Predictors of national CO_2 emissions: Do international commitments matter?

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Abstract

Carbon dioxide emissions are the main cause of anthropogenic climate change and play a central role in discussions on climate change mitigation. Previous research has demonstrated that national carbon dioxide emissions are driven mainly by population size and wealth. However, the variation in per capita emissions of nations with similar standards of living and similar population is huge. In this paper we investigate the drivers of national per capita carbon dioxide emissions over and above already known factors. In particular, we extend previous research by taking into account countries' shares of imports and exports, indicators of political interventions such as energy prices, and the use of renewable energy sources. Moreover, we also examine whether international commitments, such as the ones made by many nations at climate summits of the United Nations, matter. We use country-level data from 1980 to 2014 and estimate fixed effects panel regression models. In accordance with former research we find no environmental Kuznets curve with respect to carbon dioxide per capita emission levels. However, higher energy prices and the availability of alternative energy sources both reduce emissions. Furthermore, voluntary international environmental commitments also motivate countries to reduce carbon dioxide emissions.

Keywords: Environmental Sociology, CO_2 Emissions, Environmental Kuznets Curve, IPAT, STIRPAT, Global Environmental Behavior

1. Introduction

Carbon dioxide (CO_2) emissions are the main cause of global warming and play the central role in discussions on climate change mitigation. According to an estimate by the Intergovernmental Panel on Climate Change (IPCC), if global warming is to stay within the two-degree target, the atmosphere can absorb approximately 30 Gt of anthropogenic CO_2 yearly (Friedlingstein et al. 2014; IPCC 2014; Meinshausen et al. 2009). Given that the world population will increase to approximately 10 billion by 2050 (UN 2015) the two-degree target would allow an emission of 3 tons per person and year. In 2014 the world average per person was 5.1 tons. However, the variation in CO_2 emissions is huge. The average emission in the USA is about 16.5 tons, in the European Union 6.7 tons, in India 1.8 tons, and in Africa (excluding South Africa) less than one ton (Olivier et al. 2015). Given the IPAT formula according to which environmental impact is a function of the population, affluence, and technology (Commoner et al. 1971; Ehrlich and Holdren 1970, 1971), differences in per capita emissions between countries of different living standards are no surprise. However, inspection of country rankings (see Figure 1) reveal that the variation is also large between countries with similar living standards such as the USA and Europe, and even between similar countries in Europe such as Germany and Switzerland. Given the enormous challenge the world is facing to reduce CO_2 emissions, insight into the factors that are driving emission levels is crucial. So far research has focused on the role of population and wealth and some aspects of the economic structure. In this paper we investigate additional reasons that might be linked to CO_2 emissions. Much discussion has recently been devoted to the question of how economic imports and exports are related to CO_2 emissions. Thus, the emissions of China are often thought to be high because China is viewed as the production site of the world with high export rates. However, our analysis shows that export rates of different nations bear surprisingly little relation to CO_2 emissions. Furthermore, we are interested in scrutinizing the effect of policies such as the taxing of gasoline prices and other fossil energy sources, and of supporting non-fossil energy. Moreover, we pay attention to the effects of international environmental agreements such as those made at the world climate summits. These summits are often criticized for delivering only voluntary commitments but no enforceable obligations (Carraro and Siniscalco 1998; Young 2010). However, and maybe surprisingly, our analysis shows that even voluntary commitments without enforceable laws have some effects on national CO_2 levels.

This contribution proceeds in four further steps. In the next section, we present the latest data with respect to national CO_2 emission levels. The descriptive results are interesting since national per capita emissions change rapidly, and country rankings based on it change accordingly. Hence, we present data for 1990 (the Kyoto bench line) and 2014. The third section describes the data and the statistical model. The fourth section presents the results. We first discuss and replicate former studies that explain national CO_2 levels. We use the latest available data containing 183 countries overall with yearly reported CO_2 levels starting in 1980 through 2014 provided by the Emissions Database for Global Atmospheric Research (EDGAR) (Olivier et al. 2015). Because of its longitudinal structure the data is suitable for investigating the causal structure of some key variables by calculating fixed effects estimates. We then extend the model by incorporating new variables into the analysis, which have been discussed lately in relation to CO_2 levels such as the extent of foreign trade, or energy prices (Dietz et al. 2010; Jorgenson and Clark 2011; Rosa and Dietz 2012; Rosa et al. 2015). Moreover, we integrate indicators of political commitment such as the number of international voluntary agreements a country has signed and set into force in order to protect the environment. Finally, the main results are summarized and discussed in the last section.

