2), and the modification is explained in the text; B) 95%-confidence intervals in brackets.

Abbreviations: GOV_DC= Democratic and incorrupt government; GOV_DCP= Democratic incorrupt government with proportional representation; GOV_DCB= Democratic, incorrupt and bicameral government; GOV_DCC= Democratic and incorrupt government with a vibrant civil society; OPRODpc= oil production per capita; LEGFRAC= legislative fractionalization; SK-test= Skewness and kurtosis-test for normality.

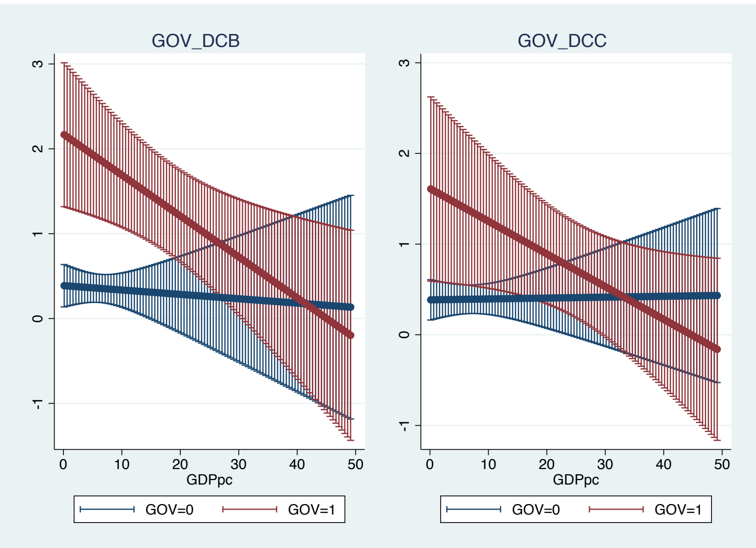
In Table 6, we examine if the linearity of the GDP per capita's effect on CO_2 emissions is moderated by the presence or absence of different political institutions. Model 1 suggests that incorrupt and democratic government does not moderate the GDPpc-CO_2 relationship. In Model 2, we add proportional representation to the government indicator, but this does not seem to make the GDPpc-CO_2 relationship less linear. Model 3 suggests that the GDPpc-CO_2 relationship is slightly less linear in countries with incorrupt, democratic and bicameral governments. Lastly, Model 4 suggests that the GDPpc-CO_2 relationship is no more or less linear in countries with incorrupt democratic governments with a vibrant civil society, compared to other countries. We continue to examine these effects in Figures 4, 5 and 6.

Figure 4. Marginal effects



Note: The left-hand panel displays the marginal effect of GOV_DC*GDPpc, which is estimated in Model 1 (Table 6). The right-hand panel displays the marginal effect of GOV_DCP*GDPpc, which is estimated in Model 2 (Table 6).
Abbreviations: GOV_DC= Democratic and incorrupt government; GOV_DCP= Democratic, incorrupt government with proportional representation.

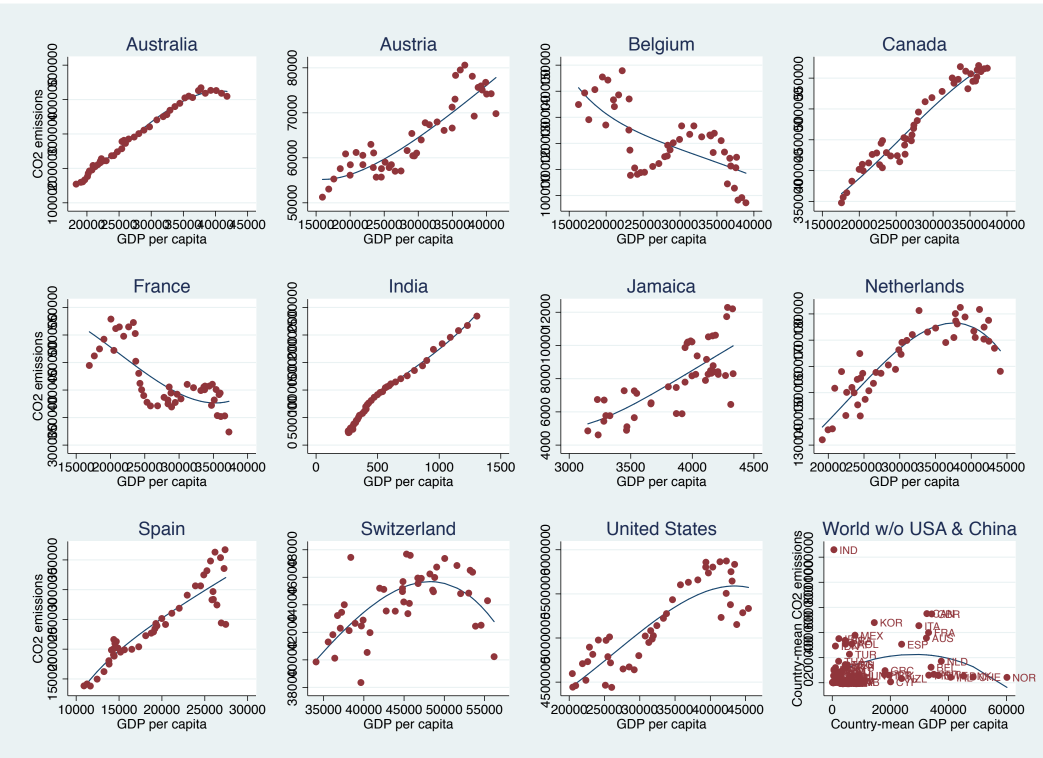
Figure 5. Marginal effects, continued



Note: The left-hand panel displays the marginal effect of GOV_DCB*GDPpc, which is estimated in Model 3 (Table 6). The right-hand panel displays the marginal effect of GOV_DCC*GDPpc, which is estimated in Model 4 (Table 6).
Abbreviations: GOV_DCB= Democratic, incorrupt and bicameral government; GOV_DCC= Incorrupt democratic government with a vibrant civil society.

