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What drives climate change?

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Content

"You can compare the situation with a ship that has sprung a leak on the high seas. Of course, there are problems besides this damage. The food in the third class is miserable, the seamen are exploited, the band plays German Schlager, but if the ship sinks, all this will be irrelevant. If we do not get on top of climate change, there will be no use thinking about income distribution, racism and good taste anymore."

Hans Joachim Schellnhuber,
founding director of the Potsdam Institute for Climate Impact Research
(translated from Süddeutsche Zeitung Online, 14th May 2018)

Abstract

Anthropogenic climate change is the most demanding challenge humanity has to face in the ongoing 21st century and beyond. This dissertation delves deeper into enhancing the knowledge on the major drivers of climate change and its mitigation. Thus, all four articles focus on the macro-level analysis of countries over time, applying causal inference. Specifically, the dissertation addresses the predictors of national carbon dioxide (CO_2) emissions (article 1), the controversial debate on carbon leakage from developed to developing countries (article 2), the influence of social inequality on CO_2 emissions (article 3), and the role of forests as climate solution as well as the drivers of forest loss and its gain (article 4). Altogether, the results suggest that population growth is a major driver of CO_2 emissions and deforestation. Another key factor is increasing wealth. However, the effect of economic growth is double-edged: On the one hand, rising gross domestic product (GDP) almost proportionally boosts carbon emissions so far. On the other hand, growth in GDP contributes to enhance forest cover. Minor carbon-abating effects are observed for energy prices, technological progress, and international environmental agreements. Designating and managing protected areas drives forest gain. Furthermore, social inequality and international trade are not substantially related to CO_2 emissions. Particularly, there is no evidence for carbon leakage from developed to developing countries. Given the challenge of emissions abatement, natural climate solutions are promising for near-term and large-scale sequestration of carbon. As the fourth article highlights, dangerous climate change could be prevented by doubling current forest cover.

Introduction and Summary

Anthropogenic climate change probably is the most demanding challenge humanity has to face in the ongoing 21st century and far beyond (IPCC 2014). Since "The Limits to Growth" (Meadows et al. 1972), the seminal report of the Club of Rome in the early 1970s, global concern for anthropogenic climate change, and its impacts on ecosystems and humanity has steadily increased – so has the awareness to reconcile human development with environmental protection. Subsequently, the so-called Brundtland Commission provided the most widely recognized definition of sustainable development in "Our Common Future" (WCED 1987). This strongly influenced the negotiations on the United Nations Framework Convention on Climate Change (UNFCCC) at the seminal Earth Summit in Rio de Janeiro in 1992. The objective of this worldwide agreement of 197 parties has been to stabilize "greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" (UN 1992: 9). Since the onset of the UNFCCC, the five assessment reports by the Intergovernmental Panel on Climate Change (IPCC) have shed light upon the geophysical relationships, impacts, and mitigation of anthropogenic climate change. These reports have inspired a vast amount of inter- and transdisciplinary research. After the adoption of the Kyoto Protocol in 1997 and its failure, it was only recently that the world community has agreed upon the limitation of global warming to well below 2 °C relative to preindustrial levels in the Paris Climate Agreement in 2015 (UNFCCC 2015).

A maximum of 2 °C of global warming until 2100 may provide a relatively safe operating space for humanity and prevent dangerous climate change alongside a lock-in of a 'Hothouse Earth' pathway with potentially hazardous consequences for ecosystems and human socio-economic systems (IPCC 2014, Steffen et al. 2018, Fischer et al. 2018, Rockström et al. 2009). However, humanity allegedly has already committed to 1.3 °C of warming (Mauritsen and Pincus 2017). Hence, limiting global warming to 1.5 °C and presumably providing an even safer operating space (IPCC 2018) seems out of reach (Raftery et al. 2017).

Meanwhile global carbon dioxide (CO_2) emissions of fossil fuel use and industrial processes – the major contributor to anthropogenic climate change – have more than doubled from 15.9 $GtCO_2$ in 1970 to 35.8 $GtCO_2$ in 2016 (Janssens-Maenhout et al. 2017). This surpasses the global annual gross carbon budget (an estimated 30 $GtCO_2$) to fulfil the 2 °C target with a probability of at least 66 % (IPCC 2014, Friedlingstein et al. 2014, Meinshausen et al. 2009). Assuming an average annual world population of around 10 billion people until 2100 (UNPD 2017), this goal translates into 3 t of gross CO_2 emissions per capita and year. In 2016, per capita carbon emissions amounted to 4.8 tCO_2 (Janssens-Maenhout et al. 2017). Hence, to prevent dangerous climate change fast and forceful measures of mitigation are inevitable (IPCC 2014). Limiting carbon emissions to current levels or even abating them to be in line with the climate target seems a tremendous challenge in the light of this development (Minx et al. 2018).

Therefore, this dissertation delves deeper into enhancing the knowledge on the major drivers of climate change and its mitigation for effective climate policies on a global scale. Thus, all four contributions of this dissertation focus on the macro-level analysis of countries over time applying causal inference. The first article entitled *“Predictors of national CO_2 emissions: Do international commitments matter?”* (pp. 9-32), co-authored by Axel Franzen (Franzen and Mader 2016), investigates the drivers of national (production-based) CO_2 emissions over and above already known factors. The paper confirms previous research that population and economic growth are the major socio-economic drivers of anthropogenic carbon emissions. Moreover, the contribution extends prior studies by analysing the role of international trade, indicators of political interventions such as energy prices, and the transition towards renewable sources of energy. Furthermore, the paper examines whether voluntary international environmental agreements matter. National commitments are often criticized for being voluntary and not enforceable. The results of fixed effects panel regression models of national carbon emissions from 1980 to 2014 indicate that higher energy prices and an energy transition both reduce carbon emissions. In addition, international environmental commitments motivate countries to reduce CO_2 emissions. Interestingly, higher shares of exports or imports of goods and services with respect to gross domestic product (GDP) do not substantially drive national carbon emissions.

Hitherto, national carbon inventories have followed IPCC guidelines based on CO_2 emissions stemming from fossil fuel combustion and industrial processes within countries (production-based accounting (PBA)). Recently, a controversial debate has evolved regarding the PBA framework, versus countries’ carbon emissions additionally incorporating those from international trade (consumption-based accounting (CBA)). So far, the debate has been predominately theoretical and has inspired only a few empirical studies. Thus, the second contribution headed *"Consumption-based versus production-based accounting of CO_2 emissions: Is there evidence for carbon leakage?"* (pp. 33-40), which is also co-authored by Axel Franzen (Franzen and Mader 2018), compares CBA with PBA of CO_2 emissions. Moreover, for the first time, the study analyses reasons for the differences between the two accounting schemes. In particular, it has been argued that wealthy nations with strict environmental regulations might outsource carbon-intensive production to less wealthy states with less strict regulations, and import these goods and services. Therefore, this paper focuses on the question, whether there is evidence for carbon leakage from developed to developing countries. The results of fixed effects panel regression models analysing 110 countries from 1997 to 2011 suggest that for most countries, the differences depending on accounting schemes are small and there is no evidence for carbon leakage. Instead, the ratio of CBA to PBA emissions rises with increasing energy efficiency and growing import rates. Given the small differences between PBA and CBA, the study suggests keeping the production-based accounting scheme of CO_2 emissions.

The third paper *"The nexus between social inequality and CO_2 emissions revisited: Challenging its empirical validity"* (pp. 41-55; Mader 2018) deals with the political economy argument that income/wealth concentration at the top leads to more political influence of rich people on environmental policy, which in turn drives environmental degradation. This notion assumes that rich producers and consumers benefit more from polluting the environment than the poor, and that the latter are more prone to bear the social costs of environmental deterioration. While not directly targeted at CO_2 emissions, this argument has often been applied to them. However, the discourse has been largely separated from the general discussion on drivers of national CO_2 emissions. The argument is now widely disputed, since macroeconomic panel studies applying fixed effects regression models and measuring inequality by the Gini coefficient have discovered a flat relationship. Only two of these studies substituting Gini by the more appropriate share held by the top 10 percent of the income or wealth distribution recently found a positive effect of social inequality on CO_2 emissions. The paper revisits this nexus and challenges the empirical validity of the contribution of an increase in wealth and income inequality to higher CO_2 emissions lately found by Knight et al. (2017) on country-level and by Jorgenson et al. (2017) on U.S. state-level. In particular, the contribution replicates these studies, relaxes their assumptions and extends the models according to Franzen and Mader (2016). The results show that the positive inequality effects spotted in Knight et al. (2017) and Jorgenson et al. (2017) are not robust with respect to the regions and time spans observed as well as to the inequality indicators, estimation techniques, and confounders selected. Hence, this investigation suggests that there is no sound empirical evidence for a substantial nexus between social inequality and CO_2 emissions. After all, lately proposed policy approaches combining efficient cap-and trade programs with income and wealth redistribution (so-called cap-and-dividend schemes) are not, by themselves, suitable for effective climate policy. In fact, the analysis points at the relevance of treating key predictors of CO_2 emissions including energy prices for the U.S. for effective climate change mitigation.

Given the enormous challenge of abating greenhouse gas emissions and recalling the major drivers of national carbon emissions – population and economic growth, a promising strategy for near-term large-scale climate change mitigation is the enhancement of natural terrestrial carbon sinks. Here, forests are considered one of the most suitable ways to sequester carbon today, as afforestation and reforestation (AR) are relatively cost-effective, and associated with least expected adverse effects on biogeochemical and biogeophysical systems (Fuss et al. 2018, Griscom et al. 2017, IPCC 2014, Smith et al. 2016, Sonntag et al. 2016) unlike most geoengineering techniques (Ussiri and Lal 2017).

Hence, finally, the fourth article of this dissertation *“Plant trees for the planet: the potential of forests for climate change mitigation and the major drivers of national forest area”* (pp. 56-98, Mader 2019) estimates the world’s land share under forests required to prevent dangerous climate change and identifies the major drivers of countries’ forest cover. Therefore, the paper combines the newest available longitudinal micrometeorological data (FLUXNET) on forests’ net ecosystem exchange of carbon (NEE) from 78 forest sites (N=607) with countries’ mean temperature and forest area. The results of this straightforward approach indicate that the world’s forests sequester 8.3 $GtCO_2yr^{-1}$ or 1.1 tCO_2 per capita and annum. The direct carbon flux-based method applied here provides estimates that are comparable to the most recent studies applying more complicated, indirect carbon stock-based inventories of NEE. To meet the 2 °C climate target, the current forest cover has to be doubled to 60 % of land area to sequester an additional 7.8 $GtCO_2yr^{-1}$, which demands less red meat consumption. This challenge is achievable, as the estimated global biophysical potential of AR is 8.0 $GtCO_2yr^{-1}$ safeguarding food supply for 10 billion people with healthy diets. Subsequently, the article identifies the countries with the largest climate liabilities, and economic capabilities, while having the greatest mitigation potential through AR. The results indicate that the most climate-responsible and wealthy countries have the highest AR potential. Hence, these states could take over their responsibility for climate change mitigation relatively easily via large-scale domestic AR activities.

Moreover, for effective policies targeted at enhancing forests, knowledge on the key drivers of forest area is essential. However, information on causal relationships of forest gain and loss is sparse, and unconsolidated with a focus on forest loss. Yet, this is only half of the story to be told. It is vital to understand the drivers of both the increase and decrease of forest land share for effective AR policies. Thus, the study identifies the major predictors of the forest land share of 98 countries from 1990 to 2015 (N=2’494). The results of fixed effects panel regression models highlight that population growth, industrialization, and increasing temperature reduce forest area, while more protected forest and economic growth generally increase it.

Altogether, the four articles of this dissertation suggest that population growth is a major driver of both anthropogenic carbon emissions and deforestation. Another key factor is increasing wealth. However, the effect of economic growth is double-edged: On the one hand, rising per capita GDP almost proportionally boosts carbon emissions so far. On the other hand, growth in GDP contributes to enhance forest cover. Hitherto minor effects for climate change mitigation targeted at abating emissions are observed for energy prices, technological progress (renewable energy transition and energy efficiency increases), and international environmental agreements. Designating and managing protected areas drives forest gain. Furthermore, social inequality and international trade are not substantially related to CO_2 emissions of countries. Trade in forest products is not linked to the land area covered by forest. Particularly, there is no evidence for carbon leakage from developed to developing countries. Given the tremendous challenge of emissions abatement, natural climate solutions are promising for the near-term and large-scale sequestration of carbon. As the fourth article highlights, dangerous climate change could be prevented by doubling current forest cover safeguarding food supply with healthy diets.

Nonetheless, the success to sustain a relatively safe operating space for humanity and prevent dangerous climate change will depend on fast and forceful action to curb major drivers of global warming like population growth while fostering a global mandatory carbon certificate market, low-carbon and large-scale carbon sequestration technologies, and commitments to safeguard vital services of ecosystems integral for human well-being. “A low-carbon world is hard to imagine, yet change often follows when we shift our vision of what is possible” (Figueres et al. 2018).

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1. Article: Predictors of national CO_2 emissions: Do international commitments matter?

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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.

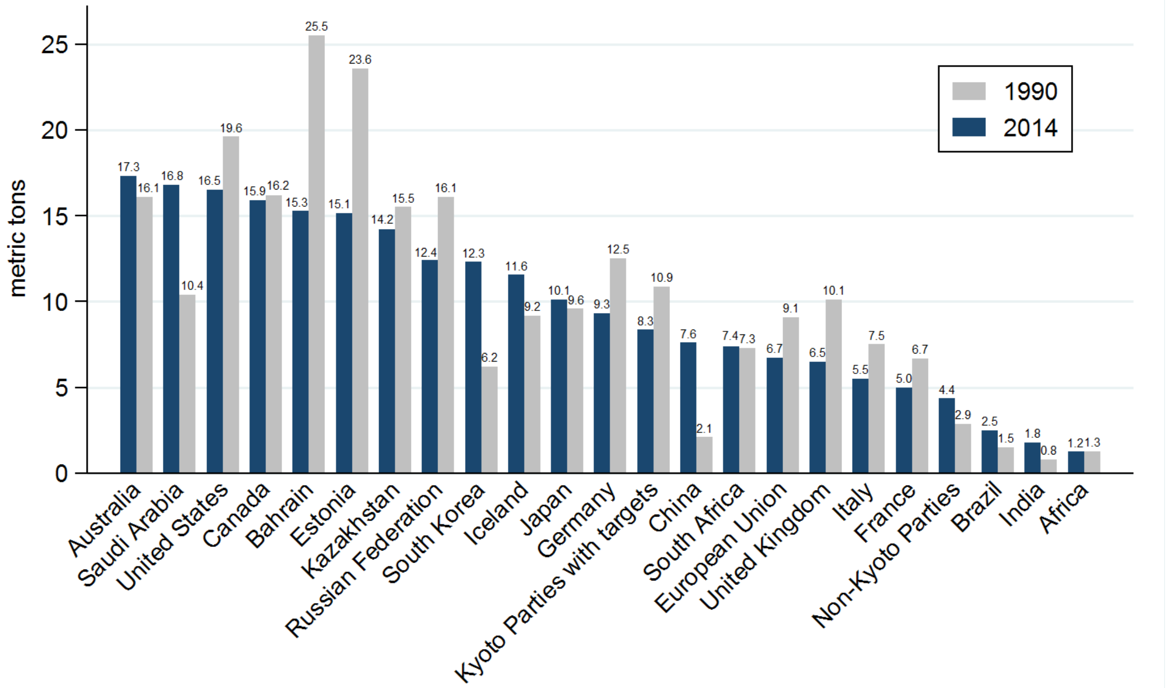
Currently, CO_2 emissions per capita (p.c.) are highest in countries such as Qatar (39 tons p.c.), Kuwait (28 tons p.c.), Trinidad and Tobago (25 tons p.c.), and Luxembourg (19 tons p.c.). At the very bottom of the world ranking are countries such as Ethiopia, Democratic Republic of the Congo, and Eritrea 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

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

(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.