2. Drivers of CO_2 emissions

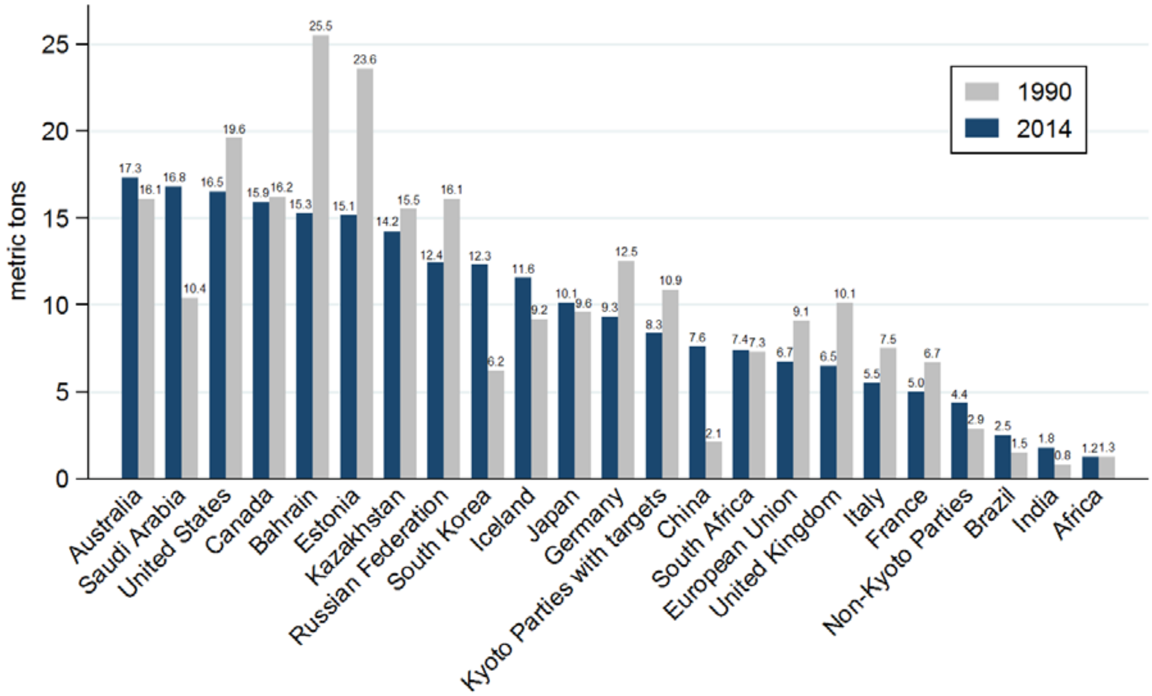
According to the latest report from EDGAR, worldwide CO_2 emissions have reached 35.7 Gt in 2014 (Olivier et al. 2015). Dividing this number by the estimated world population of approximately 7 billion people amounts to a global average of roughly 5.1 tons of CO_2 emissions per person per year. The International Panel on Climate Change (IPCC) estimates that the atmosphere can absorb an additional 1000 Gt of accumulated CO_2 until the end of the century in order to meet the two-degree goal of global warming with a probability of 66%. Given that 40% of CO_2 stays in the atmosphere (the other 60% is absorbed by plants, soil and oceans) and that the world population will increase to 10 billion (UN 2015), emissions per capita should not exceed roughly 3 tons of CO_2 emissions per capita and year in order to be sustainable.

Currently, CO_2 emissions per capita (p.c.) are highest in countries such as Qatar (39 tons p.c.), Kuwait (28 tons p.c.), Trinidad and Tobago (25 tons p.c.), and Luxembourg (19 tons p.c.). At the very bottom of the world ranking are countries such as Ethiopia, Democratic Republic of the Congo, and Eritrea where the per capita consumptions of fossil energy sources are almost zero and in which emissions are estimated to be around 100 kg per capita. However, the measurement at the very top and the very bottom of such a world ranking is biased and/or unreliable. In terms of population size the countries with the highest emissions (Qatar, Kuwait, Trinidad and Tobago, or Luxembourg) are all very small and are oil-producing (with the exception of Luxembourg), and at the bottom of the list they are very poor with notoriously unreliable data (Andres et al. 2012). Hence, a meaningful analysis should treat the small oil-producing states at the very top and the poor countries at the bottom of the distribution as statistical outliers. Therefore, our ranking (see Figure 1) starts with Australia, Saudi Arabia, and the United States, which have per capita emissions of about 17 tons each. Other large players are the Russian Confederates (12.4 tons), Japan (10.1 tons), the European Union (6.7), and China, which reached 7.6 tons per capita in 2014. In comparison the average emissions in Brazil, India or Africa are only 2.5, 1.8, and 1.2 tons respectively.