The illustrations in Figures 4-5 show that GOV_DCB has the highest intercept and the steepest slope, and it is the only condition that can be distinguished from the alternative with the 95% confidence. These findings suggest that poor countries with incorrupt, democratic and bicameral governments have a worse starting point than the other countries, but they produce a similar GDPpc-CO_2 relationship as the rest of the world when the level of GDPpc becomes sufficiently high (around $20,000). In Figure 6, we illustrate the per capita GDP-CO_2 relationship in each of the GOV_DCB-countries, and find that Jamaica, Spain and India drive the interaction effect (i.e. these are the only GOV_DCB-countries with sufficiently low GDP per capita). Among these three countries, India has particularly high CO_2 emissions and low GDPpc levels, and therefore has a large impact on the interaction coefficient. This result is somewhat consistent with theories that predict adverse effects of increased numbers of veto points, but it is unexpected to find that the effect diminishes as GDP per capita increases. We therefore encourage further research to examine why per capita GDP growth is associated with relatively higher emissions in poor countries with democratic, incorrupt and bicameral government; with a particular focus on whether it is indeed caused by bicameralism.

Figure 6. Fractional-polynomial & scatter plot of GDP per capita and CO_2 emissions in GOV_DCB-countries



Note: A fractional-polynomial & scatter plot of GDP per capita and CO_2 emissions is included in the appendix, where USA and China are included. These countries are left out of Figure 6 for illustrative purposes.
Abbreviations: GOV_DCB= Democratic, incorrupt and bicameral government.

5. Conclusion

The aim of this paper has been to investigate if political institutional arrangements can address one of the biggest environmental challenges of today – excessive emissions of carbon dioxide, which is largely driven by economic growth and contributes greatly to global warming. The paper takes its point of departure from a critical review of research in environmental economics and politics and is motivated by the shortcomings found in both strands of literature. The environmental economics literature provides rigorous tests and explanations of the per capita GDP-CO_2 relationship, but it typically fails to incorporate relevant political-institutional factors in the discussion on income and emissions. Meanwhile, research in environmental political science discusses factors that may moderate the relationship between economic growth and emissions, but it typically fails to examine interactions between political institutions and economic growth using modern econometric methods.

This paper bridges the two literatures and provides a thorough examination of the relationship between countries' economic, political and emitting behavior by analyzing CO_2 emissions in 128 countries over the time-period 1974-2014. In particular, we investigate if the relationship between GDP per capita and CO_2 emissions is curvilinear and/or moderated by non-economic factors. Our specific focus is on political and institutional factors that the existing literature expects to affect the adoption and implementation of environmental policies: the extent of democracy, corruption, civil society participation, and the number of veto points and players.

Our analysis does not provide support to the EKC hypothesis, which predicts an inverse U-shaped relationship between GDP per capita and CO_2 emissions. Instead, our results lend support to recent studies by Wagner (2008, 2015), Liddle (2015) and others who find a positive and linear per capita GDP-CO_2 relationship. Our estimates indicate that a 1-dollar increase in GDP per capita is associated with a 493-717 metric ton increase in CO_2 emissions regardless of how rich a country is. These values denote the exponent of the lower and upper confidence interval in the far-right column of Table 3. The confidence interval of our per capita GDP coefficient is slightly lower than in Wagner and Liddle's studies, and the reason is probably that we have a larger sample size and more appropriate control variables that are relevant for explaining CO_2 emissions. Consequently, we argue that our estimate is more accurate and that previous studies overestimate the positive impact of per capita GDP growth on CO_2 emissions.

Although we find a slightly lower coefficient than the studies that we cite, it is not controversial to find a positive and linear effect from an environmental economics perspective. Several environmental economic theorists suggest a more complex and policy-induced relationship than the EKC implies (Kaika & Zervas, 2013a, 2013b; Kijima et al., 2010; Pasten &

Figueroa, 2012). What might seem surprising, however, is that the results of this study do not support that variations in government capacity moderate the relationship between per capita GDP growth and CO_2 emissions. Based on common theoretical perceptions within the literature, we expected to find a negative or inverse U-shaped per capita GDP-CO_2 relationship in countries that have favorable political and institutional conditions. The results, however, indicate that none of our political or institutional factors, be it democracy, lack of corruption, high extent of civil society participation or veto points and players moderate GDP per capita's effect on CO_2 emissions in the expected direction. The positive and linear per capita GDP-CO_2 relationship is in other words highly robust, and the lack of significant moderation indicates that outlying cases of negative or inverse U-shaped effect are most likely not driven by free and fair elections, high corruption control, civil society activity or certain decision-making structures.

One reason for the lack of effect from political-institutional factors could be that the political processes in countries that have been successful in reducing CO_2 emissions have not yet contributed enough to the reduction of carbon dioxide emissions to make a significant difference when compared to the rest of the world. Another reason could be that the efforts to reduce CO_2 emissions are quite recent and the positive effect of political institutions to secure these efforts is not yet sufficiently pronounced to establish a significant difference over time. Further research should therefore continue to investigate if and how political institutions affect the relationship between economic growth and emissions as efforts to reduce carbon dioxide continue and time series become more extensive.