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

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

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 $\overline{\boldsymbol{x}}_i$ 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.

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.

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

Dependent Variables	Model 1 CO_2	Model 2 CO_2 per capita	Model 3	Model 4
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⁺ (0.02)	-0.11** (0.03)
International Environmental Agreements (Unit: 100 IEAs)			-0.06** (0.02)	-0.10* (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*

Note: ⁺ = $p < 0.10$, * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. 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).

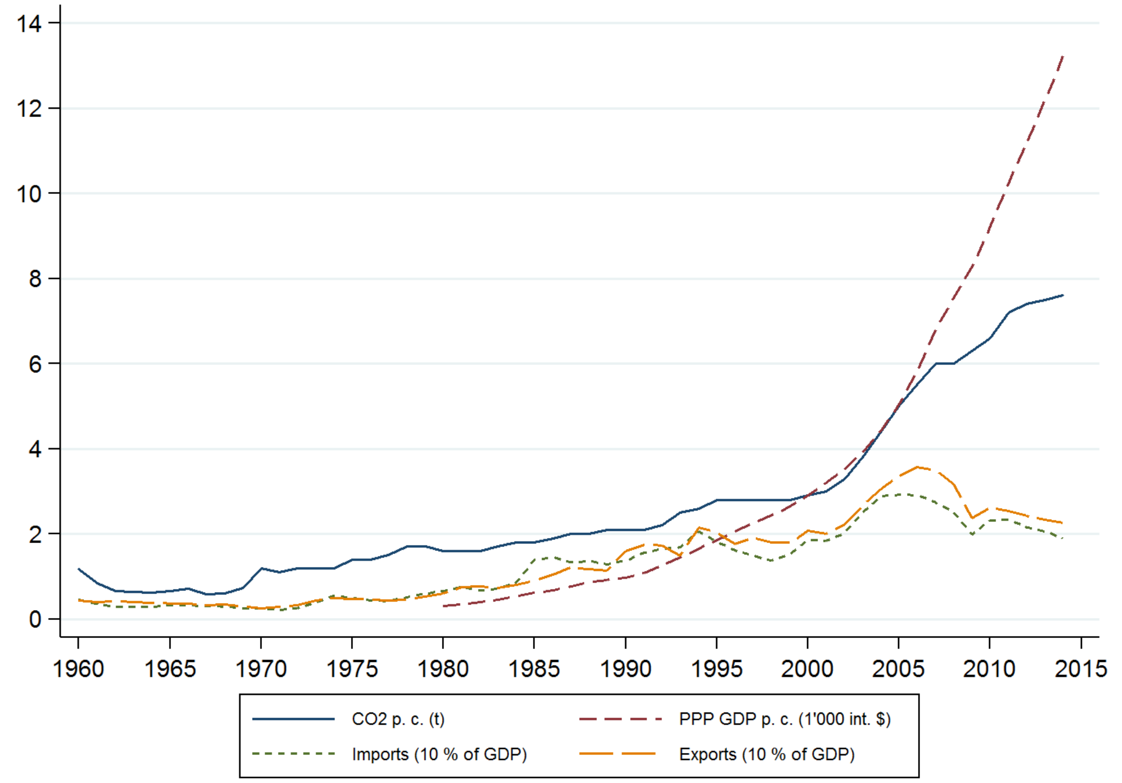
Finally, the model also contains a variable measuring how much of the total energy consumption stems from fossil sources. The effect we find is surprisingly weak. Considering only the 31 members of the OECD (Model 4) with the most reliable data, a one percent increase in the share of energy stemming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

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.

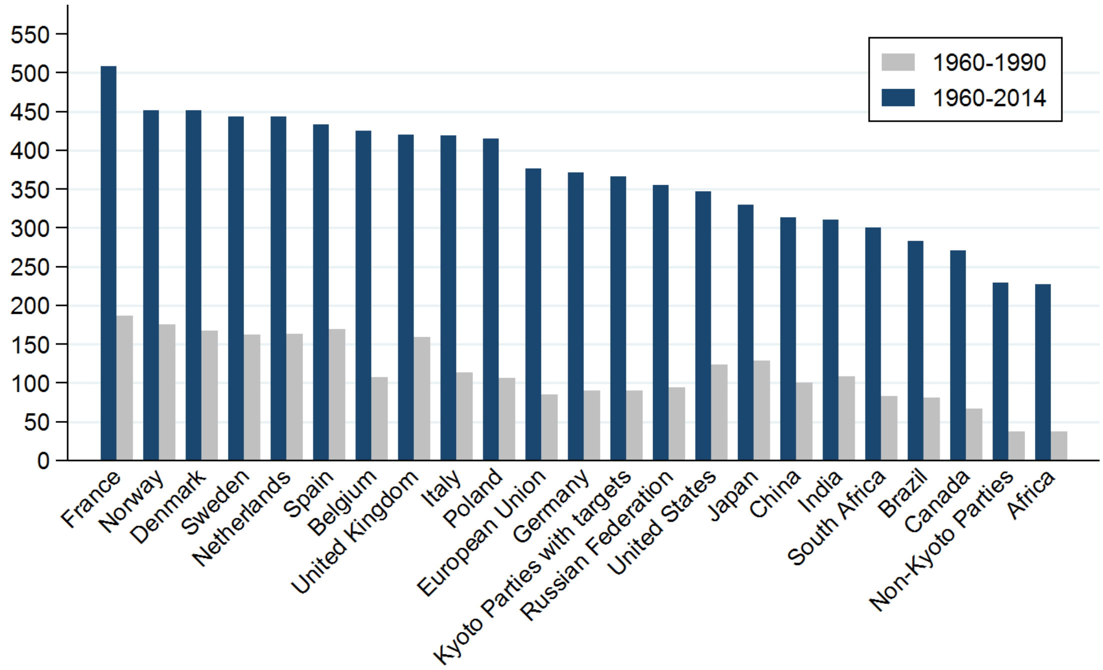
Figure 2: Comparison of Trends in CO_2 Emissions, GDP and Foreign Trade in China



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.

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.

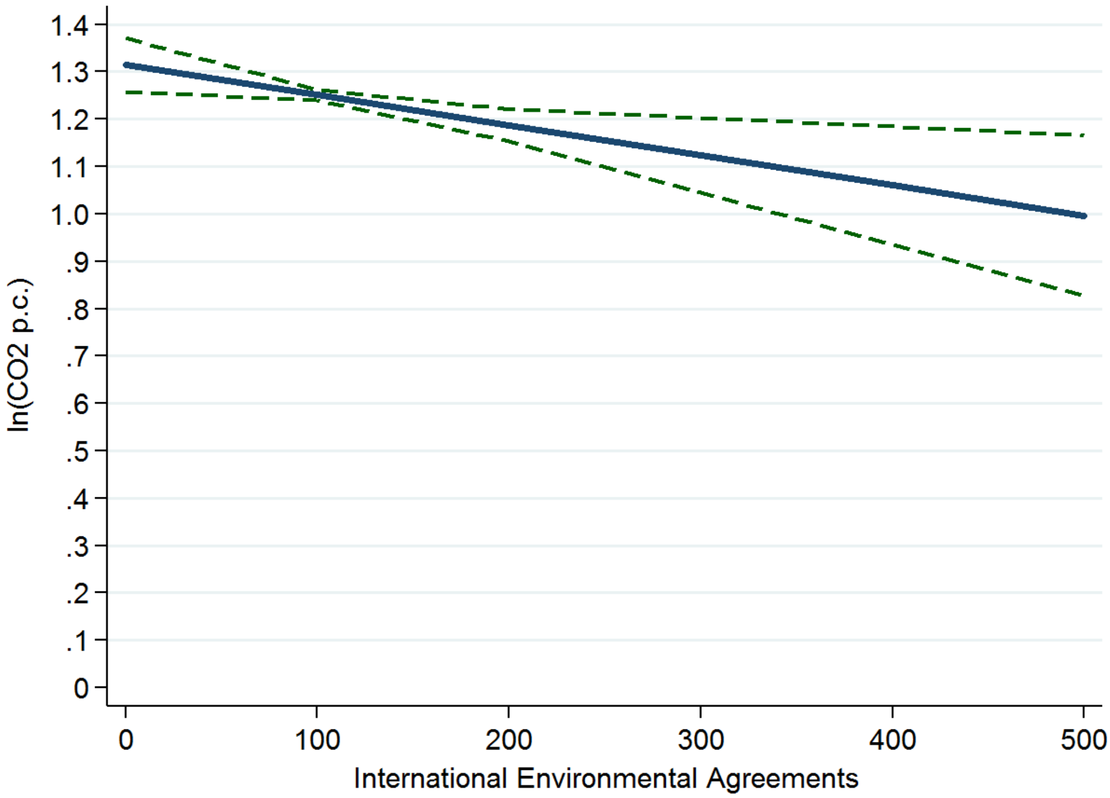
Figure 3: Cumulated Numbers of International Environmental Agreements



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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Supporting Information

Table S1: Variable description

Variable	mean	within ($\bar{x}_i$)			between ($x_{it} - \bar{x}_i + \bar{\bar{x}}$)			N (n x T)	n	Description	Data Source
		sd	min.	max.	sd	min.	max.				
CO_2 (megatons)	130.60	232.32	-2782.70	6803.67	520.26	.01	5154.42	7875	175	CO_2 emissions (p. c.) of fossil fuel use and industrial processes (cement production, carbonate use of limestone and dolomite, non-energy use of fuels and other combustion). Excluded are: short-cycle biomass burning (such as agricultural waste burning) and large-scale biomass burning (such as forest fires).	EDGAR
CO_2 p. c. (metric tons)	3.77	1.35	-6.07	14.34	4.47	.04	21.10	7875	175		
Population	27.33	26.94	-373.17	485.84	102.70	.02	1060.83	10090	184	Total population. Unit: 1 million.	WB
GDP p. c. (1000 interna-tional dollars)	9.58	5.55	-20.34	53.88	10.31	.49	71.99	5564	178	Gross domestic product (GDP) p. c. based on purchasing power parity (PPP). PPP GDP is GDP converted to international dollars using PPP rates. Data are in international dollars based on the 2011 International Comparison Program (ICP) round.	IMF
Energy Intensity	.23	.13	-.74	1.72	.17	.01	1.36	3890	157	Energy intensity level of primary energy is the ratio between energy supply and PPP GDP. Unit: kg oil equivalent per PPP GDP.	OECD/ IEA/WB, IMF
Fossil Fuel Energy Consump-tion	64.51	7.30	30.00	98.38	36.80	0	99.99	5243	159	Energy consumption from fossil fuels comprises coal, oil, petroleum, and natural gas products. Unit: % of total energy consumption	IEA/WB
Foreign Trade	74.45	22.76	-85.94	400.98	39.93	13.88	330.43	7474	178	Trade is the sum of exports and imports of goods and services measured as a share of GDP. Unit: % of GDP.	WB
Industry, value added	28.04	5.94	-4.31	73.88	10.38	7.14	74.06	6225	172	Industry corresponds to the International Standard Industrial Classification (ISIC) divisions 10-45. The origin of value added is determined by the ISIC, revision 3. Unit: % of GDP.	WB
Services, value added	51.85	7.15	12.98	112.10	13.30	22.97	81.81	6225	171	Services correspond to ISIC divisions 50-99. The industrial origin of value added is determined by the ISIC, revision 3. Unit: % of GDP.	WB
Electricity Produc-tion from Non-Fossil Sources	43.58	12.23	-20.39	98.66	32.18	0	99.38	4792	125	Sources of electricity refer to the inputs used to generate electricity. Electricity production from non-fossil sources comprises hydroelectric and other renewable as well as nuclear sources. Unit: % of electricity production.	IEA/WB
Interna-tional Environ-mental Agree-ments (IEAs)	69.72	82.53	-127.68	379.32	38.44	1.16	199.40	10120	184	An international environmental agreement is an intergovernmental document intended as legally binding with a primary stated purpose of preventing or managing human impacts on natural resources. Unit: cumulated number set into force.	IEADP
Energy Prices	80.09	31.69	-25.42	234.77	32.33	48.38	176.11	1017	34	Energy prices are consumer prices for the items electricity, gas and other fuels as defined under the Classification of Individual Consumption According to Purpose (COICOP 04.5) and fuel and lubricants for personal transport equipment (COICOP 07.2.2). Data are expressed as index corrected by IMF PPP rates (2010 = 100 for USA).	OECD, IMF

Notes: EDGAR = Emissions Database for Global Atmospheric Research, IEA = International Energy Agency, IEADP = International Environmental Agreements Database Project, IMF = International Monetary Fund, OECD = Organization for Economic Co-operation and Development, WB = World Bank; All variables in the models are included by taking their natural logarithm except for IEAs, which are included in units of 100 IEAs.

Table S2: Countries included in the analyses

Albania*	Comoros	Honduras*	Mozambique*	St. Lucia
Algeria*	Congo, Dem. Rep.*	Hungary*#	Myanmar*	St. Vincent and the Grenadines
Angola*	Congo, Rep.*	Iceland*#	Namibia*	Sudan*
Antigua and Barbuda	Costa Rica*	India*	Nepal*	Suriname
Argentina*	Cote d'Ivoire*	Indonesia*	Netherlands*#	Swaziland
Armenia*	Croatia*	Iran, Islamic Rep.*	New Zealand*#	Sweden*#
Australia*#	Cyprus*	Ireland	Nicaragua*	Switzerland*#
Austria*#	Czech Republic*#	Italy*#	Nigeria*	Syrian Arab Republic*
Azerbaijan*	Denmark*#	Jamaica*	Norway*#	Tajikistan*
Bahamas, The	Djibouti	Japan*#	Pakistan*	Tanzania*
Bahrain*	Dominica	Jordan*	Panama*	Thailand*
Bangladesh*	Dominican Republic*	Kazakhstan*	Paraguay*	Timor-Leste
Barbados	Ecuador*	Kenya*	Peru*	Togo*
Belarus*	Egypt, Arab Rep.*	Kiribati	Philippines*	Tonga
Belgium*#	El Salvador*	Korea, Rep.*#	Poland*#	Tunisia*
Belize	Eritrea*	Kyrgyz Republic*	Portugal*#	Turkey*#
Benin*	Estonia	Latvia*#	Romania*	Ukraine*
Bhutan	Ethiopia*	Lebanon*	Russian Federation*	United Kingdom*#
Bolivia*	Fiji	Lesotho	Sao Tome and Principe	United States*#
Bosnia and Herzegovina*	Finland	Libya*	Saudi Arabia*	Uruguay*
Botswana*	France*#	Lithuania	Senegal*	Uzbekistan*
Brazil*	Gabon*	Macedonia, FYR*	Seychelles	Vanuatu
Bulgaria*	Georgia*	Malaysia*	Singapore*	Venezuela, RB*
Cabo Verde	Germany*#	Maldives	Slovak Republic*#	Vietnam
Cambodia*	Ghana*	Malta*	Slovenia*#	Yemen, Rep.*
Cameroon*	Greece*#	Mauritius*	Solomon Islands	Zambia*
Canada*#	Grenada	Mexico*#	South Africa*#	Zimbabwe*
Chile*#	Guatemala*	Moldova*	Spain*#	
China*	Guinea-Bissau	Mongolia*	Sri Lanka*	
Colombia*	Guyana	Morocco*	St. Kitts and Nevis	

Notes: We only took countries into consideration that are full members of the United Nations. Models 1 and 2 of Table 1 contain all 147 countries. Model 3 of Table 1 is based on 116 countries indicated by '*', and model 4 contains mostly OECD countries plus Latvia and South Africa indicated by '#'. The maximum numbers of years observed is T = 34. However, there are some countries for which we observe less years due to missing data (e.g. for Canada T = 4 which is the minimum). The average in Model 1 is T = 22.4. We estimate unbalanced fixed effects panel regression models. As a robustness check, we also estimated models in which the minimum T is 10. There is no substantial difference in estimates.