The differences displayed in Figure 1 raise the question of what is causing them. Past research has focused on the famous IPAT formula (Commoner et al. 1971; Ehrlich and Holdren 1970, 1971), which specifies that the environmental impact of a country is a function of population size, wealth, and technology. The basic assumptions of the IPAT formula and its statistical interpretation (STIRPAT) have been confirmed by older studies using cross sectional data analysis (Dietz and Rosa 1997; Rosa et al. 2004; York et al. 2003) as well as by more recent studies that use methodologically more advanced statistical methods exploiting the longitudinal data structure (Cole and Neumayer 2004; Jorgenson et al. 2014; Liddle 2015; Poumanyvong and Kaneko 2010). Newest results from the latter line of research estimate that a one percent increase in population increases the per capita CO_2 emissions by roughly 1%.[1] Additionally, a one percent increase in wealth (measured by the purchasing power parity (PPP) of GDP per capita) increases CO_2 emissions in the range of 0.57 to 0.97 (Liddle 2015). Furthermore, some prior studies incorporate the energy intensity of the industrial sector and the share of non-fossil fuels of energy production as indicators of a country's technology. As energy intensity increases by one percent per GDP of output (measuring higher inefficiency) CO_2 emissions increase by 0.31 percent, and CO_2 is reduced if a country has a larger proportion of non-fossil energy production (Liddle 2015). Hence, also new results using longitudinal statistical analysis confirm the assumptions specified by the IPAT formula that population, wealth, and technology are the important drivers of national CO_2 emissions.

[1] See Liddle (2014) for a detailed review of demographic factors on CO_2 emissions.

Figure 1: CO_2 emissions per capita in international comparison for 1990 and 2014



Note: The figure shows the top 10 and the bottom 10 countries with respect to CO_2 emissions p.c. Excluded are some very small countries from the top and some very poor countries from the bottom of the distribution. Data Source is the Emissions Database for Global Atmospheric Research (Olivier et al. 2015).

3. Data and Method

For our statistical analyses we compiled data from newest available sources (see Table S1 in the supplement for a complete description of all variables). Most importantly, we used the Emissions Database for Global Atmospheric Research (EDGAR), which contains yearly information on CO_2 emissions from 1970 to 2014 for 183 countries. However, country numbers are reduced due to missing data in some covariates or due to statistical outliers (see Table S2 in the supporting information for a list of countries included in the analyses). In comparison to other data, EDGAR has the advantage of containing the most recent years, and includes emissions from industrial processes. Thus, the data is more complete and more accurate than the information provided by the International Energy Agency (IEA) (Andres et al. 2012, Olivier et al. 2015). Information on countries' population size is taken from the World Bank (WB). Data on GDP (converted into PPP) is obtained from the International Monetary Fund (IMF). The IMF data has the advantage of providing PPP GDP information for every country starting 1980 onwards. In comparison, data from the World Bank starts in 1990 and would restrict the observation period to 24 years. Information on the energy intensity required to produce a unit of GDP, fossil fuel consumption, and the share of electricity production from non-fossil sources are gathered from the International Energy Agency (IEA). Data on import and export rates and information about countries' GDP share of industry or service is taken from the World Bank (WB).

We estimate the effects via a standard fixed effects (FE) panel regression model in which the yearly changes of CO_2 emissions (from the mean) are regressed on the yearly changes in the independent variables (Brüderl and Ludwig 2015; Wooldridge 2010). The model can be written as

$$y_{it} - \bar{y}_i = (\boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_i)\boldsymbol{\beta} + \boldsymbol{Z}_t\boldsymbol{\gamma} + \varepsilon_{it} - \bar{\varepsilon}_i. \quad (1)$$