The practical implication of our study is that policymakers need to come up with more stringent policy initiatives and more effective implementation strategies in order to alleviate the adverse impact per capita GDP growth has on polluting behavior. If existing initiatives were sufficiently stringent and effective, we should have found a weaker per capita GDP-CO_2 relationship in countries with higher government capacity.

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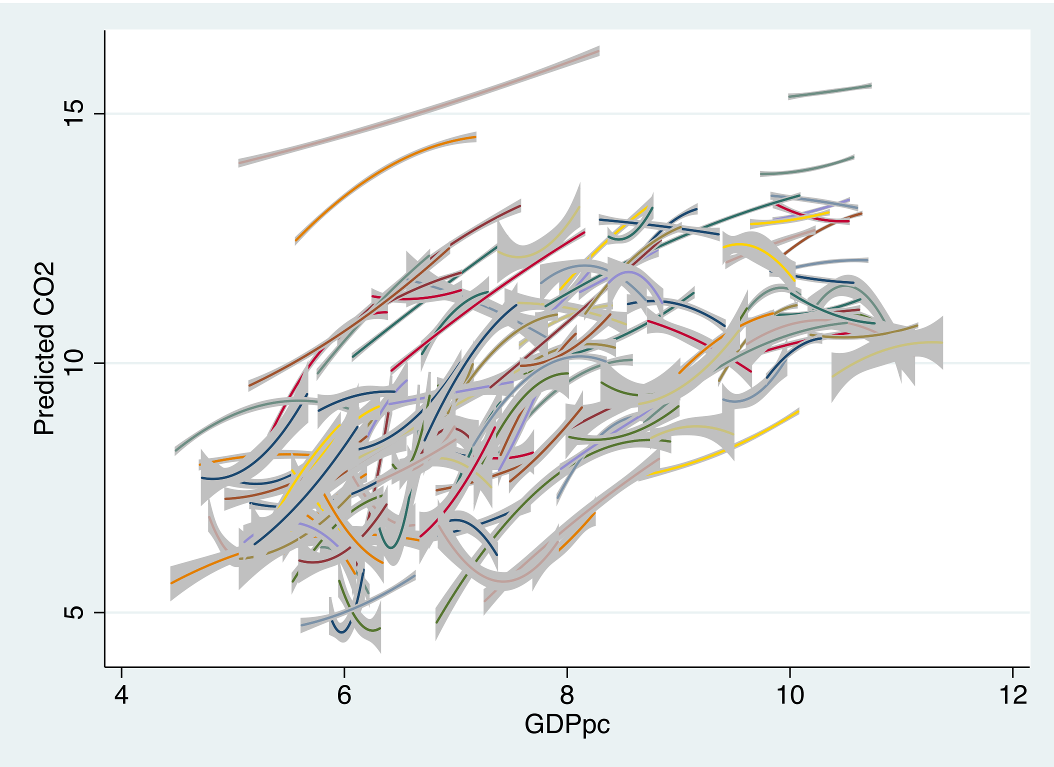
Supplementary Materials

In these supplementary materials, we perform pre-analysis diagnostic tests to discuss the practical statistical implications of parameter heterogeneity, cross-sectional dependency and unit roots. We also include a brief note to describe some details regarding Chudik and Pesaran's (2015) estimator and include supplementary figures and tables, which we refer to in the text.

Parameter heterogeneity

Figure 1. Quadratic-polynomial plot



Note: The slopes in Figure 1 are estimated with the following country-specific OLS regression: $CO2_t = \alpha + \beta_1(GDPpc)_t + \beta_2(GDPpc^2)_t + \varepsilon$.

Figure 1 illustrates the country-specific relationships between GDP per capita and CO_2 emissions. The illustration should be interpreted with caution as the underlying regressions are based on a simple methodology, but we use it nevertheless to get an impression of the extent of parameter homogeneity. The figure shows a positive tendency in the data: higher levels of GDP per capita tend to associate with higher levels of CO_2 emissions, regardless of the data source. The intercept and shape of each slope, however, seems to vary greatly. Some countries have high CO_2 emissions even at low levels of GDP per capita, while the GDP-CO_2 relationship is U-shaped in some countries and inverse-U shaped in others. We are therefore likely to get misguided results if we constrain all countries by the same intercept and functional form (Müller-

Fürstenberger & Wagner, 2007; Pesaran, 2006). For this reason, we use a heterogeneous estimator and examine linearity with an alternative routine, which we described in the main text.

Cross-sectional dependency

Eq. 1

$$\sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{i,j}\right)$$

Table 1. Cross-sectional dependency

CO2	GDPpc	POP	MIMPpc
296.47***	218.46***	508.39***	445.11***

* p<0.10, ** p<0.05, *** p<0.01
Note: The test is performed with Pesaran's methodology (see Eq. 1).

Cross-sectional dependency (CD) refers to correlation between the country-specific residuals in a heterogeneous panel analysis (Pesaran, 2007). High CD-statistics are problematic because they imply heteroscedasticity, which makes standard errors and significance testing unreliable. One way to examine if CD is a potential problem is to examine the extent to which respective variables correlate across countries. Table 1 presents CD-statistics for all the variables in our analysis and residual CD-statistics are presented later on, along with the results. The CD-test is performed with Pesaran's (2007) methodology, which collects the pair-wise correlation coefficients of variables (or residuals) in each country $(\hat{\rho}_{i,j})$ and determines the «typical» correlation coefficient with Eq. 1.[4] The results in Table 1 suggest that all variables in our dataset are strongly correlated across countries, and we therefore expect that CD will be an issue in our analysis. To amend this problem, we account for «common factors», which are described more closely in the main text.