Figure S1: Coefficient plot of Table 1 displaying the 95% confidence intervals

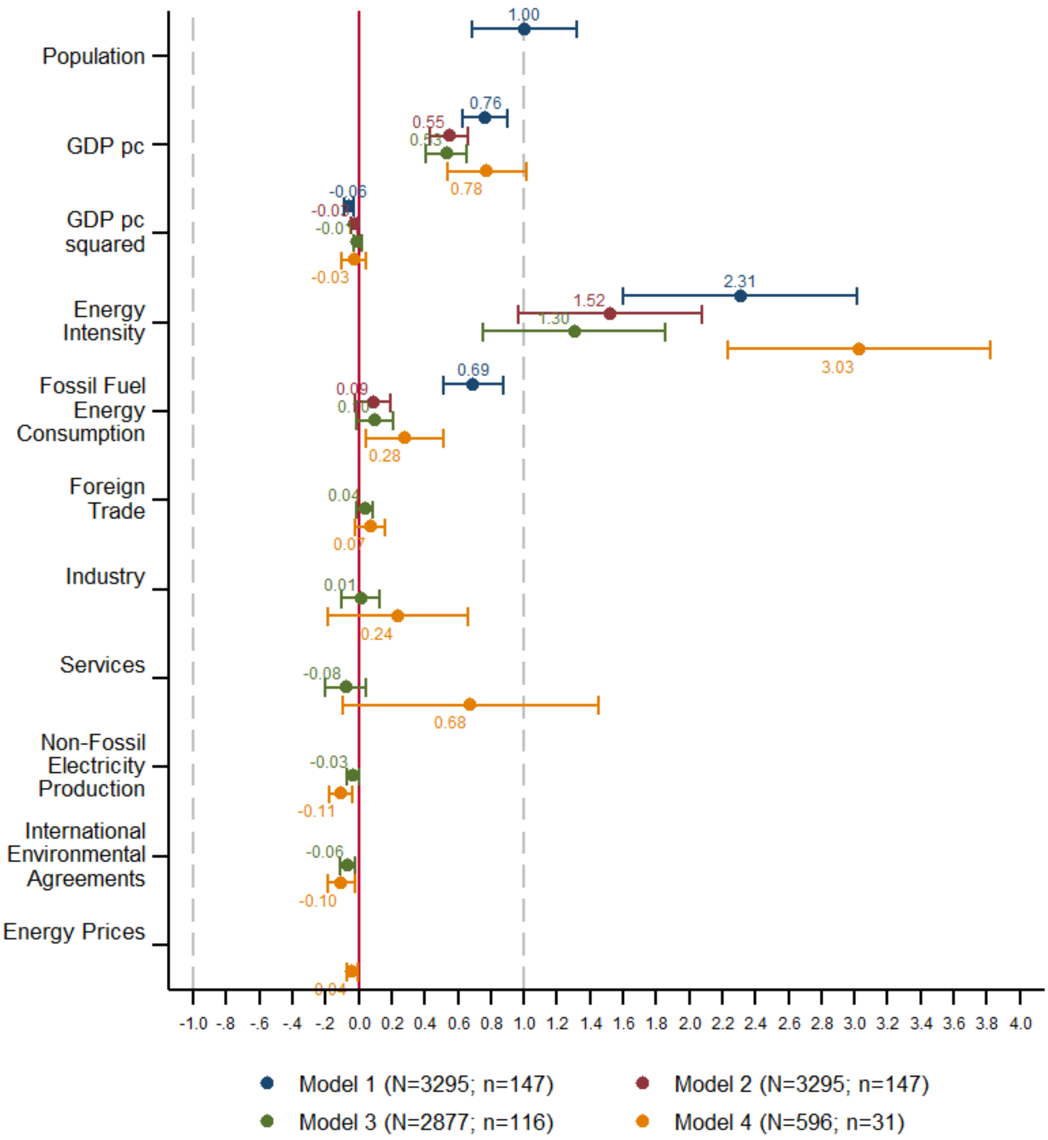
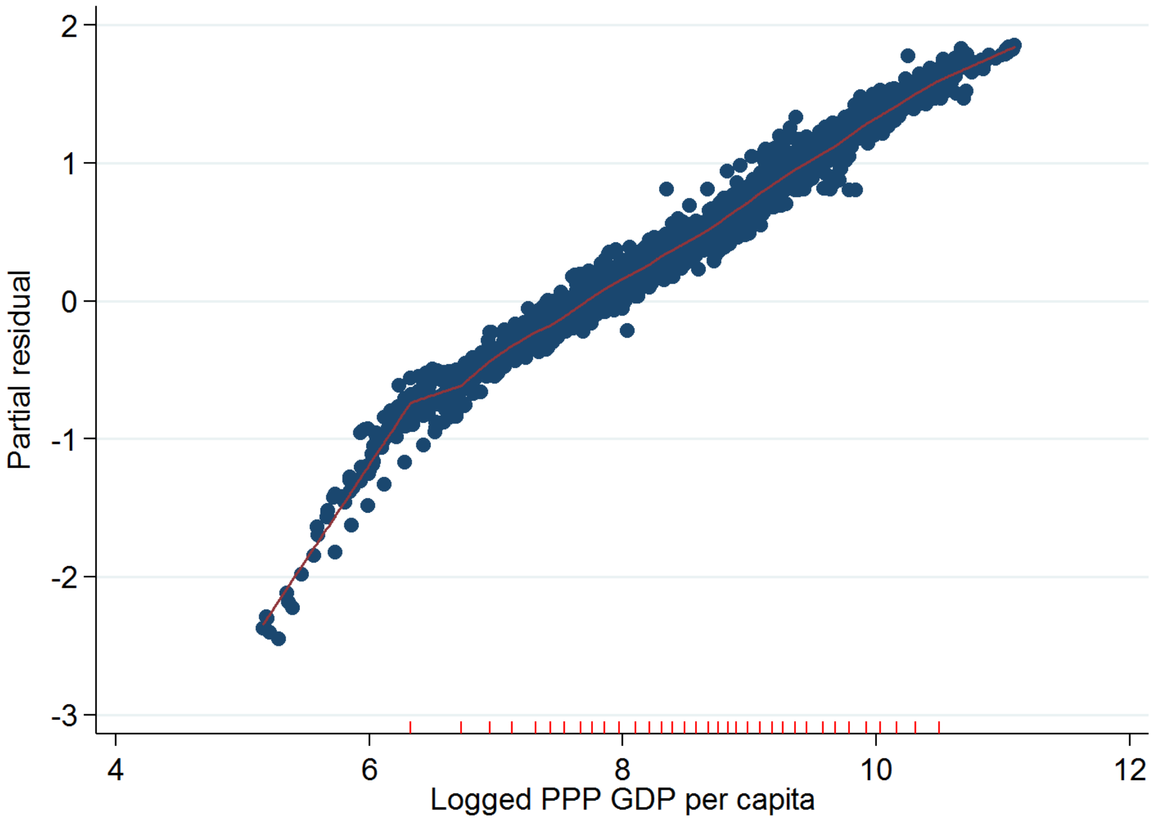


Table S3: Average within country correlations of variables included in Table 1

Variables	Within correlations
CO_2	0.45
CO_2 p.c.	0.26
Population	0.97
GDP p. c.	0.99
Energy Intensity	0.98
Fossil Fuel Energy Consumption	0.06
Foreign Trade	0.60
Industry	0.18
Services	0.60
Electricity Production from Non-Fossil Sources	0.10
International Environmental Agreements	0.99
Energy Prices	0.63

Note: The correlations display the average correlation coefficients between the time series for each panel member as estimated by the Pesaran CD-test using the stata command xtcd. All correlations are statistically significant for $p < 0.01$.

Figure S2: Partial residual plot for GDP p.c. of model 3 in Table 1



Notes: The plot shows the partial residual for every country year as calculated from the fixed effects regression with penalized splines (Ruppert et al. 2003) for logged GDP per capita. The plot shows that the effect of GDP growth on CO_2 growth is steeper for poor countries and more flat for richer countries. However, it is linear for both groups of observations and linear for the vast majority of observations.

Table S4: Country and Time Fixed Effects Regressions of CO_2 Emissions per Capita Separately for Import and Export Rates

	Model 3		Model 4	
GDP p. c.	0.53***	0.53***	0.79***	0.78***
	(0.06)	(0.06)	(0.11)	(0.12)
GDP p. c. squared	-0.01	-0.01	-0.03	-0.03
	(0.01)	(0.01)	(0.04)	(0.03)
Energy Intensity	1.30***	1.30***	3.02***	3.00***
	(0.28)	(0.27)	(0.40)	(0.39)
Fossil Fuel Energy	0.09	0.10	0.27*	0.29*
Consumption	(0.06)	(0.06)	(0.12)	(0.11)
Imports	0.04		0.04	
	(0.03)		(0.04)	
Exports		0.03		0.07
		(0.02)		(0.04)
Industry	0.01	0.01	0.24	0.24
	(0.06)	(0.06)	(0.21)	(0.20)
Services	-0.09	-0.07	0.65	0.70
	(0.06)	(0.06)	(0.38)	(0.38)
Electricity Production from	-0.03	-0.03	-0.11**	-0.11**
Non-Fossil Sources	(0.02)	(0.02)	(0.03)	(0.03)
International Environmental	-0.06**	-0.06**	-0.10*	-0.10*
Agreements (Unit: 100)	(0.02)	(0.02)	(0.04)	(0.04)
Energy Prices			-0.04*	-0.04*
			(0.02)	(0.02)
n x T	2877	2877	596	596
n	116	116	31	31
adj. R^2 within	0.5864	0.5844	0.7215	0.7262
Root MSE	0.09	0.09	0.04	0.04

Note: * p<0.05, ** p<0.01, *** p<0.001

Table S5: Country and Time Fixed Effects Regressions of CO_2 Emissions (per capita) by OECD Membership Status

	Model 1		Model 2		Model 3	
Dependent variables	CO_2		CO_2 per capita			
OECD Membership	Non OECD	OECD	Non OECD	OECD	Non OECD	OECD
Population	1.00***	1.29***				
	(0.18)	(0.33)				
GDP p.c.	0.73***	0.95***	0.51***	0.81***	0.50***	0.75***
	(0.08)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
GDP p.c. squared	-0.07***	-0.04	-0.02+	-0.03	-0.00	0.02
	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)	(0.03)
Energy Intensity	2.33***	2.78***	1.41***	2.47***	1.20***	2.72***
	(0.35)	(0.58)	(0.29)	(0.52)	(0.28)	(0.41)
Fossil Fuel Energy Consumption	0.71***	0.31+	0.09+	0.27	0.10+	0.24*
	(0.09)	(0.18)	(0.05)	(0.17)	(0.06)	(0.10)
Foreign Trade					0.05+	0.02
					(0.03)	(0.04)
Industry					0.01	0.08
					(0.06)	(0.18)
Services					-0.09	0.41
					(0.06)	(0.27)
Electricity Production from Non-Fossil Sources					-0.03	-0.06*
					(0.02)	(0.02)
International Environmental Agreements					-0.05+	-0.10*
					(0.03)	(0.04)
n x T	2489	806	2489	806	2261	616
n	115	32	115	32	87	29
adj. R^2 within	0.7444	0.8074	0.5111	0.6935	0.5623	0.8311
Root MSE	0.14	0.07	0.10	0.06	0.09	0.05

Note: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

2. Article: Consumption-based versus production-based accounting of CO_2 emissions: Is there evidence for carbon leakage?

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Consumption-based versus production-based accounting of CO_2 emissions: Is there evidence for carbon leakage?

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ABSTRACT

Lately, a controversial debate has evolved regarding consumption-based accounting (CBA) versus production-based accounting (PBA) of CO_2 emissions. So far, the debate has been predominately theoretical and has inspired only a few empirical studies. In this article, we compare production-based versus consumption-based emissions, and for the first time analyze reasons for the differences. In particular, we focus on whether there is evidence for carbon leakage from developed to developing countries. We use the newest available data for 110 countries and analyze whether there are differences between OECD and non-OECD members. Furthermore, we compare the within-country differences for the time span of 1997 to 2011 via fixed effects panel regression models in order to investigate whether increases in GDP per capita result in higher imported emissions. The results suggest that for most countries the differences depending on accounting schemes are small. Furthermore, we find no evidence for carbon leakages. In particular, the ratio of CBA to PBA is not driven by OECD membership or GDP per capita. Instead, the ratio is greater for countries with high energy efficiency and high import rates. Given the small differences between PBA and CBA, we suggest keeping the production-based accounting of CO_2 emissions.

1. Introduction

A controversial debate has recently evolved around the issue of whether national CO_2 emission inventories should be based on territory-related production or consumption (Afionis et al. 2017, Fan et al. 2016, Fernandez-Amador et al. 2017, Davis and Caldeira 2010, Davis et al. 2011, Liu 2015, Peters et al. 2012, Steininger et al. 2015). So far, national CO_2 inventories follow the guidelines of the Intergovernmental Panel on Climate Change (IPCC), which are based on the consumption of fossil fuels within a country. This accounting is called production-based and is relatively straightforward: It estimates the greenhouse gas emissions from all the oil, coal, and gas consumed in a country by private households, industrial production of goods and services, and electricity production. However, production-based accounting has some disadvantages. First, it excludes emissions stemming from international air and sea transportation. Since such emissions do not take place within a specific territory its attribution to specific countries is difficult. Second, energy-intensive industries in countries with strict emission controls, regulations or taxes might move into territories with fewer restrictions and lower energy costs. However, the goods produced in the less restrictive countries might then be exported to the more restrictive countries. Thus, decreasing emissions in one country can be directly linked to increasing emissions in the other country. This type of replacement in response to the environmental policy of a country is often termed "strong carbon leakage". Third, the emission leakage can also be weak, e.g. if international specialization encourages some countries to outsource the production of carbon-intensive goods to other countries with lower production costs. Strong and weak carbon leakages result only in reallocations of CO_2 emissions, and a decrease in one country is more or less directly related to an increase in another. Consumption-based accounting takes care of these problems. It subtracts from countries all emissions that are contained in exported products, including transportation emissions, and includes the embodied emissions in the inventories of the importing countries (Fan et al. 2016, Peters et al. 2011). If the carbon leakages due to international trade are strong then the difference between consumption-based and production-based emissions might be large. Hence, with respect to production-based

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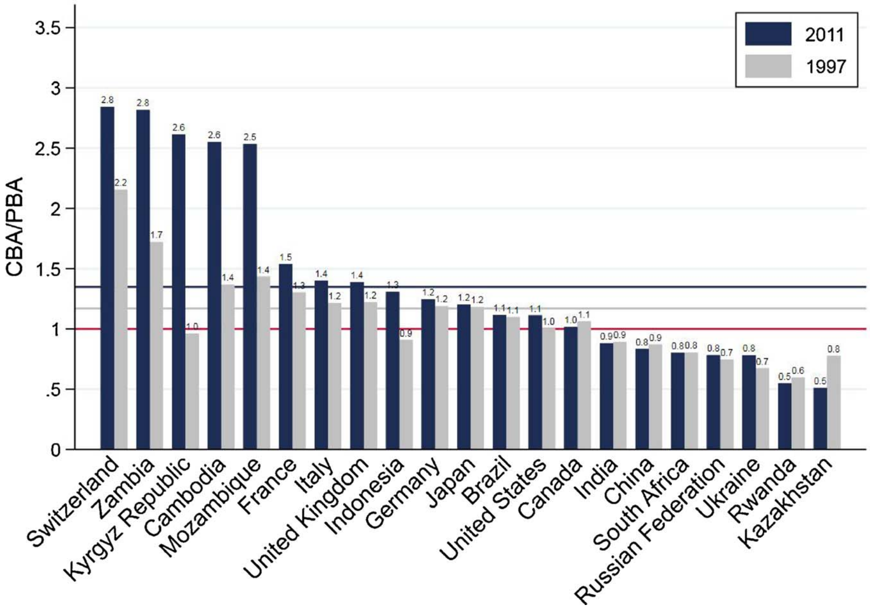

Fig. 1. The ratio of consumption- and production-based CO_2 emissions per capita (CBA/PBA) for 1997 and 2011.
Note: The figure shows the top 5 and the bottom 5 countries with respect to the ratio of CBA to PBA, the five largest emitters of CO_2, and members of the G7 or BRIICS if not already included by the other criteria. Data source is the Emissions Database for Global Atmospheric Research (Olivier et al. 2016) for production-based accounting and the Global Carbon Atlas (Peters et al. 2011) for consumption-based accounting of CO_2. The horizontal grey line denotes the average CBA/PBA ratio for 1997, and the blue line the average for 2011.

inventories, low emission countries might look less "clean" in the consumption-based framework and high emission countries might in reality produce goods for the living standard of low emission countries. Obviously, the difference in accountability of emissions might also have political implications.