y_{it} denotes the (natural logarithm of) CO_2 per capita of country i in year t. $\bar{y}_i$ denotes the countries' average for the whole observation period. $\boldsymbol{x}_{it}$ denotes the vector of all exogenous variables for country i in time t, and $\bar{\boldsymbol{x}}_i$ the averages for the whole observation period. $\boldsymbol{Z}$ is a vector of dummy variables which controls period effects for all countries. It takes the value of one if the observation year is one and zero otherwise for all $t \neq 1$. ε_{it} refers to a country's time varying stochastic error term. For statistical purposes and for ease of interpretation we took the natural logarithm of all exogenous variables, except for the number of international environmental agreements, which enter latter models in counts in steps of 100. The fixed effects model given in (1) has the advantage of taking only the within country variations into account. Any unobserved between country differences, therefore, cannot bias the estimation. Under the assumption that $\boldsymbol{x}_{it}$ and ε_{it} are not correlated (strict exogeneity) a fixed effects model is an adequate statistical tool to estimate the unbiased causal effect of the independent variables $\boldsymbol{X}$ on Y. The assumption is violated if there are measurement errors in $\boldsymbol{x}_{it}$, unaccounted period effects (external shocks), or omitted variables that are correlated with Y and $\boldsymbol{X}$. We account for possible period effects by including the yearly time dummies ($\boldsymbol{Z}$) into the analyses.

4. Results

We begin our analyses by first replicating former models, who regress the CO_2 levels of countries on population size, wealth (PPP GDP per capita), energy intensity, and fossil fuel consumption (particularly Liddle 2015). Our results (see Model 1 in Table 1) replicate former studies rather closely with respect to the effect of population and wealth. Our population estimate of 1% suggests that CO_2 emissions are simply proportional to population size. A quadratic population term (not shown in Table 1) is statistically not significant suggesting that there are neither exponential nor marginal decreasing effects of population (for similar results see also Jorgenson and Clark 2010).

Proportionality suggests that models of CO_2 emissions are better specified by using emissions per capita instead of total country level emissions, because this incorporates population into the dependent variable and thereby circumvents potential problems of multicollinearity. The results of such a model using the CO_2 emissions per capita are displayed in Model 2 of Table 1. The results suggest that every increase in GDP per capita by 1% increases CO_2 emissions by 0.5%. The quadratic term of logged GDP is very small and in latter models (Models 3 and 4) not statistically significant, suggesting that also we find no environmental Kuznets curve with respect to the growth of CO_2 per capita emissions like prior studies (Aslanidis and Iranzo 2009; Azomahou et al. 2006; Cavlovic et al. 2000; Jorgenson 2012; Jorgenson and Clark 2012; Liddle 2015; Wagner 2008). Next, we take indicators of technology into account and find in comparison to former studies (e.g. Liddle 2015) much stronger effects of the energy intensity (Model 2). Thus, a one percent increase in the energy intensity to produce a unit of GDP increases CO_2 emissions by 1.5 percent, suggesting that technology and foremost efficiency has a strong impact on CO_2 emissions.

Table 1: Country and Time Fixed Effects Regressions of CO_2 Emissions (per capita)

	Model 1	Model 2	Model 3	Model 4
Dependent Variables	CO_2	CO_2 per capita		
Population	1.00***			
	(0.16)			
GDP p. c.	0.76***	0.55***	0.53***	0.78***
	(0.07)	(0.06)	(0.06)	(0.12)
GDP p. c. squared	-0.06***	-0.03*	-0.01	-0.03
	(0.01)	(0.01)	(0.01)	(0.03)
Energy Intensity	2.31***	1.52***	1.30***	3.03***
	(0.36)	(0.28)	(0.28)	(0.39)
Fossil Fuel Energy Consumption	0.69***	0.09	0.10^{+}	0.28*
	(0.09)	(0.05)	(0.06)	(0.11)
Foreign Trade			0.04	0.07
			(0.03)	(0.04)
Industry			0.01	0.24
			(0.06)	(0.20)
Services			-0.08	0.68^{+}
			(0.06)	(0.36)
Electricity Production from Non-Fossil Sources			-0.03^{+}	-0.11**
			(0.02)	(0.03)
International Environmental Agreements			-0.06**	-0.10*
(Unit: 100 IEAs)			(0.02)	(0.04)
Energy Prices				-0.04*
				(0.02)
n x T	3295	3295	2877	596
n	147	147	116	31
adjusted R^2 within	0.7631	0.5355	0.5850	0.7245
Root MSE	0.13	0.09	0.09	0.04
Test for Residual Cross-Section Independence (H_0)	1.40	1.00	1.35	1.44
Residual Non-Stationarity Panel Unit Root Test (H_0)	6.48***	4.775***	2.46**	2.23*