Stationarity

Unit root variables are non-stationary and do not revert towards a mean value if there is a shock in the time-series, which causes spurious regression unless it is treated appropriately. Unit root variables need to be differentiated to become stationary, and they are integrated in a certain order, depending on the amount of differentiation that is required to make the variable

[4] When the panel is unbalanced, Pesaran's (2004) CD-test takes the following form: $\sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{i,j}\right)$

stationary, i.e. a variable is integrated in the first order, I(1), if it becomes stationary by first-difference. To determine if we need to difference our data, and to what extent it is necessary to difference it, we perform Pesaran's (2007) panel unit root test. This test emanates from Dickey and Fuller (1979), as well as Im, Pesaran and Shin's (2003) unit root tests. Dickey and Fuller (1979) examine unit roots by examining if β_1 in the following equation is statistically significant:

Eq. 2

$$\Delta Y_{i,t} = \alpha + \beta_1(Y_{i,t}) + \varepsilon$$

It is also possible to add lags of the dependent variable to the equation above, in which case it becomes the «augmented Dickey-Fuller test». Im, Pesaran and Shin (2003) add another augmentation to Dickey and Fuller's test, as it calculates the equation with Pesaran's (1995) mean group estimator. Pesaran's (2007) PUR test is often called «CIPS», since it augments Im, Pesaran and Shin's (IPS) approach with accounts for a common factor (i.e. cross-sectional dependency). More specifically, CIPS accounts for cross-sectional averages of each parameter, as well as lags of differenced regressors, and the following equation illustrates CIPS with two lags of the dependent variable:

Eq. 3

$$\Delta Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 \Delta Y_{t-1} + \beta_3 \overline{Y_{\iota,t-1}} + \beta_4 \Delta Y_{t-2} + \beta_5 \overline{\Delta Y_{\iota,t-2}} + \varepsilon$$

CIPS solves Eq. 3 with a heterogeneous estimator, which means that a regression analysis is performed in each country and the presence of unit roots is evaluated with the average t-score (or «t-bar») of β_1.[5] The t-bar is calculated non-parametrically, following Eq. 4, and it is interpreted according to the critical values that are listed in Pesaran (1995).[6]

Eq. 4

$$\sqrt{\left(\frac{1}{N(N-1)}\sum_{i=1}^{N}(\widehat{\phi_\iota} - \hat{\phi})^2\right)}$$

[5] We follow the common practice (e.g., Liddle 2015) and transform all variables in our panel analysis with a natural logarithm.

[6] In equation (1), N represents the number of countries, $\widehat{\phi_\iota}$ indicates country-specific coefficients and $\hat{\phi}$ represents the coefficient of the cross-sectional mean.

Table 2. Panel unit root tests

	CO2		ΔCO2	
	w/o trend	w/trend	w/o trend	w/trend
0 lags	-2.853***	2.181	-47.03***	-45.902***
1 lag	-1.924**	4.424	-31.344***	-29.222***
2 lags	-.914	6.034	-18.809***	-15.97***
3 lags	-1.762**	5.548	-11.847***	-9.059***
4 lags	.114	7.827	-5.785***	-2.265**
	GDPpc		**ΔGDPpc**	
	w/o trend	w/trend	w/o trend	w/trend
0 lags	6.161	-.264	-34.631***	-32.546***
1 lag	2.974	-4.961***	-27.076***	-24.428***
2 lags	3.597	-1.733**	-16.352***	-13.504***
3 lags	1.734	-3.747***	-12.908***	-10.232***
4 lags	3.972	-1.099	-8.641***	-5.669***
	POP		**ΔPOP**	
	w/o trend	w/trend	w/o trend	w/trend
0 lags	10.285	14.005	-1.824**	5.594
1 lag	-16.64***	-17.087***	-26.317***	-30.615***
2 lags	8.693	13.763	-1.173	3.636
3 lags	-2.431***	-4.617***	-6.412***	-4.373***
4 lags	4.454	4.415	-4.785***	-1.015
	MIMPpc		**ΔMIMPpc**	
	w/o trend	w/trend	w/o trend	w/trend
0 lags	-1.15	-3.318***	-45.597***	-43.761***
1 lag	-1.493*	-2.805***	-32.945***	-29.72***
2 lags	-.257	-.719	-21.676***	-18.179***
3 lags	-.304	-1.24	-15.587***	-12.701***
4 lags	.952	1.796	-11.054***	-7.409***

* $p<0.10$, ** $p<0.05$, *** $p<0.01$
Abbreviations: POP= population; MIMPpc= merchandise trade per capita.

The results in Table 2 indicate that we should treat the remaining variables as non-stationary unless they are first-differenced. Some statistics suggest that POP needs to be differenced more than once to become stationary, and it is therefore necessary to examine if the residual in our regression model is non-stationary before we interpret the coefficients. The results for GDPpc and MIMPpc differ greatly depending on whether the test accounts for a linear time-trend or not. More specifically, the variables appear to be non-stationary when the trend is omitted, whereas several tests suggest stationarity when the trend is included. Consequently, the tests suggest that we include a linear time-trend in our regression model to account for the possibility that GDPpc and MIMPpc are trend-stationary.

Notes regarding the «Dynamic Common Correlated Mean Group Effects» estimator

Other popular estimators, such as the first-difference model and the error correction model, do not address cross-sectional dependency and they are therefore inappropriate. The fixed effects model addresses neither non-stationarity nor cross-sectional dependency (Chudik & Pesaran, 2015; Eberhardt & Presbitero, 2015; Liddle, 2015; Pesaran, 2006; Söderbom et al., 2014).

Following Chudik and Pesaran (2015), we augment the regression model with a number of cross-sectional averages that equals the number of annual observations per country, raised to a third power: $\mathrm{INT}(T^{1/3})$.