In this paper we will take a look at the differences between consumption-based and production-based accounting of emissions. First, after a short literature review in Section 2, we describe the differences by using the most up-to-date data for the 110 countries for which both inventories are available in Section 3. Second, we also analyze the differences by using fixed effects panel regression models for the period of 1997 to 2011 for these 110 countries in this section. Proponents of the consumption-based method often assume (more or less explicitly) that developing countries produce carbon emissions mainly for exports into developed countries. Hence, the former would profit from deducting emissions contained in exports with respect to their CO_2 footprint. In contrast, developed countries might only have low emissions because of leakages and this bias would be corrected by consumption-based accounting. We wonder how big these differences are and whether or not they are driven by GDP. Third, and also in that section, we take a look at the development of the differences of the two inventories for the available time period. If leakages are responsible for the difference, then they should increase over time since regulations became stricter and specialization has also increased over time. The final section concludes with a discussion of the advantages and disadvantages of the consumption-based approach.

2. Literature review

In recent years a number of studies have called attention to the fact that a substantial amount of CO_2 emissions are embodied in international trade. Thus, Davis and Caldeira (2010) report that in 2004 23% of global CO_2 emissions were contained in exports stemming predominantly from developing countries (e.g. China) to developed nations (e.g. Switzerland, Sweden, UK, or the USA). An analysis by Peters et al. (2012) suggests that the proportion related to international trade is increasing over time (to 26% in 2008). These findings have inspired a controversial discussion about the extent to which CO_2 emissions are outsourced by developed nations to developing countries. Some authors propose that since both consumers and producers of goods and services are equally responsible for CO_2 emissions, they should also share mitigation responsibilities (e.g. Steininger et al. 2014, Jakob et al. 2014). How this could be accomplished and whether switching from production-based accounting to consumption-based accounting is beneficial with respect to the efficiency of CO_2 abatement policies is an ongoing debate (e.g. Liu 2015). The consideration of switching to consumption-based accounting depends also on empirical assessments of the size of carbon leakages, and on the reasons for them. So far such empirical investigations are still sparse. Some studies compare consumption-based emissions of Annex I countries (those who committed themselves to CO_2 reductions in the Kyoto Protocol) before and after the commitment. They find very small or no evidence for strong carbon leakages. Similar results hold for studies investigating EU countries before and after the implementation of the European Union Emissions Trading System (EU ETS) (for a review see Branger and Quirion 2014). However, the authors of these studies point out that carbon prices in the EU have been very low so far providing only small incentives for a reallocation of carbon intensive industries such as cement or aluminum production. Furthermore, energy intensive industries received generous emission permits by the EU to avoid reallocation. Hence, outsourcing might increase when the supply of pollution permits is reduced to meet the emission targets.

Other recent empirical studies investigate the question of whether the predictors of CO_2 depend on the accounting scheme. Econometric analyses of production-based emissions usually find that national CO_2 emissions are predominantly driven by population size, GDP, and the energy intensity of a nation's economy. Moreover, further but smaller predictors are countries' commitment to environmental protection (measured by ratification of international agreements), non-fossil energy sources, and energy prices (see Franzen and Mader 2016). Fernandez-Amador et al. (2017) compare the effects of GDP per capita on CO_2 per capita of models using production-based data with those of

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consumption-based data. The estimated elasticity in models using production-based data is 0.65, and the one using consumption-based data 0.81. Similar results are reported by Liddle (2018) who finds an elasticity of 0.57 using production-based CO_2 emissions, and an elasticity of 0.66 analyzing consumption-based data. Hence, the difference of the estimated income elasticity between both accounting schemes is small, and statistically not significant. However, import and export rates also matter if consumption-based accounting is applied. Surprisingly, import and export rates do not matter with respect to production-based emissions. But a country's export rate has a small negative effect on consumption-based CO_2 emissions, while import rates increase them, in line with expectations. None of the two studies finds compelling evidence for an Environmental Kuznets Curve (EKC) independent of the accounting scheme. Thus, CO_2 per capita emissions increase somewhat more slowly at higher income levels than at lower income levels but the diminishing increase is very small, and statistically not significant.

In this paper, we are not interested in analyzing the difference of the predicted estimates by the two different accounting schemes but rather in identifying the factors that drive the ratio of CBA to PBA. Put differently, we identify countries with high and low ratios and analyze the differences between them. Hence, we analyze the question of which countries would be affected by shifting the accounting scheme. The literature on consumption-based accounting assumes that wealthy nations are those with stricter environmental laws e.g. higher carbon prices and thereby that they tend to outsource carbon-intensive industries. Hence, if there were carbon leakages, then wealthy nations should have higher ratios than poorer nations. Moreover, assuming that international specialization increases, the ratios should over time become larger in wealthy nations and smaller in poorer nations. In the following we test both assumptions for the first time.

3. Comparing consumption- and production-based emissions

We compare the two accounting methods for CO_2 per capita by using the latest available data; for the production-based accounting (PBA) we take data from the Emissions Database for Global Atmospheric Research (Olivier et al. 2016), and for the consumption-based approach (CBA) data is taken from the Global Carbon Atlas (Peters et al. 2011). Both sources are recognized as the most exact inventories and are commonly used in the literature (Fan et al. 2016, Fernandez-Amador et al. 2017, Franzen and Mader 2016). Consumption-based accounting uses the multi-regional input-output (MRIO) model and depends on the availability of detailed import and export data (Peters et al. 2011). The latest available accounting stems from 2011 and contains 110 countries. First, we compare both inventories by simply calculating the Pearson and Spearman correlations for a country's CO_2 emissions per capita. Pearson's correlation between the two inventories for 2011 is $r = 0.89$. Since both inventories depend on estimates and are not very exact (particularly the CBA), a robustness check of the Pearson correlation is accomplished by also calculating the rank correlation (Spearman's r) which is $r_S = 0.96$. Hence, both correlations are extremely high indicating that statistically CBA and PBA are very similar. On average a country's ranking with respect to CO_2 per capita does not depend on consumption- or production-based accounting. Countries high in production-based emissions are also high in terms of consumption-based emissions. However, there are some differences and they are quite surprising. Fig. 1 displays the ratio of CBA to PBA emissions per capita for 2011 and 1997 (see Fig. 1).

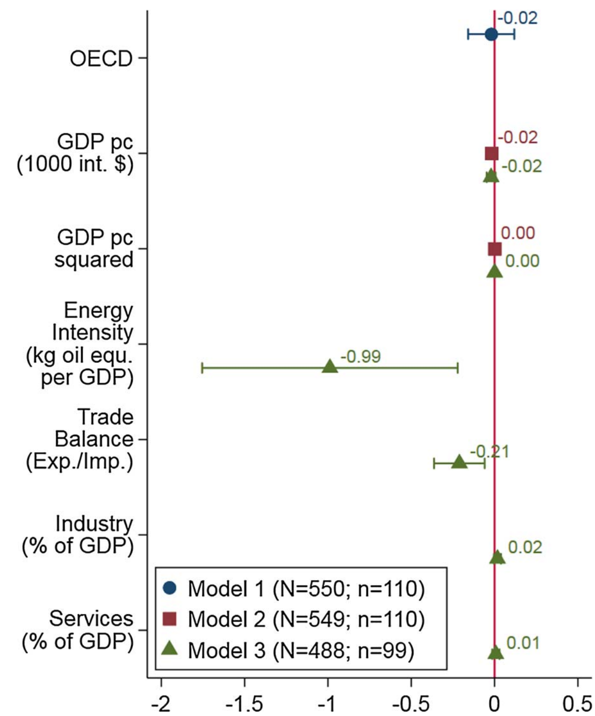

Fig. 2. Regressions of the ratio of CBA to PBA of CO_2 emissions per capita.
Notes: Unstandardized regression coefficients with 95% confidence intervals. All models contain dummy variables for each year in order to control for overall time-trends. All standard errors are clustered by country and year, and therefore robust with respect to heteroscedasticity and autocorrelation. Robustness checks comprise FE panel regressions with country-specific constants and slopes (FEIS) (Brüderl and Ludwig 2015), and penalized splines FE models (Ruppert et al. 2003) to test all parameters for linearity. Furthermore, we ran 110 regressions dropping one country each time to test for statistical outliers. In addition, the robustness of standard errors was checked using non-parametric bootstrapping. Moreover, we tested for the influence of omitted variables using the method suggested by Frank (2000). None of these checks had any substantial influence on the estimates. "n" refers to the number of countries, and "N" to the number of observations (number of countries (n) multiplied by the number of years). Table A1 in Appendix A describes all variables and Table A2 lists all countries included in the models. All models as well as all the robustness checks were conducted using the statistical software package STATA 14.2. See also Table A3 for the exact regression results of all three models.

The figure lists the top and bottom five countries with respect to the ratio of CBA to PBA, the ratios for the five largest CO_2 emitters (China, USA, India, Japan, Russian Federation), and members of the G7 or BRIICS if not already contained by the other criteria. A ratio of 1 means that consumption-based emissions are exactly the same as production-based emissions. This is pretty much the case for Canada. A ratio below 1 means that a country would profit (decrease in CO_2 per capita) from switching to consumption-based accounting. Ratios above 1 indicate that inhabitants of a country consume more CO_2 than under the PBA. If carbon leakages exist, then developed countries should have ratios above 1 and developing nations ratios below 1. Inspection of Fig. 1 shows that this is not confirmed by the frequency distribution of CBA/PBA. The top five countries with the largest ratios are almost all developing nations. Switzerland is the only exception. Also, countries with low ratios are mixed and include the Russian Federation and South Africa. The most extreme deviation is observed for Switzerland. The PBA for Switzerland results in 5.4 tons per capita of CO_2 in 2011 and in 15.3 if accounting is consumption-based.

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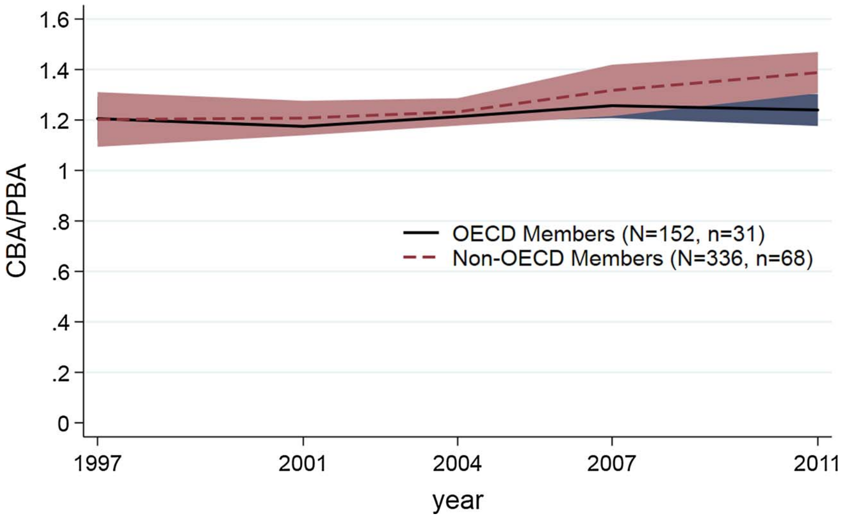

Fig. 3. Growth curves of CBA/PBA ratio of model 3.
Note: The graph displays the predictive CBA/PBA ratios including 95% confidence intervals for OECD and Non-OECD countries. "n" refers to the number of countries, and "N" to the number of observations (number of countries (n) multiplied by the number of years). The analysis (model 3 of Fig. 2) contains 99 countries and five observations (1997, 2001, 2004, 2007, and 2011), however, not all countries have valid measurements for every year.

However, Switzerland's imports stem from Germany (32%), Italy (10%), and France (9%) (World Bank 2017). Hence, Switzerland does not predominantly import CO_2 emissions from developing countries but mainly from developed countries that have higher production-based CO_2 emissions.

Fig. 1 only delivers a first descriptive impression. More reliable insight is obtained by a more rigorous statistical analysis of all 110 countries contained in the database of Peters et al. (2011). Results of such an analysis are depicted in Fig. 2. First, Model 1 of Fig. 2 shows the regression result of a random effects (RE) panel regression (Wooldridge 2010) in which we regress the ratio of CBA to PBA on a dummy variable for OECD membership. The coefficient is almost zero and statistically not significant. Models 2 and 3 use fixed effects (FE) panel regression models in which the ratio of CBA to PBA as well as all independent variables are demeaned (Wooldridge 2010). Model 2 only incorporates countries' GDP per capita (purchasing power adjusted) and its square to control for possible non-linear effects. Again, the coefficients are zero or very close to it and are not statistically significant. Hence, a country's change in GDP per capita does not change the ratio of CBA to PBA.

Model 3 extends the model by including four variables, energy intensity, trade balance, and an economy's share of the industrial or service sector. Energy intensity is obtained by calculating the ratio of a country's energy consumption per unit of GDP. The larger the ratio the more energy is used per unit of GDP. Hence, the variable can also be interpreted as a country's energy inefficiency. The results suggest that energy inefficiency is negatively related to the CBA/PBA ratio. If the energy consumption per unit of GDP increases the CBA/PBA ratio decreases. Put the other way round, if the energy efficiency increases over time (energy/GDP decreases) then the import of CO_2 increases as well.

A negative effect is obtained for the ratio of exports to imports. If exports increase in comparison to imports, the CBA/PBA ratio decreases. Or put the other way round, if the imports are large in comparison to exports then the CBA/PBA ratio increases. Hence, this effect is very intuitive. Finally, an economy's share of the industry or service sector is not related to the CBA/PBA ratio.

Furthermore, we take a look at the growth curve of the CBA/PBA ratio for OECD members and non-members (see Fig. 3). The graph shows no clear trend for both types of countries. Hence, it is not the case that OECD members increase in CBA over time, at least not for the observation period at hand. If anything then OECD members decrease imports of CO_2, but this trend for 2011 is not statistically significant.

4. Conclusion and discussion

An analysis of the CBA/PBA ratio reveals that there is no empirical evidence for carbon leakage from developed to developing countries. On average, countries increase imports of CO_2 if they become more energy efficient. A good example is Switzerland, which has high energy efficiency and also a very high ratio of CBA to PBA. Countries also increase consumption-based CO_2 emissions if they do have large imports in relation to exports, which is a very intuitive effect. However, on average OECD members or countries with high levels of GDP per capita do not have larger CO_2 imports or have increased them over time. In fact, the difference in accounting is rather small for most large emitters such as China (6.1 vs 7.3 or -16%) or the USA (19.2 vs 17.3 or + 11%).