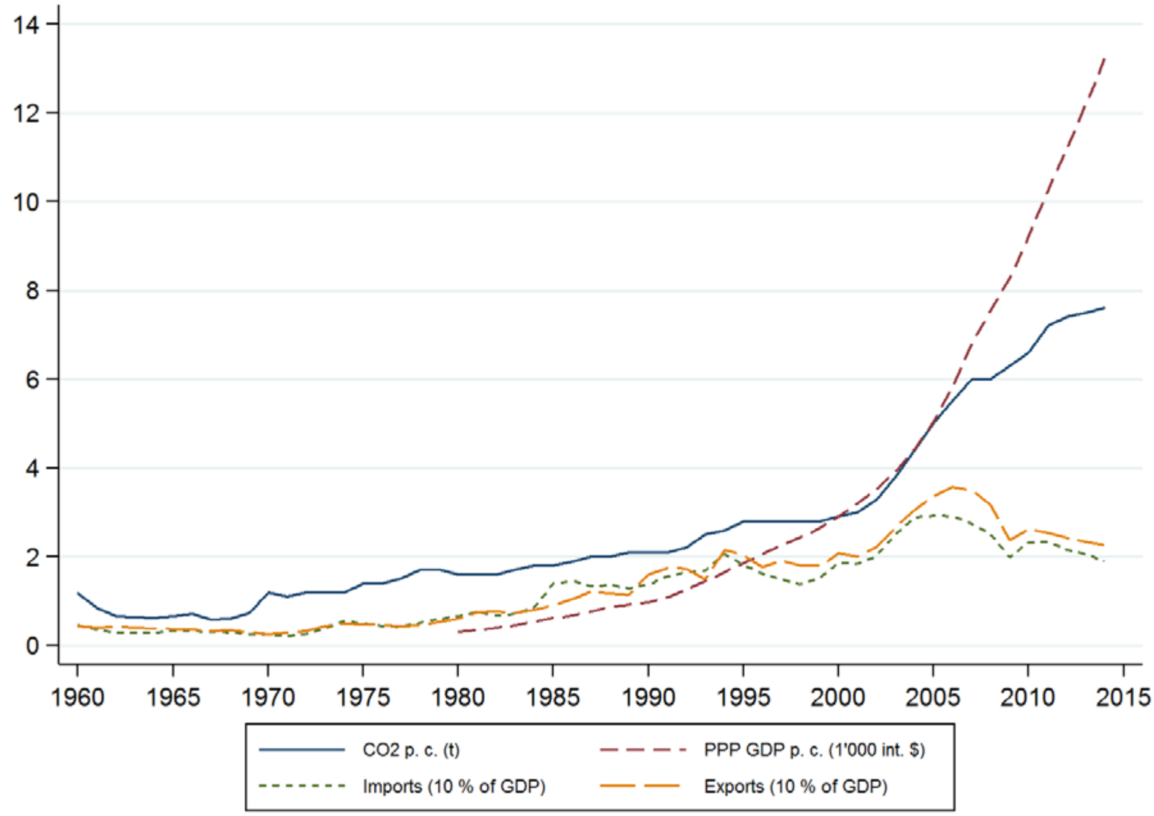
Notes: $^{+}$ = $p < 0.10$, * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. Unstandardized regression coefficients with standard errors in brackets. Models 1 to 4 contain dummy variables for each year in order to control for overall time-trends. All standard errors are clustered by country and year, and therefore robust with respect to heteroscedasticity and autocorrelation. The test values of the Residual Cross-Section Independence Test and the values of the Residual Non-Stationarity Panel Unit Root Test are standard normally distributed. Thus, values below 1.96 indicate that H_0 cannot be rejected. Hence, the residuals are cross-sectionally independent and stationary (homoscedastic without any time trend). Model 4 contains most OECD countries plus Latvia and South Africa. A coefficient plot of the results including the 95% confidence intervals is contained in the supplement (Figure S1).

This difference in effect size might partly be due to the fact that our data on CO_2 emissions includes emissions from industrial processes. In comparison, former research only takes emissions from fossil fuel use into account and excludes other sources. However, the definition of energy intensity is a unit of energy divided by a unit of GDP and the definition of the dependent variable is CO_2 divided by population. Hence, the two variables are partly linked by data construction.