The mean group estimator calculates ordinary least square estimates in each of the panel's time series and examines if the mean of the time-series estimates is statistically significant. The significance test is performed with non-parametric standard errors and Pesaran's (2006) critical values. The non-parametric standard errors of the estimate are calculated with the following equation: $\sqrt{(\frac{1}{N(N-1)}\sum_{i=1}^{N}(\hat{\phi}_i - \hat{\phi})^2)}$

In practice, we calculate panel-mean coefficients and p-values by collecting the time-series coefficients of each variable and regressing them against an intercept. We use robust regression in this procedure to account for outlying time-series estimates.

A list of supplementary figures and tables

Figure 2. Residual diagnostics for Model 3 in Table 2

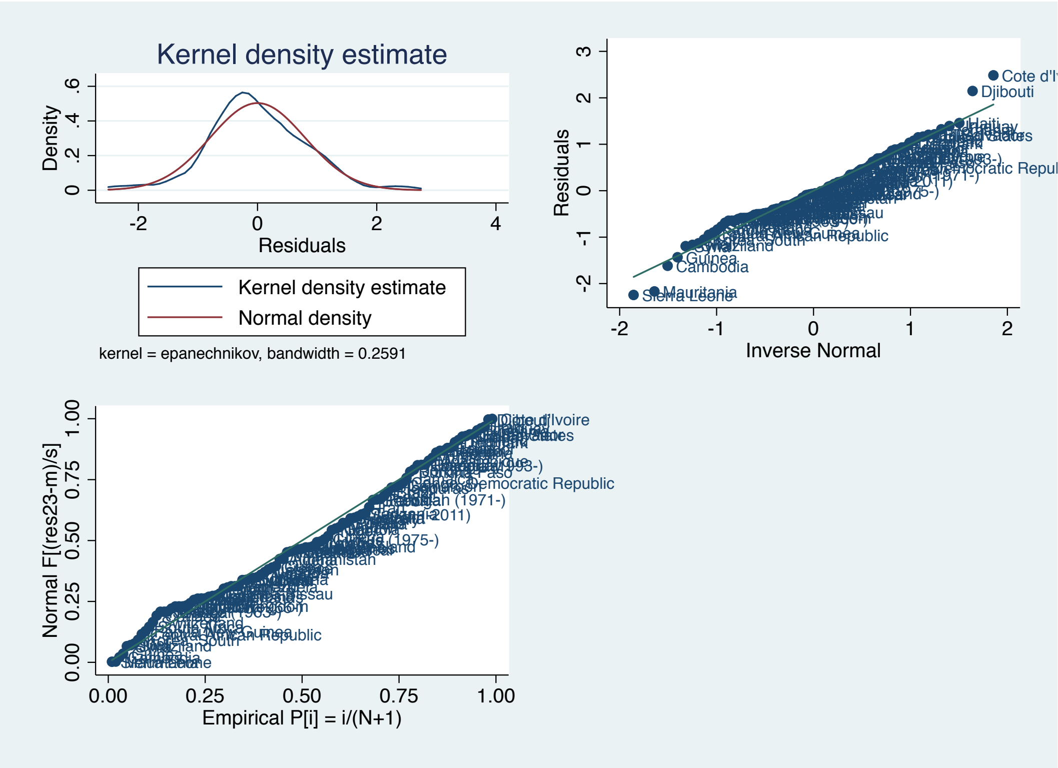


Figure 3. Fractional-polynomial and scatter plot of GDP per capita and CO_2 emissions