Given these small differences should we switch to consumption-based accounting? Consumption-based accounting has the advantage of incorporating CO_2 emissions from international transportation. It also incorporates carbon leakages and attributes them to the countries who more or less directly externalize CO_2 emissions. However, the empirical analysis reveals that there are no systematic carbon leakages from developed countries. Furthermore, the consumption-based approach also has some disadvantages.

It is based on rather complicated input-output matrices, and thus, involves more assumptions than the production-based approach. This makes the consumption-based accounting more inaccurate than the production-based approach. The consumption-based approach also violates the principle of product liability, which states that producers are responsible for the quality and safety of their products. Of course, this principle applies to companies and it is less clear whether it should also apply to countries. However, the balance of small advantages and large disadvantages would suggest keeping the production-based approach.

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Declaration of interests

None.

Appendix A

Table A1
Variable description.

Variable	mean/ share	within ($\bar{x}_i$) sd	within min.	within max.	between ($x_{it} - \bar{x}_i + \bar{\bar{x}}$) sd	between min.	between max.	N (n x T)	n	Description	Data Source
PBA CO_2 p. c. (metric tons)	3.75	.63	-1.17	8.02	4.26	.05	19.99	875	175	PBA CO_2 emissions p. c. of fossil fuel use and industrial processes (cement production, carbonate use of limestone and dolomite, non-energy use of fuels and other combustion) attributed to the country in which goods and services are produced. Excluded are: short-cycle biomass burning (such as agricultural waste burning) and large-scale biomass burning (such as forest fires).	EDGAR
CBA CO_2 p. c. (metric tons)	5.48	.93	1.56	12.43	5.48	.06	25.50	550	110	CBA CO_2 emissions p. c. of fossil fuel use and industrial processes attributed to the country in which goods and services are consumed (CBA CO_2 = PBA CO_2– CO_2 exports + CO_2 imports).	GCA
CO_2 Trade Balance	1.25	.23	.14	3.09	.38	.57	2.49	550	110	Ratio of CBA to PBA (CBA/PBA).	
OECD Member-ship	.18	0	.18	.18	.37	0	1	920	184	Dummy variable for OECD membership (1) and non-membership (0)	OECD
GDP p. c. (1000 internatio-nal dollars)	11.65	3.54	-14.42	33.14	12.65	.47	73.86	871	178	Gross domestic product (GDP) p. c. based on purchasing power parity (PPP). PPP GDP is GDP converted to international dollars using PPP rates. Data are in international dollars based on the 2011 International Comparison Program (ICP) round.	IMF
Energy Intensity	.18	.07	-.29	.88	.13	.01	.90	687	158	Energy intensity level of primary energy is the ratio between energy supply and PPP GDP. Unit: kg oil equivalent per PPP GDP.	OECD/ IEA/WB, IMF
Trade Balance	.88	.16	.02	1.86	.32	.09	2.43	852	174	Trade balance the ratio of exports to imports of goods and services as shares of GDP.	WB
Industry, value added	28.29	3.31	13.05	55.82	11.62	7.15	79.76	826	174	Industry corresponds to the International Standard Industrial Classification (ISIC) divisions 10-45. The origin of value added is determined by the ISIC, revision 3. Unit: % of GDP.	WB
Services, value added	56.35	3.76	37.57	76.33	13.68	19.03	81.98	822	173	Services correspond to ISIC divisions 50-99. The industrial origin of value added is determined by the ISIC, revision 3. Unit: % of GDP.	WB

Notes: EDGAR = Emission Database for Global Atmospheric Research, GCA = Global Carbon Atlas, IEA = International Energy Agency, IMF = International Monetary Fund, OECD = Organization for Economic Co-operation and Development, WB = World Bank; All variables in the models are included in the units reported above.

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Table A2
Countries included in the analyses.

Albania*	Costa Rica*	India*	Morocco*	Slovak Republic*
Argentina*	Cote d'Ivoire*	Indonesia*	Mozambique*	Slovenia*
Armenia*	Croatia*	Iran, Islamic Rep.*	Namibia*	South Africa*
Australia*	Cyprus*	Ireland*	Nepal*	South Korea*
Austria*	Czech Republic*	Israel	Netherlands*	Spain*
Azerbaijan*	Denmark*	Italy*	New Zealand*	Sri Lanka
Bahrain	Dominican Rep.*	Jamaica*	Nicaragua*	Sweden*
Bangladesh*	Ecuador*	Japan*	Nigeria*	Switzerland*
Belarus*	Egypt, Arab Rep.*	Jordan*	Norway*	Tanzania*
Belgium*	El Salvador*	Kazakhstan*	Pakistan*	Thailand*
Benin*	Estonia*	Kenya*	Panama*	Togo*
Bolivia*	Ethiopia	Kyrgyz Republic*	Paraguay*	Tunisia*
Botswana*	Finland*	Lao PDR	Peru*	Turkey*
Brazil*	France*	Latvia*	Philippines*	Uganda
Bulgaria*	Georgia*	Lithuania*	Poland*	Ukraine*
Burkina Faso	Germany*	Madagascar	Portugal*	United Kingdom*
Cambodia*	Ghana*	Malawi	Romania*	United States*
Cameroon*	Greece*	Malaysia*	Russia*	Uruguay*
Canada*	Guatemala*	Malta*	Rwanda	Venezuela, RB*
Chile*	Guinea	Mauritius*	Saudi Arabia*	Vietnam*
China*	Honduras*	Mexico*	Senegal*	Zambia*
Colombia*	Hungary*	Mongolia*	Singapore*	Zimbabwe*

Notes: We only took countries into consideration that are full members of the United Nations. Models 1 and 2 of Fig. 2 contain all 110 countries. Model 3 of Fig. 2 is based on 99 countries indicated by '*'.

Table A3
Regressions of the ratio of CBA to PBA of CO_2 Emissions per capita.

Model	(1) RE	(2) FE	(3) FE
OECD Membership	−0.02		
	(0.07)		
GDP p.c.		−0.02	−0.02
		(0.01)	(0.01)
GDP p.c. squared		0.00	0.00
		(0.00)	(0.00)
Energy Intensity			−0.99*
			(0.28)
Trade Balance (Exports/Imports)			−0.21*
			(0.06)
Industry			0.02
			(0.01)
Services			0.01
			(0.01)
2001	0.03	0.05*	0.01
	(0.03)	(0.02)	(0.03)
2004	0.06	0.11*	0.04
	(0.03)	(0.03)	(0.04)
2007	0.14**	0.22*	0.12
	(0.04)	(0.05)	(0.07)
2011	0.18***	0.28**	0.16*
	(0.04)	(0.05)	(0.06)
n x T	550	549	488
n	110	110	99
adj. R^2 within	0.0855	0.0912	0.1276
theta	.71		

Notes: * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. Unstandardized regression coefficients with standard errors in brackets. All models 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. Robustness checks comprise FE panel regressions with country-specific constants and slopes (FEIS) (Brüderl and Ludwig, 2015), and penalized splines FE models (Ruppert et al., 2003) to test all parameters for linearity. Furthermore, we ran 110 regressions dropping one country each time to test for statistical outliers. In addition, the robustness of standard errors was checked using non-parametric bootstrapping. Moreover, we tested for the influence of omitted variables using the method suggested by Frank (2000). None of these checks had any substantial influence on the estimates. Table A1 in Appendix A describes all variables and Table A2 lists all countries included in the models. All models as well as all the robustness checks were conducted using the statistical software package STATA 14.2.

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The nexus between social inequality and CO_2 emissions revisited: Challenging its empirical validity

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ABSTRACT

Recently, a discussion about the ambiguity of the nexus between social inequality and anthropogenic CO_2 emissions has emerged. Macroeconomic panel studies applying region and time fixed effects (FE) regression models and measuring inequality by the Gini coefficient discovered a flat relationship. Only two of these studies substituting Gini by the more appropriate share held by the top 10 percent of the income or wealth distribution find a positive effect. This paper revisits this nexus and challenges the empirical validity of the contribution of an increase in wealth and income inequality to higher CO_2 emissions lately found by Knight et al. (2017) on country-level and by Jorgenson et al. (2017) on U.S. state-level. The positive inequality effects spotted in these two studies are not robust with respect to the regions and time spans observed as well as to the inequality indicators, estimation techniques, and confounders selected. Hence, this in-depth investigation suggests that there is no sound empirical evidence for a substantial nexus between social inequality and CO_2 emissions. After all, lately proposed policy approaches combining efficient cap-and trade programs with income and wealth redistribution (so-called cap-and-dividend schemes) are not, by themselves, suitable for an effective climate policy. In fact, the analysis points at the relevance of treating key predictors of CO_2 emissions including energy prices for the U.S. for effective climate change mitigation.

1. Introduction

Abating anthropogenic carbon dioxide (CO_2) emissions is a focus for climate change mitigation (IPCC, 2014). To achieve this ambitious goal it is of great political importance to identify the predictors of the CO_2 emissions of countries. Newest longitudinal studies in this line of research confirm that the main drivers are population size and gross domestic product (GDP, e.g. Dietz et al., 2010; Franzen and Mader, 2016; Liddle, 2015; Rosa and Dietz, 2012; Rosa et al., 2015). Smaller impacts are observed for non-fossil energy production, energy prices and international environmental agreements (e.g. Franzen and Mader, 2016).

A largely separate discussion on the nexus between social inequality and CO_2 emissions has emerged since the 1990s. Boyce (1994) introduced a now widely disputed political economy argument. He hypothesizes that more social inequality leads to more environmental degradation. According to Boyce (1994) income/wealth concentration at the top leads to more political influence of rich people on environmental policy. His 'power-weighted social decision rule' assumes that rich producers and consumers benefit more from polluting the environment than the poor, and that the latter are more prone to bear the social costs of environmental deterioration. While not directly targeted at spatially and temporally dispersed pollutants like CO_2 emissions, this argument has often been applied to them (see for instance Jorgenson et al., 2017; Knight et al., 2017).

Because of the ambiguity of Boyce's (1994) and others' arguments (e.g. Borghesi, 2006; Grunewald et al., 2017; Ravallion et al., 2000), a debate on the empirical validity of a substantial nexus between social inequality and carbon emissions arose. Though early studies using cross-sectional data find both a positive (e.g. Ravallion et al., 2000) and a negative (e.g. Heerink et al., 2001) effect, more recent panel studies utilizing region and time fixed effects (FE) regression models and measuring inequality by the Gini coefficient discover no substantial relation between income inequality and CO_2 (Borghesi, 2006; Grunewald et al., 2017; Hübler, 2017; Jorgenson et al., 2016 and 2017; Knight et al., 2017). Most recently, two of these studies substituting Gini by the more appropriate share held by the top ten percent of the income or wealth distribution spot a positive effect (Jorgenson et al., 2017; Knight et al., 2017).

This paper revisits this nexus and challenges the empirical validity of the contribution of an increase in wealth and income inequality to CO_2 emissions recently found by Knight et al. (2017) on country-level and by Jorgenson et al. (2017) on U.S. state-level for various methodological reasons.

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This contribution proceeds in four further steps: the second section discusses the ambiguous theoretical approach of Boyce (1994) on the positive nexus between social inequality and CO_2 emissions, and it presents the latest empirical evidence utilizing FE panel regression models. Sections three and four provide an in-depth investigation of the empirical validity of the two most recent contributions. In particular, the third section replicates the country-level analysis of Knight et al. (2017), relaxing its assumptions and extending the model, while in the fourth section the same is undertaken for the U.S. state-level analysis of Jorgenson et al. (2017). The last section summarizes and discusses the main results, and closes with some concluding remarks.

2. Theoretical considerations and empirical evidence

Political economist James K. Boyce (1994) argues that more social inequality yields higher levels of environmental deterioration. According to him a more pronounced income/wealth concentration at the top of the distribution leads to more political influence of rich people on environmental policy causing higher levels of environmental pollution. The proponents of this so-called 'power-weighted social decision rule' of producers and consumers of goods and services claim that when the economic elite gains more power, more benefits can be generated from polluting activities. Also, the social costs of pollution can more easily be externalized on the poor respectively less powerful population. In other words, it is easier for more wealthy rich producers and consumers to achieve a level of emissions higher than the one incorporating the social costs of environmental degradation related to these economic activities. This is because the higher economic and in turn political power of the rich allegedly makes it easier to externalize the social costs of polluting activities on the relatively poorer population within a country/state. This in turn increases the rich's benefits and makes the poor more vulnerable to bear the social costs of environmental pollution.

As Borghesi (2006), Grunewald et al. (2017), Jorgenson et al. (2017), Knight et al. (2017), and Ravallion et al. (2000) suggest, Boyce's (1994) argument is a priori ambiguous: The argument is prone to the assumption that "the net benefit from polluting activities is positively correlated with individual income" (Grunewald et al. 2017: 250, see also Scruggs, 1998). In other words and building on the demand function for carbon dioxide emissions from the consumption or production of goods and services, Ravallion et al. (2000) reason that the effect of an increase in social inequality on CO_2 emissions depends on the relation of poor to rich people's marginal propensities to emit (MPE). More specifically, if poor people's MPE is greater than rich people's, an increase in inequality lowers CO_2 emissions. Conversely, if poor people have a lower MPE than the rich, an increase in inequality raise CO_2. It is hard to identify the MPE ratio of poor and rich people a priori, leaving the validity of a substantial inequality –CO_2 emissions nexus an empirical question (see also Borghesi, 2006).

Moreover, Boyce's (1994) argument is formulated for pollutants with spatially and temporally limited but direct hazardous impact like sulfur and nitrogen oxides (SO_X and NO_X) as well as water pollution. It is questionable, whether the argument also applies to CO_2 emissions, as its impact on the climate is spatially and temporally dispersed. First, CO_2 emissions of both poor and rich people in a country contribute to warming on a global scale. Second, dangerous climate change will primarily harm future generations (IPCC, 2014). Therefore, both poor and rich people are expected to have the same MPE, as both groups benefit equally from carbon emitting activities and can externalize the social costs of dangerous climate change and its mitigation to either other countries and – even more so – to future generations. Consequently, this perspective does not expect a substantial effect of increasing inequality in a country on carbon emission levels. Nevertheless, Boyce's argument has been applied to them assuming a positive inequality –CO_2 emissions nexus (see for instance Jorgenson et al., 2017; Knight et al., 2017).

Other arguments hypothesizing a positive, negative, inverted U-shaped, or GDP-depending relation between inequality and CO_2 are more targeted at overall GDP than its distribution or not directed at causal explanation and therefore not repeated here (see also Berthe and Elie, 2015; Borghesi, 2006; Cushing et al., 2015; Grunewald et al., 2017; Hübler, 2017; Jorgenson et al., 2017; Knight et al., 2017).

Turning to the existing empirical evidence, I only refer to macroeconomic studies applying fixed effects panel regressions of CO_2 emissions on social inequality. In comparison to cross-sectional ordinary least squares regression, the FE model has the advantage of exploiting the longitudinal data structure as it only takes within country variations into account. Thus, the FE model is not biased by cross-sectional unobserved heterogeneity (Brüderl and Ludwig, 2015; Wooldridge, 2010). If the strict exogeneity assumption ($r\ (\boldsymbol{x}_{it},\ \varepsilon_{it}) = 0$) holds, FE models adequately estimate unbiased causal effects (Vaisey and Miles, 2017). The model can be written as

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

y_{it} denotes the CO_2 emissions of country i in year t. $\bar{y}_i$ represents country i's average of the whole observation period. $\boldsymbol{x}_{it}$ stands for the vector of all exogenous variables for country i at time t, and $\bar{\boldsymbol{x}}_i$ for the mean of the whole observation period. The model also comprises a vector of dummy variables ($\boldsymbol{Z}$) for every year, which controls period effects for all countries (time FE). A country's time varying stochastic error term is represented by ε_{it}.