Finally, the model also contains a variable measuring how much of the total energy consumption stems from fossil sources. The effect we find is surprisingly weak. Considering only the 31 members of the OECD (Model 4) with the most reliable data, a one percent increase in the share of energy stemming from fossil fuels increases CO_2 emissions just by 0.28 percent.

Next, we are concerned with extending the IPAT formula and the analyses of prior studies by taking further possible causes of CO_2 intensity into account. One argument often heard in the debate is that some developing countries have high emission rates because they have become industrial production sites of the world. Hence, CO_2 emissions are created in developing countries, but the goods are consumed in the affluent nations (so-called Pollution Haven Hypothesis) (Chichilnisky 1994; Jorgenson 2012). In particular, China is supposed to have high emission rates because of high export rates. However, export rates often go hand-in-hand with import rates. In our extension we first incorporated import and export rates separately into the model, finding no statistically significant effects (see Table S4 in the supplement). Next, we combined import and export rates into a variable measuring the percentage of foreign trade relative to a country's GDP. However, the percentage of foreign trade also does not produce any significant result in our model (see Models 3 and 4). Hence, this finding suggests that the amount of foreign trade is not an important source of CO_2 emissions ceteris paribus (see also Jorgenson et al. 2014). This finding can also be demonstrated with regard to China. Figure 2 shows that GDP and CO_2 per capita have been rising steeply in China since 2005. However, both import and export rates have been falling during the same time period. Hence, exports are not the main driver of CO_2 levels in China (see also Arto and Dietzenbacher 2014). We also find no reliable evidence regarding an economy's share of the industrial or service sector with respect to GDP, suggesting that there is no empirical evidence supporting the notion that a shift to the service sector goes hand-in-hand with reductions of CO_2 per capita.

Figure 2: Comparison of Trends in CO_2 Emissions, GDP and Foreign Trade in China

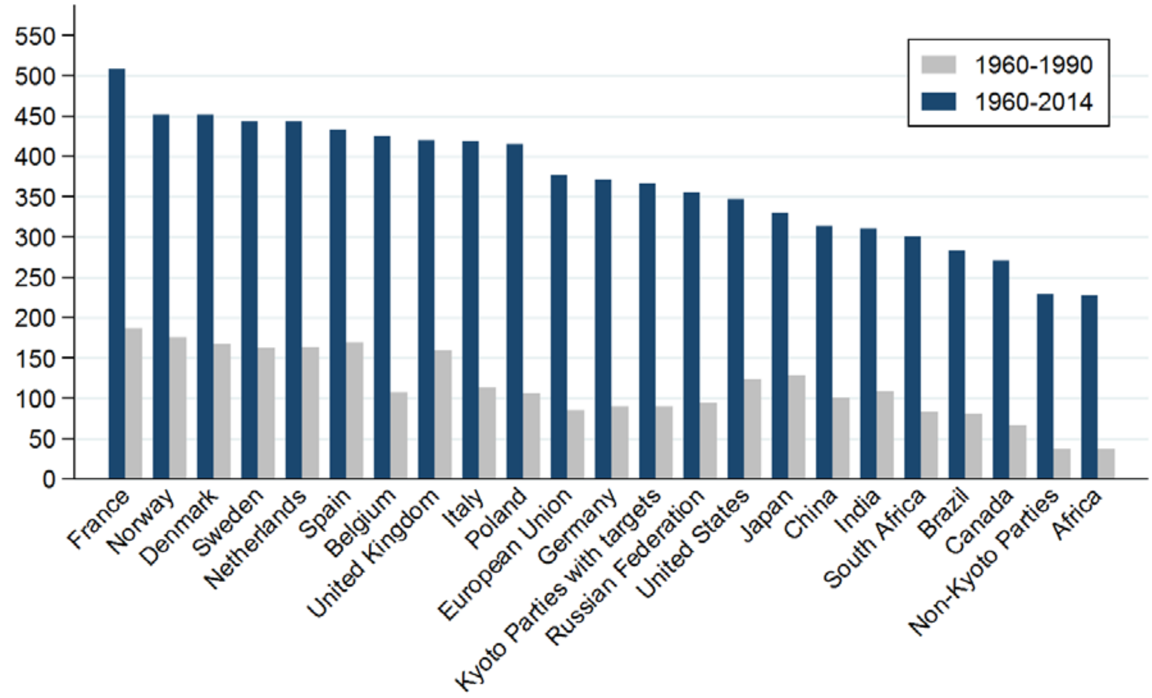


Note: CO_2 data sources are the Carbon Dioxide Information Analysis Center (CDIAC) for the years 1960 through 1969 and EDGAR for 1970 to 2014.