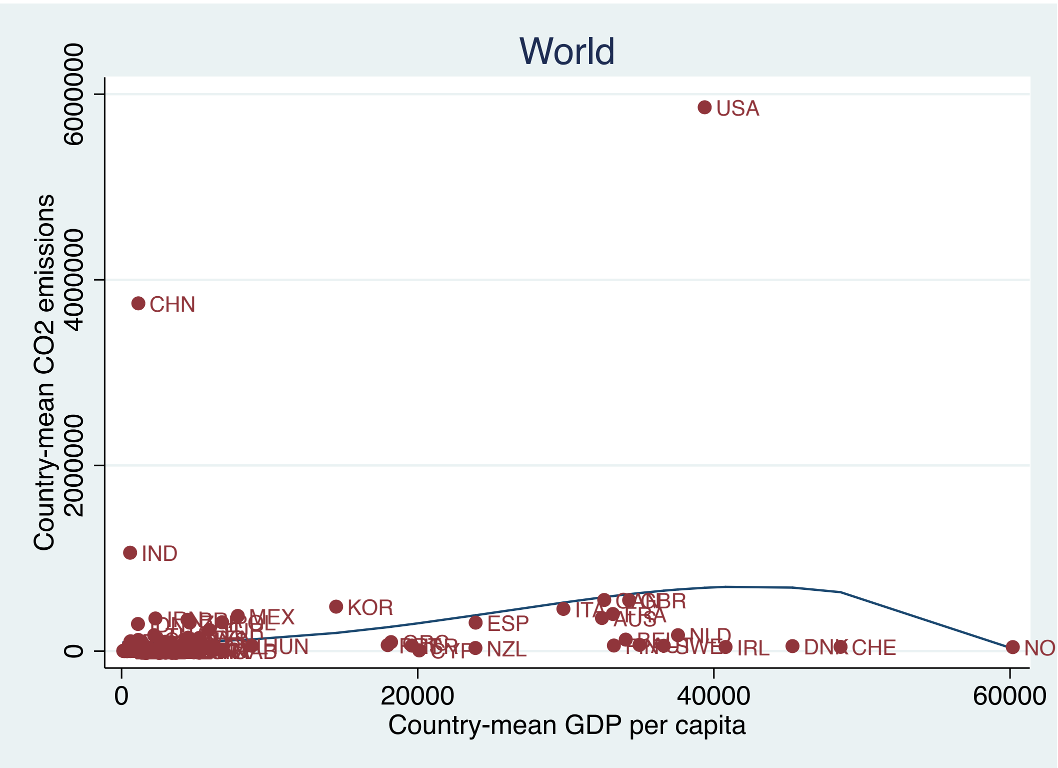


Table 3. List of countries in the panel analysis

Afghanistan	Djibouti	Korea, South	Poland
Algeria	**Dominican Rep.**	**Kuwait**	Portugal
Angola	Ecuador	Laos	**Qatar**
Argentina	Egypt	Lebanon	Romania
Australia	El Salvador	Lesotho	Rwanda
Austria	Ethiopia (1993-)	Liberia	**Saudi Arabia**
Bahrain	Fiji	**Libya**	Senegal
Bangladesh	Finland	Madagascar	Sierra Leone
Belgium	France (1963-)	Malawi	**Singapore**
Benin	Gabon	Malaysia (1966-)	South Africa
Bhutan	Gambia	Mali	Spain
Bolivia	Ghana	Mauritania	**Sri Lanka**
Botswana	Greece	**Mauritius**	Sudan
Brazil	Guatemala	Mexico	Swaziland
Bulgaria	Guinea	**Mongolia**	Sweden
Burkina Faso	Guinea-Bissau	Morocco	Switzerland
Burundi	Guyana	Mozambique	Syria
Cambodia	Haiti	**Myanmar**	Tanzania
Cameroon	Honduras	Nepal	Thailand
Canada	Hungary	Netherlands	Togo
CAF	India	New Zealand	**Trinidad and Tobago**
Chad	Indonesia	Nicaragua	Tunisia
Chile	Iran	Niger	Turkey
China	Iraq	Nigeria	Uganda
Colombia	Ireland	Norway	**United Arab Emirates**
Congo	Israel	**Oman**	United Kingdom
Congo, Dem. Rep.	Italy	Pakistan (1971-)	United States
Costa Rica	Jamaica	Panama	Uruguay
Cote d'Ivoire	**Japan**	Papua New Guinea	Venezuela
Cuba	Jordan	Paraguay	Vietnam
Cyprus (1975-)	Kenya	Peru	Zambia
Denmark	**Korea, North**	Philippines	Zimbabwe

Note: Table 1 contains all countries in the panel analysis-sample. Countries in bold are omitted from the cross-sectional analysis because of their extreme values. Underlined countries are omitted from the cross-sectional analysis because of data limitations.

Table 4. Descriptive statistics

	Obs	Mean	Std. Dev.	Min	Max
CO2	5422	9.533923	2.292206	3.610918	16.17076
GDPpc	5422	7.719854	1.67706	4.447695	11.3638
POP	5422	16.13885	1.513881	11.86436	21.03389
MIMPpc	5422	6.113554	1.809105	.2968567	11.17715
ESITMATE	104	.5613372	1.083944	-2.580812	4.391585
GDPpc	104	7333.582	11533.41	143.8117	49580.05
OPRODpc	104	.6876586	2.295179	0	18.23284
LAT	104	23.50962	16.35409	0	60
LEGFRAC	104	.4566616	.215694	0	.8608026
GOV_DC	104	.2403846	.4293864	0	1
GOV_DCP	104	.1826923	.3882853	0	1
GOV_DCB	104	.1057692	.3090313	0	1
GOV_DCC	104	.2403846	.4293864	0	1

Note: The first four variables listed consist of panel data (T: 1972-2014) and the remaining variables consist of cross-sectional data (i.e. cross-sectional averages for the time-period 1972-2014). The panel data-variables are expressed as logarithms and the cross-sectional variables are expressed in their original values, as they are in the analyses.

Abbreviations: POP= Population; MIMPpc= Merchandise imports per capita; ESTIMATE= the country-specific long-run multipliers of GDPpc, which are estimated in the panel analysis; GOV_DC= Democratic and incorrupt government; GOV_DCP= Democratic and incorrupt government with proportional representation; GOV_DCB= Democratic, incorrupt and bicameral government; GOV_DCC= Democratic and incorrupt government with a vibrant civil society; OPRODpc= oil production per capita; LEGFRAC= legislative fractionalization.

Table 5. Cross-sectional estimates with outliers included

	[1]	[2]	[3]	[4]
GDPpc	-0.00280	0.00397	-0.0141	-0.00489
	[-0.0863,0.0807]	[-0.0330,0.0410]	[-0.0530,0.0249]	[-0.0387,0.0289]
GOV_DC	1.089*			
	[-0.161,2.340]			
GOV_DC*GDPpc	-0.0278			
	[-0.115,0.0596]			
GOV_DCP		0.962		
		[-0.446,2.370]		
GOV_DCP*GDPpc		-0.0298		
		[-0.0833,0.0236]		
GOV_DCB			1.473***	
			[0.437,2.509]	
GOV_DCB*GDPpc			-0.0333	
			[-0.0778,0.0112]	
GOV_DCC				1.747**
				[0.280,3.214]
GOV_DCC*GDPpc				-0.0460*
				[-0.0993,0.00723]
LEGFRAC			0.679	
			[-0.623,1.981]	
OPRODpc	-0.00501	-0.0108	-0.00988	0.00269
	[-0.0579,0.0479]	[-0.0645,0.0429]	[-0.0662,0.0465]	[-0.0550,0.0603]
LATITUDE	-0.0153	-0.0153	-0.0111	-0.0124
	[-0.0358,0.00516]	[-0.0357,0.00515]	[-0.0315,0.00923]	[-0.0311,0.00632]
Constant	0.894***	0.902***	0.603*	0.848***
	[0.389,1.399]	[0.414,1.390]	[-0.0767,1.283]	[0.367,1.329]
N	110	110	110	110
R2	0.0608	0.0492	0.0698	0.0820
RMSE	1.2703	1.2782	1.2704	1.2559
SK-test	32.43***	31.78***	33.09***	33.00***

* p<0.1, ** p<0.05, *** p<0.01

Note: A) The dependent variable is a modified set of DCCE coefficients. The coefficients are estimated with Model 4 (Table 2), and the modification is explained in the text; B) 95%-confidence intervals in brackets.