To the best of my knowledge, there are only six studies that apply region and time FE panel regression to directly test whether changes in income or wealth inequality affect CO_2 emissions. Table 1 summarizes the results, data, and methods of these studies.

As Table 1 reveals, Borghesi (2006), Grunewald et al. (2017), Jorgenson et al. (2016), and Knight et al. (2017), utilizing FE regression models, find no substantial effect of the income Gini coefficient on CO_2 emissions on country-level. This finding is independent from the time spans (8 to 29 years covering 1980 to 2010) and the number of countries (26 to 141) observed as well as from the use of either production-based accounting (PBA) or consumption-based accounting (CBA) of CO_2, the different data sources employed, and the covariates included. However, Grunewald et al. (2017) report a substantially negative inequality –CO_2 emissions nexus making use of group fixed effects (GFE) estimation (Bonhomme and Manresa, 2015) to account for grouped patterns of unobserved heterogeneous growth. Nonetheless, the data-driven grouping of regions might be artificial, as the trajectories of individual countries or states are the natural sampling and statistical unit of interest here. FE regression that allows for individual constants and slopes (FEIS) accounts for heterogeneous growth over time by simply fixing the interaction between regions and years in addition to the independent incorporation of region and time fixed effects. This cancels out potential individual time-varying unobserved heterogeneity (Brüderl and Ludwig, 2015; Polachek and Kim, 1994; Wooldridge, 2010). Thus, the use of FEIS is more appropriate than GFE here. Replication of Grunewald et al. (2017) utilizing FE and FEIS models finds no substantial effect of income Gini on CO_2 p.c. emissions. The results are available from the author upon request.

Another recent study by Hübler (2017) applies quantile FE regression with 149 countries from 1985 to 2012. Quantile regressions are more robust to influential cases than conventional mean estimators (Cameron and Trivedi, 2010). Also this study finds no substantial effect of income Gini on the 0.1, 0.25, 0.5, 0.75, and 0.9 quantile of CO_2 per capita (p.c.).

Aside from the advantage of being a broad indicator of inequality, the Gini coefficient a priori has the limitation of not being unique for a specific distribution. Different distributions can result in the same Gini coefficient value (e.g. Atkinson, 1970; Schutz, 1951) and it is not a direct measure of income and wealth concentration at the top of the distribution (Jorgenson et al., 2017). A more appropriate, albeit partial, measure of social inequality and in turn power concentration is the income/wealth share held by a given percentile group at the top (Alker

Table 1
Macroeconomic studies applying region and time fixed effects panel regressions of CO_2 emissions on social inequality.

Study	Income Inequality	Wealth Inequality	Dependent Variable	Included Confounders	Data	Model
Borghesi (2006)	0.03 (G)	n.a.	PBA CO_2 p.c.	GDP p.c., population density, industry (% of GDP)	35 countries, 1988-1995	FE
Grunewald et al. (2017)	-1.18 (G)	n.a.	PBA CO_2 p.c.	GDP p.c., (GDP p.c.)^2, Gini*GDP p.c.	141 countries, 1980-2008	FE
Hübler (2017)	[-0.13, 0.04] (G)	n.a.	PBA CO_2 p.c.	GDP p.c., industry (% of GDP), domestic investment (% of GDP)	149 countries, 1985-2012	Quantile FE
Jorgenson et al. (2016)	-0.16 (G)	n.a.	CBA CO_2	population, urban population, GDP p.c.	67 countries, 1991-2008	Prais-Winsten FE
Jorgenson et al. (2017)	0.12 (G) *0.12* (S)*	n.a.	PBA CO_2	population, urban population, GDP p.c., fossil fuel production, manufacturing (% of GDP)	50 U.S. states + D.C., 1997-2012	Prais-Winsten FE
Knight et al. (2017)	-0.15 (G)	*0.80** (S)*	CBA CO_2 p.c.	GDP p.c.	26 countries, 2000-2010	Prais-Winsten FE

Note: * = $p < 0.05$, ** = $p < 0.01$. G = Gini coefficient, S = share held by the top 10%, n.a. = not available, CBA = consumption-based accounting, PBA = production-based accounting, FE = fixed effects panel regression. All the reported estimates for income and wealth inequality are elasticities.

and Russett, 1964; Jorgenson et al., 2017).

Most recently, two studies revealed a positive relationship between social inequality and CO_2 utilizing the income/wealth share of the top 10% and applying Prais-Winsten FE regression (Greene, 2012): Knight et al. (2017) is the first study focusing on wealth inequality as a better indicator for power concentration than income inequality. Analyzing wealth inequality data from Credit Suisse (Shorrocks et al., 2014), they find a substantial positive relation of the wealth share of the top 10% with CBA of CO_2 p.c. for 26 countries between 2000 and 2010 while controlling for income Gini and p.c. GDP. They estimate that with an increase of wealth concentration of 1%, per capita emissions increase by 0.80% ($p < 0.01$, $se = 0.30$). This elasticity is about twice the size of the elasticity for GDP p.c. ($\beta = 0.39, p < 0.01, se = 0.14$). Jorgenson et al. (2017) analyze the 50 U.S. states and District of Columbia between 1997 and 2012. They find that a rise in the income concentration of 1% yields a 0.12% ($p < 0.05$, $se = 0.06$) rise in total state CO_2 emissions while controlling for population size, urban population (%), GDP p.c., fossil fuel production, and manufacturing (% of GDP).

As the remainder of this article demonstrates, the findings of Jorgenson et al. (2017) and Knight et al. (2017) are not robust for various methodological reasons. In sum, this investigation suggests that there is no sound empirical evidence for a substantial nexus between social inequality and CO_2 emissions.

3. Country-level analysis: investigation of Knight et al. (2017)

The country-level analysis begins with a replication of Knight et al. (2017). Like Knight et al. (2017), I regress CBA per capita CO_2 emissions gathered from the Global Carbon Atlas (Peters et al., 2011) on the wealth share of the top 10% taken from the Credit Suisse Global Wealth Databook 2014 (Shorrocks et al., 2014). The newest available data is for 2014. In this year the top 10% held 56.4% ($sd = 12.0$, median = 58.4%) of net worth on average, which matches Canada's value. The distribution ranges from a minimum of 23.3% for the United Kingdom to a maximum of 71.9% for Switzerland. The time series date back to 2000 with a mean of 57.2% ($sd = 12.2$, median = 58.0). The analysis only includes countries that have good or satisfactory wealth distribution data quality according to Shorrocks et al., 2014 (17–25). However, Knight et al. (2017) also exclude Colombia and Mexico, which have satisfactory data quality (Shorrocks et al., 2014: 22, 24). This restricts the analysis to 26 countries instead of 28. GDP p.c. is drawn from the International Monetary Fund (IMF) and is converted into international dollars using purchasing power parities (PPP). The income Gini coefficient is taken from the Standardized World Income Inequality Database (SWIID, Solt, 2016). These variables are available for the years 2000 to 2014. However, Knight et al. (2017) restrict their analysis to the years 2000 to 2010. For a description of all variables included in the models of Tables 2–4 see Table S1 of the Supplementary Information. Allowing the estimation of elasticities, all variables enter the models by taking their natural logarithm. A list of all countries included in these models is provided in Table S2.

Knight et al. (2017) apply Prais-Winsten country and time fixed effects regressions (Greene, 2012) with panel-corrected standard errors, allowing for disturbances that are heteroskedastic and contemporaneously correlated across panels. Additionally, these models correct for first-order autocorrelation (AR(1) process) within panels. The models further include interaction terms of wealth inequality and time in order to identify potential fluctuation of the wealth inequality effect over time. As described above, Knight et al. (2017) find a substantial positive effect on CO_2 p.c. of around 0.80% for an increase in wealth inequality of 1%. This effect is close to proportionality and highly statistically significant (see models 1 and 2 of Table 2).

As the models 3 and 4 of Table 2 indicate, this article virtually replicates the results of Knight et al. (2017). An increase of wealth inequality by 1% yields a statistically significant rise in per capita CBA of CO_2 of around 0.60%. In line with other studies, the income Gini coefficient is not connected to CO_2. The elasticity of GDP p.c. is statistically significant around 0.40. This is also the case, when standard country and time FE regression with heteroscedasticity and autocorrelation robust standard errors (clustered by country and year) is used instead of the Prais-Winsten model (see models 5 and 6 of Table 2). Standard FE regression has the comparative advantage of not depending on the assumption of an AR(1) process and is therefore used in the remainder of the analyses.

Nonetheless, the effect of wealth inequality disappears in the models 3 to 6 of Table 2, when either Australia, Greece, Norway, Singapore or South Korea is excluded separately from the analysis. This is also the case when FE panel regression allows for individual constants and slopes (FEIS) or the wealth share of the top 10% is substituted by the corresponding share held by the top 1%. See Table S3 in the Supplement for detailed regression results of these sensitivity checks exemplarily for model 5 of Table 2. Thus, the wealth inequality effect is sensitive to influential cases, a conservative estimation technique, and the wealth inequality indicator chosen.

Moreover, further relaxation of the analyses made by Knight et al. (2017) reveals the absence of a wealth inequality effect for both CBA and PBA of CO_2 emissions (see Table 3). First, the wealth inequality effect loses statistical significance, when Colombia and Mexico are

Table 2
: Replication of Knight et al., 2017.

Model	(1)	(2)	(3)	(4)	(5)	(6)
	Knight et al., 2017 (6, Table 2) Prais-Winsten Country and Time FE Regression		Replication Prais-Winsten Country and Time FE Regression		Replication Country and Time FE Regression	
Dependent Variable	CBA of CO_2 p.c.					
Wealth Share of Top 10% (Wealth Inequality)	.80** (.30)	.84** (.30)	0.61* (0.26)	0.63* (0.27)	0.62* (0.27)	0.65* (0.28)
GDP p. c.	.39** (.14)	.38** (.14)	0.42** (0.14)	0.41** (0.14)	0.38* (0.16)	0.37 (0.17)
Income Gini Coefficient	−.15 (.18)	−.15 (.18)	0.03 (0.14)	−0.00 (0.14)	0.07 (0.21)	0.03 (0.26)
Wealth Inequality * 2001		−.08 (.04)		−0.03*** (0.01)		0.62* (0.28)
Wealth Inequality * 2002		−.17*** (.05)		−0.03*** (0.01)		0.61 (0.28)
Wealth Inequality * 2003		.03 (.04)		0.02 (0.01)		0.66* (0.28)
Wealth Inequality * 2004		−.09* (.04)		−0.02* (0.01)		0.63 (0.28)
Wealth Inequality * 2005		−.08* (.04)		−0.01 (0.01)		0.64 (0.30)
Wealth Inequality * 2006		−.12** (.04)		0.03** (0.01)		0.68 (0.31)
Wealth Inequality * 2007		−.06 (.05)		0.00 (0.01)		0.65 (0.30)
Wealth Inequality * 2008		−.03 (.05)		0.02 (0.02)		0.67 (0.31)
Wealth Inequality * 2009		−.10* (.04)		0.01 (0.01)		0.66 (0.30)
Wealth Inequality * 2010		−.01 (.04)		0.03 (0.01)		0.68 (0.31)
n x T	286	286	286	286	286	286
n	26	26	26	26	26	26
adj. R^2 within					0.09	0.09

Notes: * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. Unstandardized regression coefficients with standard errors in brackets. All six models include the years 2000–2010 and contain dummy variables for each year in order to control for overall time-trends. All standard errors in the models 1–4 are panel-corrected, allowing for disturbances that are heteroskedastic and contemporaneously correlated across panels. Additionally, these models correct for first-order autocorrelation (AR(1) process) within panels. All standard errors of models 5 and 6 are clustered by country and year, and therefore robust with respect to heteroscedasticity and autocorrelation.

included (see model 2 of Table 3). Second, and in addition to the statistical insignificance, the effect size drops from 0.60 to 0.10 when the time span is extended from 2000-2010 to 2000-2014 (model 3 of Table 3). As the models 4 to 6 of Table 3 show, the same applies for PBA of CO_2 gathered from the Emissions Database for Global Atmospheric Research (EDGAR, Olivier et al., 2016).

Beyond that, the analysis of Knight et al. (2017) is extended by additionally controlling for wealth levels. This has never been done before. But it is important, as the wealth inequality effect is hypothesized independently from wealth levels. Data on the average net worth per adult is also provided by Credit Suisse (Shorrocks et al., 2016) and enters the models corrected by PPP rates from the IMF. Model 1 of Table 4 shows, that with an increase of wealth per adult of 1% CBA of

Table 3
Relaxation of Knight et al., 2017.

Model	(1)	(2)	(3)	(4)	(5)	(6)
	Country and Time FE Regression					
Dependent Variable	CBA of CO_2 p.c.			PBA of CO_2 p.c.		
Wealth Share of Top 10%	0.62* (0.27)	0.57 (0.28)	0.09 (0.24)	0.44 (0.36)	0.36 (0.37)	0.15 (0.27)
GDP p. c.	0.38* (0.16)	0.43* (0.17)	0.71** (0.18)	0.25 (0.21)	0.25 (0.20)	0.51** (0.16)
Income Gini Coefficient	0.07 (0.21)	−0.01 (0.20)	−0.02 (0.26)	−0.01 (0.17)	−0.07 (0.17)	−0.10 (0.21)
n x T	286	308	404	286	308	404
n	26	28	28	26	28	28
adj. R^2 within	0.09	0.10	0.25	0.07	0.06	0.22

Notes: * = $p < 0.05$, ** = $p < 0.01$. Unstandardized regression coefficients with standard errors in brackets. All six models 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. Model 4 replicates Model 1 with PBA as dependent variable instead of CBA of CO_2 p.c. emissions. Models 2, 3, 5, and 6 also include Colombia and Mexico which have satisfactory wealth distribution data quality according to Shorrocks et al. (2014: 22, 24). Moreover, models 3 and 6 do not restrict the time span to 2000–2010 as in Knight et al. (2017). They include the years 2000–2014.

Table 4
Extension of Knight et al., 2017.

Model	(1)	(2)	(3)	(4)
	Country and Time FE Regression			
Dependent Variable	CBA of CO_2 p.c.		PBA of CO_2 p.c.	
Wealth per adult	0.20** (0.05)	0.12** (0.04)	0.08 (0.05)	−0.04 (0.03)
Wealth Share of Top 10%	0.32 (0.24)	0.25 (0.19)	0.24 (0.29)	−0.09 (0.19)
GDP p. c.	0.42* (0.15)	0.38** (0.10)	0.39* (0.16)	0.55** (0.15)
Income Gini Coefficient	0.00 (0.22)	0.24 (0.13)	−0.09 (0.20)	0.16 (0.15)
GDP p. c. squared		−0.01 (0.03)		−0.04 (0.05)
Fossil Fuel Energy Consumption		0.54*** (0.13)		0.67*** (0.14)
Trade Balance		−0.46*** (0.09)		−0.07 (0.12)
Industry		−0.19 (0.30)		0.17 (0.25)
Services		−0.96 (0.56)		0.01 (0.49)
Electricity Production from Non-fossil Sources		−0.08* (0.03)		−0.06* (0.02)
International Environmental Agreements		0.05 (0.07)		−0.01 (0.07)
Energy Prices		−0.06 (0.03)		−0.06 (0.04)
n x T	404	365	404	365
n	28	26	28	26
adj. R^2 within	0.38	0.68	0.25	0.63

Notes: * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. Unstandardized regression coefficients with standard errors in brackets. All four models 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. All four models include all countries with at least satisfactory wealth distribution data quality according to Shorrocks et al. (2014: 17–25) and the years 2000–2014.