Following Rosa and Dietz (2012) (see also Rosa et al. 2015) we extend the model further by incorporating indicators of environmental policies. Environmental policies can more or less directly intervene with regards to energy supply and energy consumption. The supply side is often influenced by encouraging (and subsidizing) non-fossil sources such as energy produced by solar, water, nuclear, or other renewable sources. We integrated the percentage change in energy supply produced by non-fossil sources. As expected the results indicate that every increase of one percent reduces the per capita CO_2 emissions by 0.11%. The effect is only observable in Model 4 (Table 1) controlling for energy prices. This substitution effect of fossil fuel by non-fossil fuel sources is surprisingly small. However, the result replicates former findings (York 2012). One reason for this might be that renewable energy sources are very volatile depending on weather conditions such as wind, sunshine, or water supply. Supposedly, high volatility reduces the substitution effect, particularly if storage capacity or smart grids are not available.

Countries often indicate their willingness to protect the environment by signing international agreements. The most prominent examples in this context are of course the Kyoto Protocol and other voluntary international agreements like those made at world climate summits. Another recent example is the Agreement on Cooperation on Marine Oil Pollution, Preparedness and Response in the Arctic, which was signed by the neighboring countries of the Arctic Sea in 2013. These summits and agreements are often criticized for not being very successful since many agreements are not binding and violations cannot be sanctioned (Carraro and Siniscalco 1998; Young 2010). Using data from the International Environmental Agreements Database Project (IEADP) (Mitchell 2015) we counted all international environmental agreements that countries signed and put into force from 1960 to 2014, and incorporated this variable into the model. The distribution varies from 90 agreements (Zambia) to 509 (France) and is displayed in Figure 3.

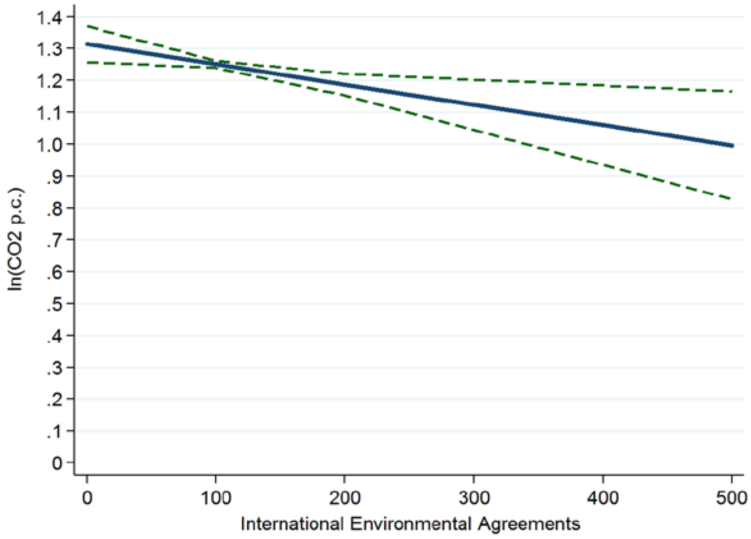
Figure 3: Cumulated Numbers of International Environmental Agreements



Note: Displayed are the 10 countries at the top and 10 countries at the bottom of the distribution in addition to some averages such as for the European Union.

The results indicate that for every 100 additional agreements CO_2 emissions indeed decrease by about 0.06% respectively 0.10% (see Models 3 and 4 in Table 1). Thus, the effect is relatively small but voluntary agreements matter and are an indicator of a nation's willingness to reduce emissions. This result is visualized in Figure 4.

Figure 4: Predicted Marginal Effect of International Environmental Agreements on CO_2 Emissions per Capita (Obtained from Model 3 of Table 1)



Note: Dashed lines indicate the 95% confidence interval.

An often used instrument for reducing emissions is the price mechanism, and many countries tax oil and electricity in order to encourage reduction efforts. Internationally comparable energy price time series are hard to find in international statistics and are only available for OECD countries. This reduces the number of countries for this analysis to 31. The results are displayed in Model 4 of Table 1 and show that an increase in energy prices by one percent reduces CO_2 emissions by 0.04 percent. The effect is small and far from proportional. One possible interpretation is that the elasticity of the price effect depends on the substitutability of energy. Prices are expected to have only small effects if the substitutability is low. This seems to be the case for the overall energy demand. A further reason might be that many energy prices, particularly the oil price, are volatile. High volatility makes it hard for consumers to adapt persistently to energy reducing life styles. However, the results still suggest, that price increases are contributing to reductions in CO_2 emission levels.