Abbreviations: GOV_DC= Democratic and incorrupt government; GOV_DCP= Democratic incorrupt government with proportional representation; GOV_DCB= Democratic, incorrupt and bicameral government; GOV_DCC= Democratic and incorrupt government with a vibrant civil society; OPRODpc= oil production per capita; LEGFRAC= legislative fractionalization; SK-test= Skewness and kurtosis-test for normality.

Table 6. Cross-sectional estimates with lower threshold on institutional variables

	[1]	[2]	[3]	[4]
GDPpc	0.0343	0.00505	0.00211	0.00454
	[-0.0683,0.137]	[-0.0244,0.0344]	[-0.0247,0.0289]	[-0.0196,0.0287]
GOV_DC	0.475			
	[-0.198,1.148]			
GOV_DC*GDPpc	-0.0429			
	[-0.145,0.0589]			
GOV_DCP		0.0845		
		[-0.482,0.651]		
GOV_DCP*GDPpc		-0.00842		
		[-0.0412,0.0243]		
GOV_DCB			1.330***	
			[0.564,2.095]	
GOV_DCB*GDPpc			-0.0254	
			[-0.0589,0.00813]	
GOV_DCC				0.973**
				[0.221,1.725]
GOV_DCC*GDPpc				-0.0274*
				[-0.0592,0.00435]
LEGFRAC			-0.231	
			[-1.240,0.778]	
OPRODpc	-0.00309	-0.00578	-0.00209	0.00650
	[-0.0278,0.0216]	[-0.0308,0.0193]	[-0.0253,0.0211]	[-0.0184,0.0314]
LATITUDE	-0.00849	-0.00503	-0.0101	-0.00837
	[-0.0228,0.00579]	[-0.0187,0.00868]	[-0.0257,0.00558]	[-0.0220,0.00522]
Constant	0.508***	0.534***	0.642**	0.535***
	[0.134,0.883]	[0.212,0.855]	[0.0396,1.245]	[0.214,0.856]
N	103	103	103	103
R2	0.0317	0.0139	0.126	0.0647
RMSE	.8495	.85728	.81141	.83492
SK-test	2.66	2.99	3.74	3.01

* p<0.1, ** p<0.05, *** p<0.01

Note: A) The dependent variable is a modified set of DCCE coefficients. The coefficients are estimated with Model 4 (Table 2), and the modification is explained in the text; B) 95%-confidence intervals in brackets; C) A government is considered democratic if the country has a higher score than 0.55 (instead of 0.5), incorrupt if the country has a lower score than 0.45 (instead of 0.5), and a civil society is considered vibrant if the country has a higher score than 1.4 (instead of 1.5) (see variable description in the text).

Abbreviations: GOV_DC= Democratic and incorrupt government; GOV_DCP= Democratic incorrupt government with proportional representation; GOV_DCB= Democratic, incorrupt and bicameral government; GOV_DCC= Democratic and incorrupt government with a vibrant civil society; OPRODpc= oil production per capita; LEGFRAC= legislative fractionalization; SK-test= Skewness and kurtosis-test for normality.

Table 7. Cross-sectional estimates with higher government-threshold

	[1]	[2]	[3]	[4]
GDPpc	0.0251	0.00506	0.00300	0.00350
	[-0.0702,0.120]	[-0.0244,0.0345]	[-0.0238,0.0298]	[-0.0182,0.0252]
GOV_DC	0.569			
	[-0.180,1.319]			
GOV_DC*GDPpc	-0.0362			
	[-0.131,0.0587]			
GOV_DCP		0.139		
		[-0.503,0.782]		
GOV_DCP*GDPpc		-0.00957		
		[-0.0435,0.0244]		
GOV_DCB			1.503***	
			[0.733,2.272]	
GOV_DCB*GDPpc			-0.0306*	
			[-0.0641,0.00297]	
GOV_DCC				1.081***
				[0.381,1.782]
GOV_DCC*GDPpc				-0.0296**
				[-0.0584,-0.000766]
LEGFRAC			-0.181	
			[-1.173,0.811]	
OPRODpc	-0.000561	-0.00493	-0.00289	0.00547
	[-0.0251,0.0240]	[-0.0304,0.0205]	[-0.0261,0.0203]	[-0.0200,0.0309]
LATITUDE	-0.00901	-0.00539	-0.0114	-0.00706
	[-0.0234,0.00542]	[-0.0192,0.00843]	[-0.0272,0.00445]	[-0.0201,0.00599]
Constant	0.525***	0.536***	0.649**	0.545***
	[0.154,0.896]	[0.215,0.858]	[0.0472,1.251]	[0.222,0.868]
N	103	103	103	103
R2	0.0363	0.0143	0.132	0.0391
RMSE	.84749	.85711	.80855	.84627
SK-test	2.54	3.03	3.83	3.99

* p<0.1, ** p<0.05, *** p<0.01

Note: A) The dependent variable is a modified set of DCCE coefficients. The coefficients are estimated with Model 4 (Table 2), and the modification is explained in the text; B) 95%-confidence intervals in brackets; C) A government is considered democratic if the country has a higher score than 0.45 (instead of 0.5), incorrupt if the country has a lower score than 0.55 (instead of 0.5), and a civil society is considered vibrant if the country has a higher score than 1.6 (instead of 1.5) (see variable description in the text).