CO_2 p.c. rise by 0.20%. This effect is highly statistically significant. However, the effects of wealth inequality, income inequality, and GDP p.c. are not affected by the inclusion of the wealth level. Nevertheless, wealth per adult is not a substantial predictor for PBA of CO_2 emissions (see models 3 and 4 of Table 4).

Next, following the latest literature on drivers of anthropogenic carbon emissions (e.g. Dietz et al., 2010; Franzen and Mader, 2016; Rosa and Dietz, 2012; Rosa et al., 2015), this analysis extends models 1 and 3 of Table 4 by accounting for the possibility of confounding variables. The literature on the environmental Kuznets curve assumes that the impact of GDP on CO_2 is inversely U-shaped. To test this, the model includes the square of GDP. Data for fossil fuel energy consumption (share of total) as an indicator of technology is provided by the International Energy Agency (IEA) and the World Bank (WB).[1] Moreover, it is often argued, that CBA carbon emissions fall with a greater trade balance (ratio of exports to imports) of goods and services (e.g. Afionis et al., 2017; Fan et al., 2016; Franzen and Mader, 2018). Trade balance data is drawn from the WB database. The economic structure is represented by the share of the industrial and service sector with respect to GDP also gathered from the WB. Furthermore, the share of electricity production from non-fossil sources as an indicator of environmental policies is added (data source: IEA/WB). Likewise, the number of international environmental agreements a country signed and set into force as an indicator of a country's formal commitment to environmental protection is included (data source: Mitchell, 2015). Lastly, the price mechanism is often used to reduce emissions. Internationally comparable energy price time series are available from the Organisation for Economic Co-operation and Development (OECD) and are corrected by IMF PPP rates.

As the models 2 and 4 of Table 4 demonstrate, the results of the models 1 and 3 of Table 4 are not substantially affected by the inclusion of confounders – neither for CBA nor for PBA carbon emissions. The results show, that a rise in fossil fuel energy consumption by 1% increases CO_2 by about 0.60%. Besides, substitution of fossil electricity production by non-fossil sources by 1% reduces carbon emissions by about 0.07%. As other studies confirm, this effect is far from being proportional (Franzen and Mader, 2016; York, 2012). Furthermore and as expected, a higher trade balance yields lower CBA CO_2 emissions, but does not affect PBA CO_2. All the other additional variables are not related to CO_2 in this analysis of 26 countries between 2000 and 2014. Amongst others, the models 2 and 4 do not find any evidence for an environmental Kuznets curve.

The reported regression results of the Tables 3 and 4 were thoroughly tested for robustness: First, all models were recalculated by performing FEIS regression. Second, all models were rerun excluding one country each time from the regression. None of these checks had any substantial influence on the estimates. Furthermore, all parameters were tested for linearity including penalized splines FE regression models (Ruppert et al., 2003). The robustness of standard errors was investigated via non-parametric bootstrapping. Also these checks detected no fundamental deviations from the reported results. Also, there is no substantial interaction between GDP/wealth and income/wealth inequality. Further sensitivity checks comprise the implementation of different indicators of wealth and income inequality retrieved from different data sources: The wealth share held by the top 10% was substituted by the wealth share held by the top 1% also provided by Credit Suisse (Shorrocks et al., 2014: 125). In addition, the income Gini coefficient of the SWIID is replaced by the ones provided by the WB and the OECD. The income Gini coefficient is also replaced by the income share held by the top 10%, the top 5%, and the top 1%. This data is retrieved from the WB (only top 10%) and the World Wealth and Income Database (WWID, www.wid.org), but comes with much shorter time series compared to Gini. Lastly, further indicators were used to operationalize income inequality as provided by the OECD. These include the P90/P10 disposable income decile ratio, the S90/S10 disposable income decile share, and the poverty rates (lines 50 and 60). However, none of these variations affected the reported results in any substantial way. All the analyses were conducted using the statistical software package STATA 15.1.

Altogether, this rigorous country-level analysis finds no robust relation between income/wealth inequality and CO_2 emissions. The positive wealth inequality effect disappears, when arbitrary restrictions introduced by Knight et al. (2017) on the countries and years included are relaxed. Hence, this analysis invalidates the positive wealth inequality – carbon emissions nexus found by Knight et al. (2017).

4. U.S. State-level analysis: investigation of Jorgenson et al. (2017)

Jorgenson et al. (2017) provide a second recent study that finds a positive relation between inequality and CO_2 emissions measuring income inequality with the share held by a certain percentile group at the top. Using data for the 50 states of the U.S. and the District of Columbia between 1997 and 2012, they perform FE regression of total PBA CO_2 emissions on the income share of the top 10% while controlling for population size, and GDP p.c. in the first model. Their second model further controls for the population share living in urban areas, fossil fuel production measured in trillion British thermal units (Btu), and manufacturing as a share of GDP. The U.S. state-level analysis also begins with a replication of Jorgenson et al. (2017). Similar to their study, CO_2 emissions data is gathered from the U.S. Environmental Protection Agency (EPA). State-level information on the income share of the top 10% is available from the World Wealth and Income Database (WWID). On average the top 10% accounted for 45.8% of income in 2014 ($sd = 5.0$, median = 45.5%), which resembles Montana. The minimum is 34.5% (Alaska) and the maximum 60.0% (New York). In 1997 the mean was at 42.1% ($sd = 3.9$, median = 41.8%). Data on population size and the population share living in urban areas is taken from the U.S. Census Bureau. Information on real GDP p.c. is gathered from the U.S. Bureau of Economic Analysis (BEA). The BEA also provides information on the GDP share of the manufacturing sector. Data on fossil fuel production is taken from the U.S. Energy Information Administration (EIA). All these variables are now available for the years 1997 to 2014. For a description of all variables included in the models of Tables 5 and 6 see Table S4 of the Supplementary Information. Utilizing Prais-Winsten State and Time FE regression as described above, Jorgenson et al. (2017) discover that total U.S. state CO_2 emissions rise statistically significant by about 0.12% with an increase of income inequality by 1% (see models 1 and 2 of Table 5).

As the models 3 and 4 of Table 5 show, this result could not be reproduced using Prais-Winsten FE regression. Income inequality is not statistically significantly related to CO_2. The sources of the data of this analysis are the same as in Jorgenson et al. (2017). Thus, a reason for divergent results might be data updates since the download of Jorgenson et al. (2017) in 2015. Nonetheless, the models 5 and 6 of Table 5 reveal that standard FE regression as described above provides a statistically significant income inequality elasticity of around 0.70. However, the effects of the other covariates are virtually replicated by either using Prais-Winsten or standard FE regression models except for urban population.

Moreover, the robustness of the missing income inequality effect in the models 3 and 4 of Table 5 is confirmed by substituting the income share of the top 10% by the top 5% and top 1% also provided by the WWID (see models 1 and 2 of Table S5). Table S5 (models 3 and 4) additionally reports the regression results for the replication of

[1] Jaforullah and King (2017) argue that the inclusion of an energy consumption variable might lead to biased results. However, excluding fossil fuel energy consumption from the analysis does not alter the reported results in any substantial way. This is also the case for the U.S. state-level analysis. The results are available from the author upon request.

Table 5
Replication of Jorgenson et al., 2017.

Model	(1)	(2)	(3)	(4)	(5)	(6)
	Jorgenson et al. (2017) (43, Table 3)		Replication		Replication	
	Prais-Winsten State and Time FE Regression		Prais-Winsten State and Time FE Regression		State and Time FE Regression	
Dependent Variable	CO_2					
Income Share of Top 10%	0.13* (0.06)	0.12* (0.06)	0.37 (0.20)	0.34 (0.19)	0.90* (0.31)	0.72* (0.30)
Population	0.51** (0.10)	0.43** (0.11)	0.59*** (0.10)	0.54*** (0.11)	0.54* (0.19)	0.51* (0.20)
GDP p. c.	0.25** (0.06)	0.23** (0.06)	0.26*** (0.05)	0.24*** (0.05)	0.28** (0.09)	0.27** (0.08)
Urban Population		0.91** (0.29)		0.79** (0.27)		0.74 (0.39)
Fossil Fuel Production		0.00 (0.00)		0.02** (0.01)		0.02 (0.01)
Manufacturing		−0.01 (0.02)		−0.16 (0.17)		−0.28 (0.16)
n x T	816	816	816	816	816	816
n	51	51	51	51	51	51
adj. R^2 within					0.14	0.18

Notes: * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. Unstandardized regression coefficients with standard errors in brackets. All six models include the years 1997–2012 and contain dummy variables for each year in order to control for overall time-trends. All standard errors in the models 1–4 are panel-corrected, allowing for disturbances that are heteroskedastic and contemporaneously correlated across panels. Additionally, these models correct for first-order autocorrelation (AR(1) process) within panels. All standard errors of the models 5 and 6 are clustered by state and year, and therefore robust with respect to heteroscedasticity and autocorrelation.

Table 6
Relaxation and Extension of Jorgenson et al., 2017.

Model	(1)	(2)	(3)	(4)
	State and Time FE Regression			
Dependent Variable	CO_2 per capita			
Income Share of Top 10%	0.66* (0.30)	0.50 (0.31)	0.34 (0.25)	0.36 (0.26)
GDP p. c.	0.39** (0.10)	0.45*** (0.11)	0.48*** (0.12)	0.48*** (0.12)
GDP p. c. squared		−0.50*** (0.07)	−0.52*** (0.08)	−0.36* (0.14)
Fossil Fuel Production p.c.			0.09 (0.06)	0.08 (0.06)
Manufacturing			−0.72** (0.21)	−0.69** (0.22)
Renewable Energy Production			0.24 (0.14)	0.23 (0.13)
Energy Prices			−0.30** (0.10)	−0.38** (0.10)
State Environmentalism				0.01 (0.01)
n x T	918	918	918	900
n	51	51	51	50
adj. R^2 within	0.11	0.20	0.31	0.30

Notes: * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. Unstandardized regression coefficients with standard errors in brackets. All four models include the years 1997–2014 and 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. Model 4 excludes District of Columbia, as data on state environmentalism is not available.

Jorgenson et al. (2017) utilizing the income Gini coefficient retrieved from the U.S. State-Level Income Inequality Database (USIID, Frank, 2014). In line with Jorgenson et al. (2017) none of these models finds a statistically significant and substantial effect of income Gini on CO_2 emissions.

However, the substantial effect of income inequality found in the standard state and time FE models 5 and 6 of Table 5 disappears when either Delaware or District of Columbia are excluded separately from the analysis. This is also the case when FE panel regression allows for individual constants and slopes. See Table S6 in the Supplement for detailed regression results of these sensitivity checks exemplarily for model 6 of Table 5. Moreover and apart from the fact that the results are sensitive to influential cases and a conservative estimation technique, relaxation and further extension of the analyses made by Jorgenson et al. (2017) reveal the absence of an income inequality effect for CO_2 emissions per capita (see Table 6). Franzen and Mader (2016), and Liddle (2015) argue to utilize CO_2 per capita instead of total CO_2 as used in Jorgenson et al. (2017). The incorporation of population in the dependent variable circumvents potential problems stemming from multicollinearity. Moreover, CO_2 emissions per capita are the unit of primary political interest here. Standard FE regression of per capita CO_2 on income inequality and GDP p.c. for 1997 to 2014 reveals that the income inequality effect remains relatively stable and substantial (see model 1 of Table 6) in comparison to model 5 of Table 5. Nevertheless, also in model 1 of Table 6 the effect is sensitive to influential cases, as it vanishes when ten states or the District of Columbia are excluded separately from the analysis. These states are Alaska, Arkansas, Delaware, Hawaii, Maryland, Michigan, Missouri, Oklahoma, South Dakota, and Washington.

In any case, the effect of income inequality disappears when substantial confounders are considered (see models 2, 3, and 4 of Table 6). This is already true when the square of GDP p.c. is in the model along with GDP p.c. and the income share of the top 10% (see model 2). Interestingly, model 2 reveals an inversely U-shaped effect for GDP p.c., which confirms the environmental Kuznets curve hypothesis on U.S. state-level.

In addition to that, Model 3 comprises fossil fuel production p.c., the GDP share of manufacturing, the share of the renewable energy production, and energy prices (both taken from the EIA). Furthermore and in line with Jorgenson et al. (2017), Model 4 incorporates an indicator of state environmentalism. Following the suggestion of Dietz et al. (2015) this is captured by a score of pro-environmental voting by states' congressional delegations based on the League of Conservation Voters scorecard ranging from 0 to 100. Also for these two extensions of model 2 the income inequality effect remains statistically insignificant and loses in magnitude. This is because of the effects of the GDP share of manufacturing and energy prices. For an increase in the value added of manufacturing by 1%, CO_2 p.c. fall statistically highly significantly by about 0.70% (see models 3 and 4 of Table 6). Besides that, policies targeted at the price mechanism are promising for the U.S. to mitigate carbon emissions: As model 3 of Table 6 reveals, an increase in energy prices by 1% yield a decrease in CO_2 of 0.30%. This effect is highly statistically significant. However, the rest of the covariates is not substantially related to CO_2. Particularly, model 4 of Table 6 shows that there is also no effect for the indicator of state environmentalism proposed by Dietz et al. (2015).

The results in Table 6 were tested for robustness similar to the country-level analysis. Moreover, the income share held by the top 10% was replaced by the income share of the top 5%, and the top 1% as also provided by the WWID. None of these examinations altered the reported results in any substantial way. None of the models reported in Table 6 finds a statistically significant and substantial effect of income Gini on CO_2 emissions per capita, which is in line with the findings of Jorgenson et al. (2017).

All things considered, the U.S. state-level analysis also demonstrates, that there is no robust and substantial connection between income inequality and carbon emissions. The positive income inequality effect disappears, when substantial confounders and newest available data are taken into account. Thus, this rigorous investigation invalidates the positive income inequality effect found by Jorgenson et al. (2017).

5. Discussion and conclusion

All in all, this contribution reconsiders the positive relationship between social inequality and CO_2 emissions lately found by Knight et al. (2017) for wealth inequality on country-level and by Jorgenson et al. (2017) for income inequality on U.S. state-level. The paper challenges the empirical validity of the contribution of an increase in wealth and income inequality to higher CO_2 emissions for various reasons: Rigorous inquiry exposes that the results of these two studies are sensitive to the regions and time spans observed as well as to the inequality indicators, estimation techniques, and covariates selected. Thence, this in-depth investigation invalidates the findings of Knight et al. (2017) and Jorgenson et al. (2017) and suggests that there is no sound empirical evidence for a substantial nexus between social inequality and CO_2 emissions.

This in turn means that Boyce's (1994) a priori ambiguous idea of a 'power-weighted social decision rule' does not apply to CO_2. Given a certain income/wealth level, both poor and rich people of a country can accrue the social costs of climate change and its mitigation to other countries and – even more so – to future generations. Independently from the income or wealth distribution, people benefit equally from the externalization of costs. The results suggest that the marginal propensity to emit (MPE) of poor people equals the MPE of rich people within a country. However, seminal future research in this field will depend on the availability of valid income and wealth inequality data for many countries and years. Still, the problem remains that data of good quality is sparsely obtainable only for a few relatively rich countries for a short period of time.

Finally, some propose policy approaches that combine cost-efficient and dynamically efficient cap-and-trade programs with income redistribution as a promising avenue for progressive climate change mitigation (e.g. Boyce and Riddle, 2009). Yet, the results of this analysis suggest that these so-called cap-and-dividend schemes are not, by themselves, the best means of reducing carbon emissions. Rather, implementing efficient cap-and-trade schemes together with an enforceable international CO_2 compensation framework appear more promising for an effective climate policy complemented by measures affecting key predictors of CO_2 emissions.

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Conflict of interest

The author declares that he has no conflict of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.envsci.2018.08.009.