We performed a number of robustness checks for the models in Table 1. First, we calculated all models by allowing for country-specific constants and slopes (FEIS models) (see Brüderl and Ludwig 2015; Wooldridge 2010; Polachek and Kim 1994). This extension did not refine the results in any substantial way. Second, we deleted the upper and lower 5% of countries with respect to the CO_2 emissions and PPP GDP per capita in order to control for statistical outliers. Additionally, all models were recalculated by dropping one country each time from the regression. Separately, we also excluded countries with less than 10 observations. None of these checks had any substantial influence on our estimates. Furthermore, all parameters were tested for linearity, including penalized splines two-way (country and time) FE models (Ruppert et al. 2003). The partial residual plot for GDP is shown in the supplement (Figure S2). In addition, we checked the robustness of standard errors via non-parametric bootstrapping and found no substantial differences. Moreover, we conducted subgroup-specific analyses with regard to OECD membership and non-membership (see Table S5 in the supplement), and with respect to different world regions as defined by the World Bank (Europe and Central Asia, Latin America and Caribbean, Middle East and Africa, South East Asia and Pacific). Subgroup specific analysis was also performed with respect to the geographical position of countries (tropical and non-tropical regions). None of these variations led to essentially different results. Also, we substituted the overall energy intensity as shown in Table 1 by the industrial energy intensity (taken from the IEA). Lastly, all models were estimated by using CO_2 data from CDIAC, and GDP data from Penn World Table 8.1. None of these variations leads to different conclusions. All models presented in Table 1 as well as all the robustness checks were conducted using the statistical software package STATA 14.1.

5. Summary and Discussion

This paper investigates the determinants of national CO_2 emissions per capita by using more extensive and more accurate data sources than prior studies. The analyses are based on 147 countries for which yearly measurements of CO_2 per capita and various covariates exist for the period between 1980 and 2014. We analyze the data using fixed effects panel regression models. Such models avoid cross-sectional comparisons, which are often biased due to unobserved heterogeneity between the countries. First, we replicate former studies (particularly Liddle 2015) and show that a country's population size is proportionally related to CO_2 emissions. Therefore, CO_2 per capita becomes our dependent variable. Second, our analyses suggest that the growth of wealth (GDP per capita) is mostly linearly related to growth in CO_2 emissions. Moreover, the estimated elasticity 0.5 means that the absolute emissions are marginally decreasing at higher levels of GDP.

Besides these replications our paper offers some new and interesting findings. First, we find that a shift from the industrial sector to the service sector is not related to reductions in CO_2

emissions as is often assumed (e.g. Fourcroy et al. 2012). Second, we show that the share of foreign trade does not determine CO_2 levels. This result is surprising since the literature often hypothesizes that some developing countries (e.g. China) have high emission levels because they have become the workbench for more affluent countries. Third, we incorporate countries' political effort by taking the number of international environmental commitments into account. Our results suggest that countries that have signed many international agreements have indeed reduced emission levels as compared to those that signed fewer agreements. Hence, international voluntary commitments matter. Finally, we also take national price levels into account and show that higher energy prices reduce CO_2 emission levels.

The most surprising result is the finding that voluntary agreements matter. However, this does not imply that voluntary agreements are sufficient to meet the international goal of limiting climate change to 1.5 or 2 degrees. Assuming that the world population will reach roughly 10 billion by the middle of the century and given that the atmosphere of the earth can cope with roughly 30 Gt of CO_2 emissions the sustainable per capita emission is about 3 tons per year. Certainly most industrialized countries exceed 3 tons per capita extensively. Even the most sustainable countries in Europe (e.g. France, or Switzerland) still have emission levels of about 5 tons per capita and would need a reduction of around 40% to become sustainable with respect to greenhouse gas emissions. Reduction levels of 40% are still very ambitious but appear feasible. Other countries such as the USA, Australia or Canada have emission levels of about 16 or 17 tons and would therefore need reductions of about 80%. Hence, many countries have a long way to go and will have to take ambitious measures in order to keep the 2-degree goal. Voluntary agreements which are not binding and which will not cause sanctions if missed will probably be not sufficient.

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