Abbreviations: GOV_DC= Democratic and incorrupt government; GOV_DCP= Democratic incorrupt government with proportional representation; GOV_DCB= Democratic, incorrupt and bicameral government; GOV_DCC= Democratic and incorrupt government with a vibrant civil society; OPRODpc= oil production per capita; LEGFRAC= legislative fractionalization; SK-test= Skewness and kurtosis-test for normality.

Table 8. Cross-sectional estimates with CCE estimates as the dependent variable

	[1]	[2]	[3]	[4]
GDPpc	0.0338	0.0162**	-0.00899	0.00342
	[-0.0159,0.0835]	[0.000689,0.0317]	[-0.0311,0.0131]	[-0.0278,0.0347]
GOV_DC	0.894***			
	[0.364,1.424]			
GOV_DC*GDPpc	-0.0567**			
	[-0.106,-0.00699]			
GOV_DCP		0.776**		
		[0.179,1.372]		
GOV_DCP*GDPpc		-0.0406***		
		[-0.0645,-0.0166]		
GOV_DCB			0.759**	
			[0.0628,1.456]	
GOV_DCB*GDPpc			-0.0163	
			[-0.0447,0.0122]	
GOV_DCC				0.918**
				[0.211,1.625]
GOV_DCC*GDPpc				-0.0309*
				[-0.0667,0.00491]
ABS			0.424	
			[-0.301,1.150]	
OPRODpc	0.0256	0.0284	0.0244	0.0312*
	[-0.00991,0.0611]	[-0.00593,0.0628]	[-0.0131,0.0619]	[-0.000677,0.0630]
LATITUDE	-0.00666	-0.00547	-0.00193	-0.00334
	[-0.0167,0.00334]	[-0.0151,0.00418]	[-0.0118,0.00791]	[-0.0130,0.00635]
Constant	0.530***	0.551***	0.389**	0.540***
	[0.301,0.758]	[0.324,0.778]	[0.0258,0.753]	[0.311,0.770]
N	108	108	108	108
R2	0.0920	0.0773	0.0551	0.0644
RMSE	.62906	.63416	.64489	.63856
SK-test	0.90	1.37	0.93	0.68

* p<0.1, ** p<0.05, *** p<0.01

Note: A) The dependent variable is a set of CCE estimates that is estimated with Model 3 (Table 2); B) 95%-confidence intervals in brackets; C) Outliers excluded: Benin and Spain.

Abbreviations: GOV_DC= Democratic and incorrupt government; GOV_DCP= Democratic incorrupt government with proportional representation; GOV_DCB= Democratic, incorrupt and bicameral government; GOV_DCC= Democratic and incorrupt government with a vibrant civil society; OPRODpc= oil production per capita; LEGFRAC= legislative fractionalization; SK-test= Skewness and kurtosis-test for normality.

Table 9. Cross-sectional estimates with the original DCCE estimates as dependent variable

	[1]	[2]	[3]	[4]
GDPpc	0.0254	0.0246	-0.00393	0.0192
	[-0.0480,0.0987]	[-0.0134,0.0626]	[-0.0398,0.0319]	[-0.0208,0.0592]
GOV_DC	0.999**			
	[0.0765,1.921]			
GOV_DC*GDPpc	-0.0429			
	[-0.116,0.0306]			
GOV_DCP		0.731		
		[-0.166,1.628]		
GOV_DCP*GDPpc		-0.0382*		
		[-0.0825,0.00617]		
GOV_DCB			1.751***	
			[0.684,2.818]	
GOV_DCB*GDPpc			-0.0390	
			[-0.0860,0.00801]	
GOV_DCC				1.270**
				[0.193,2.348]
GOV_DCC*GDPpc				-0.0474*
				[-0.0961,0.00130]
ABS			0.456	
			[-0.810,1.721]	
OPRODpc	-0.0125	-0.0162	-0.00933	-0.00672
	[-0.0581,0.0332]	[-0.0619,0.0295]	[-0.0611,0.0425]	[-0.0531,0.0396]
LATITUDE	-0.0137*	-0.0125*	-0.00909	-0.0114
	[-0.0290,0.00154]	[-0.0273,0.00233]	[-0.0247,0.00656]	[-0.0260,0.00328]
Constant	0.688***	0.690***	0.488	0.669***
	[0.314,1.062]	[0.328,1.052]	[-0.159,1.135]	[0.309,1.029]
N	104	104	104	104
R2	0.0493	0.0354	0.0936	0.0482
RMSE	1.0155	1.0229	.99664	1.016
SK-test	4.40	4.32	5.47*	4.49

* p<0.1, ** p<0.05, *** p<0.01

Note: A) The dependent variable is a set of DCCE estimates that is estimated with Model 4 (Table 2); B) 95%-confidence intervals in brackets; C) Outliers excluded: Benin, China, Congo, Costa Rica, Nepal and Zambia.

Abbreviations: GOV_DC= Democratic and incorrupt government; GOV_DCP= Democratic incorrupt government with proportional representation; GOV_DCB= Democratic, incorrupt and bicameral government; GOV_DCC= Democratic and incorrupt government with a vibrant civil society; OPRODpc= oil production per capita; LEGFRAC= legislative fractionalization; SK-test= Skewness and kurtosis-test for normality.