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Supplementary Information of “The nexus between social inequality and CO_2 emissions revisited: Challenging its empirical validity”

Table S1: Country-level: Variable description

Variable	mean	within ($\bar{x}_i$)			between ($x_{it} - \bar{x}_i + \bar{\bar{x}}$)			N (nxT)	n	Description	Data Source
		sd	min.	max.	sd	min.	max.				
PBA CO_2 p. c.	3.5	1.6	-11.6	19.2	4.3	.1	21.3	9467	175	PBA CO_2 emissions p. c. of fossil fuel use and industrial processes (cement production, carbonate use of limestone and dolomite, non-energy use of fuels and other combustion) attributed to the country in which goods and services are produced (Olivier et al. 2016). Unit: metric tons.	EDGAR
CBA CO_2 p. c.	5.4	1.2	-.3	15.8	5.5	.1	26.1	2750	110	CBA CO_2 emissions p. c. of fossil fuel use and industrial processes attributed to the country in which goods and services are consumed (CBA CO_2 = PBA CO_2 - CO_2 exports + CO_2 imports) (Peters et al. 2011). Unit: metric tons.	GCA
Wealth per Adult	2.3	3.5	-48.2	43.6	9.0	0.0	93.0	2587	162	Wealth per adult (Wpa, individual net worth held by adults aged 20 and up, Shorrocks et al. 2016) based on purchasing power parity (PPP). PPP Wpa is Wpa converted to international dollars using PPP rates from the IMF. Data are in million international dollars.	CS, IMF
Wealth Share of Top 10%	.59	.02	.52	.68	.12	.21	.78	645	43	Wealth (individual net worth held by adults aged 20 and up) share held by a given percentile group (Shorrocks et al. 2014).	CS
GDP p. c.	9.9	5.8	-21.4	55.2	10.5	.5	71.4	5736	178	Gross domestic product (GDP) p. c. based on PPP. PPP GDP is GDP converted to international dollars using PPP rates. Data are in 1000 international dollars.	IMF
Income Gini Coefficient	.37	.03	.19	.56	.09	.23	.63	3831	162	Household disposable (post-tax, post-transfer) Income Gini coefficient ranging from 0 (perfect equality) to 1 (perfect inequality).	SWIID
Fossil Fuel Energy Consumption	.64	.07	.29	1.00	.37	0	1.00	5382	161	Energy consumption from fossil fuels comprises coal, oil, petroleum, and natural gas products. Unit: share of total.	IEA/WB
Trade Balance	.87	.23	-.19	3.88	.26	.04	1.75	7595	177	Trade balance is the ratio of exports to imports of goods and services as share of GDP.	WB
Industry, value added	28.0	6.0	-4.8	73.9	10.9	7.2	76.0	6333	175	Industry corresponds to the International Standard Industrial Classification (ISIC) divisions 10-45. The origin of value added is determined by the ISIC, revision 3. Unit: % of GDP.	WB
Services, value added	52.3	7.2	8.6	112.4	13.4	22.8	82.1	6333	174	Services correspond to ISIC divisions 50-99. The industrial origin of value added is determined by the ISIC, revision 3. Unit: % of GDP.	WB
Electricity Production from Non-fossil Sources	.43	.12	-.21	.98	.32	0	.99	5318	130	Sources of electricity refer to the inputs used to generate electricity. Electricity production from non-fossil sources comprises hydroelectric and other renewable as well as nuclear sources. Unit: share of total.	IEA/WB
International Environmental Agreements	72.7	85.2	-130.3	378.7	39.4	1.6	205.0	10304	184	An international environmental agreement is an intergovernmental document intended as legally binding with a primary stated purpose of preventing or managing human impacts on natural resources (Mitchell 2015). Unit: cumulated number set into force.	IEADP
Energy Prices	85.9	35.1	-30.3	270.8	36.1	49.6	189.4	1127	38	Energy prices are consumer prices for the items electricity, gas and other fuels as defined under the Classification of Individual Consumption According to Purpose (COICOP 04.5) and fuel and lubricants for personal transport equipment (COICOP 07.2.2). Data are expressed as index corrected by IMF PPP rates (2010 = 100 for USA).	OECD, IMF

Notes: CBA = Consumption-based Accounting, CS = Credit Suisse, EDGAR = Emissions Database for Global Atmospheric Research, GCA = Global Carbon Atlas, IEA = International Energy Agency, IEADP = International Environmental Agreements Database Project, IMF = International Monetary Fund, PBA = Production-based Accounting, OECD = Organisation for Economic Co-operation and Development, p. c. = per capita, SWIID = Standardized World Income Inequality Database (Solt 2016), WB = World Bank; All variables in the models are included by taking the natural logarithm allowing for the estimation of elasticities.

Table S2: Countries included in the analyses

Australia*	Finland*	Japan*	Singapore*
Austria*	France*	Mexico	South Korea*
Belgium*	Germany*	Netherlands*	Spain*
Canada*	Greece*	New Zealand*	Sweden*
Colombia	Ireland*	Norway*	Switzerland*
Czech Republic*	Israel*	Poland*	United Kingdom*
Denmark*	Italy*	Portugal*	United States*

Notes: All countries are full members of the United Nations. All 28 countries with good and satisfactory quality wealth distribution data are included in the relaxed and extended models. 26 countries indicated by '*' are included in the restricted models by Knight et al. (2017). For the further model extension (models 2 and 4 of Table 4) data on the additional control variables is missing for Israel and Singapore.

Table S3: Replication of Knight et al. 2017: Sensitivity Checks

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Replication						
	Country and Time FE Regression						
Dependent Variable	CBA of CO_2 p.c.						
Wealth Inequality	0.58	0.54	0.53	0.37	0.52	1.10	0.27
	(0.27)	(0.28)	(0.26)	(0.25)	(0.29)	(0.66)	(0.13)
GDP p. c.	0.37*	0.43*	0.43*	0.47*	0.32	0.85*	0.35
	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)	(0.33)	(0.17)
Income Gini	0.04	-0.01	0.12	0.12	0.09	-0.05	0.09
Coefficient	(0.21)	(0.21)	(0.21)	(0.22)	(0.22)	(0.23)	(0.22)
n x T	275	275	275	275	275	286	286
n	25	25	25	25	25	26	26
adj. R^2 within	0.08	0.10	0.13	0.13	0.04	0.12	0.09

Notes: * = $p < 0.05$. Unstandardized regression coefficients with standard errors in brackets. All seven models 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. Model 1 excludes Australia, model 2 Greece, model 3 Norway, model 4 Singapore, and model 5 South Korea. Model 6 applies fixed effects panel regression allowing for individual constants and slopes. Model 7 substitutes the wealth share held by the top 10% by the wealth share held by the top 1% also provided by Credit Suisse (Shorrocks et al. 2014: 125).

Table S4: US State-level: Variable description

Variable	mean	within ($\bar{x}_i$) sd	min.	max.	between ($x_{it} - \bar{x}_i + \bar{\bar{x}}$) sd	min.	max.	N (n x T)	n	Description	Data Source
CO_2 (million tons)	108.8	10.1	40.7	154.5	111.3	3.8	663.0	1275	51	Production-based accounting of CO_2 emissions (p. c.) from the combustion of fossil fuels from the commercial, industrial, residential, transportation, and electric power sectors.	EPA
CO_2 p. c. (metric tons)	24.4	2.3	9.4	34.7	19.2	6.5	122.3	1275	51		
Population	4870.0	1566.0	-7130.0	15994.1	5288.8	454.1	27870.0	2856	51	Resident population including armed forces in thousands.	CB
Urban Population	73.46	1.40	67.85	79.06	15.00	38.66	100	1020	51	Resident population in urbanized areas and urban clusters as percentage of total. As this data is only available each decade with measure-ments in 2000 and 2010, missing values were inter-polated as done in Jorgenson et al. (2017).	CB
Real GDP p. c.	47.3	3.9	23.0	71.1	17.4	30.7	155.6	969	51	Real gross domestic product (GDP) p. c. in thousand chained 2009 US$.	BEA
Income Gini Coefficient	.48	.08	.24	.71	.02	.45	.54	4863	51	Income Gini coefficient ranging from 0 (perfect equality) to 1 (perfect inequality).	USIID
Income Share of Top 10%	.37	.06	.18	.88	.03	.24	.46	4998	51	Pre-tax national income share held by a given percentile group.	WWID
of Top 5%	.27	.05	.11	.74	.03	.15	.35	4998	51		
of Top 1%	.13	.04	.01	.61	.02	.06	.21	4998	51		
Fossil Fuel Production	993.5	750.6	-2825.2	7029.2	2006.9	0	12190.8	2856	51	Total fossil fuel production (coal, natural gas, and crude oil) in trillion Btu.	EIA
Fossil Fuel Production p.c.	.5	.9	-6.2	10.6	1.5	0	9.8	2856	51	Fossil fuel production in trillion Btu p.c..	
Manufacturing	.12	.02	.01	.25	.06	.00	.28	1020	51	Value added by manufacturing of durable and nondurable goods as share of GDP.	BEA
Renewable Energy Production	38.8	15.0	-6.4	106.3	34.9	.5	100	2856	51	Total renewable energy production as percentage of total energy production.	EIA
Energy Prices	10.3	6.2	-2.6	36.0	1.6	7.3	14.6	2346	51	Total energy average price of all end-use sectors in US$ per million Btu.	EIA
State Environ-mentalism	46.8	12.1	3.1	92.5	25.2	4.9	92.1	1350	50	Score of pro-environmental voting by states' Congressional delegations based on the LCV scorecard ranging from 0 to 100 (Dietz et al. 2015).	LCV

Notes: Btu = British thermal unit, CB = U.S. Census Bureau, BEA = U.S. Bureau of Economic Analysis, EIA = U.S. Energy Information Administration, EPA = U.S. Environmental Protection Agency, p. c. = per capita, LCV = U.S. League of Conservation Voters, USIID = U.S. State-Level Income Inequality Database (Frank 2014), WWID = World Wealth and Income Database. All variables in the models are included by taking the natural logarithm allowing for the estimation of elasticities.

Table S5: Replication of Jorgenson et al. 2017: Sensitivity Checks

Model	(1)	(2)	(3)	(4)
	Prais-Winsten State and Time FE Regression			State and Time FE Regression
Dependent Variable		CO_2		
Income Share of Top 5%	0.29 (0.18)			
Income Share of Top 1%		0.30 (0.18)		
Income Gini Coefficient			-0.04 (0.32)	-0.00 (0.32)
Population	0.54*** (0.11)	0.54*** (0.11)	0.55*** (0.12)	0.52* (0.20)
GDP p.c.	0.23*** (0.05)	0.22*** (0.05)	0.24*** (0.05)	0.28** (0.09)
Urban Population	0.81** (0.28)	0.82** (0.28)	0.82** (0.28)	0.82 (0.41)
Fossil Fuel Production	0.02** (0.01)	0.02** (0.01)	0.02** (0.01)	0.02 (0.01)
Manufacturing	-0.14 (0.17)	-0.13 (0.17)	-0.13 (0.17)	-0.26 (0.16)
n x T	816	816	816	816
n	51	51	51	51
adj. R^2 within				0.16

Notes: * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. Unstandardized regression coefficients with standard errors in brackets. All four models include the years 1997-2012 and contain dummy variables for each year in order to control for overall time-trends. All standard errors in the models 1, 2, and 3 are panel-corrected, allowing for disturbances that are heteroskedastic and contemporaneously correlated across panels. Additionally, these models correct for first-order autocorrelation (AR(1) process) within panels. All standard errors of model 4 are clustered by state and year, and therefore robust with respect to heteroscedasticity and autocorrelation.

Table S6: Replication of Jorgenson et al. 2017: Further Sensitivity Checks

Model	(1)	(2)	(3)
		Replication	
		State and Time FE Regression	
Dependent Variable		CO_2	
Income Share	0.65	0.65	0.44
of Top 10%	(0.32)	(0.32)	(0.26)
Population	0.63**	0.63**	1.29**
	(0.19)	(0.19)	(0.32)
GDP p. c.	0.28**	0.28**	0.11
	(0.10)	(0.10)	(0.10)
Fossil Fuel Production	0.02	0.02	0.01
	(0.01)	(0.01)	(0.02)
Manufacturing	-0.38*	-0.38*	-0.54
	(0.16)	(0.16)	(0.30)
n x T	800	800	816
n	50	50	51
adj. R^2 within	0.16	0.16	0.12

Notes: * = $p < 0.05$, ** = $p < 0.01$. Unstandardized regression coefficients with standard errors in brackets. All three models include the years 1997-2012 and contain dummy variables for each year in order to control for overall time-trends. All standard errors are clustered by state and year, and therefore robust with respect to heteroscedasticity and autocorrelation. Model 1 excludes Delaware, and model 2 drops District of Columbia. Model 3 performs FE panel regression with individual constants and slopes (FEIS).

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4. Article: Plant trees for the planet: the potential of forests for climate change mitigation and the major drivers of national forest area.

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Plant trees for the planet:

the potential of forests for climate change mitigation and the major drivers of national forest area

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Plant trees for the planet: the potential of forests for climate change mitigation and the major drivers of national forest area

Abstract

Forests are one of the most cost-effective ways to sequester carbon today. Here, I estimate the world's land share under forests required to prevent dangerous climate change. For this, I combine newest longitudinal data of FLUXNET on forests' net ecosystem exchange of carbon (NEE) from 78 forest sites (*N*=607) with countries' mean temperature and forest area. This straightforward approach indicates that the world's forests sequester 8.3 $GtCO_2yr^{-1}$. For the 2 °C climate target the current forest land share has to be doubled to 60.0 % to sequester an additional 7.8 $GtCO_2yr^{-1}$, which demands less red meat consumption. This afforestation/reforestation (AR) challenge is achievable, as the estimated global biophysical potential of AR is 8.0 $GtCO_2yr^{-1}$ safeguarding food supply for 10 billion people. Climate-responsible countries have the highest AR potential. For effective climate policies, knowledge on the major drivers of forest area is crucial. Enhancing information here, I analyse forest land share data of 98 countries from 1990 to 2015 applying causal inference (*N*=2,494). The results highlight that population growth, industrialization, and increasing temperature reduce forest land share, while more protected forest and economic growth generally increase it. In all, this study confirms the potential of AR for climate change mitigation with a straightforward approach based on the direct measurement of NEE. This might provide a more valid picture given the shortcomings of indirect carbon stock-based inventories. The analysis identifies future regional hotspots for the AR potential and informs the need for fast and forceful action to prevent dangerous climate change.

Keywords: Forest area; climate change mitigation; carbon sequestration; net ecosystem exchange; fixed effects panel regression; FLUXNET; FAO;

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1 Introduction

Forests provide many tangible and intangible ecosystem services integral for human well-being (e.g. Ellison et al. 2017, Federici et al. 2015). Beyond this, forests are considered one of the most suitable ways to sequester carbon today, as afforestation and reforestation (AR) are relatively cost-effective, and associated with least expected adverse effects on biogeochemical and biogeophysical systems (Fuss et al. 2018, Griscom et al. 2017, IPCC 2014, Smith et al. 2016, Sonntag et al. 2016).

Recent global estimates on the current net carbon sink of established forests (i.e. carbon sequestration) range from 2.2 (Federici et al. 2015) to 8.0 (Grassi et al. 2018, Oleson et al. 2013)[2] to 8.8 gigatons of carbon dioxide per year ($GtCO_2yr^{-1}$; Pan et al. 2011). Evaluations of the maximum biophysical sequestration potential of AR vary from 1.1 to 12.1 $GtCO_2yr^{-1}$ (Smith et al. 2016, Minx et al. 2018, Ciais et al. 2013). However, all these estimates are based on the calculation of changes in carbon stocks along Intergovernmental Panel on Climate Change (IPCC) guidelines (IPCC 2006) or the Houghton bookkeeping method (Houghton et al. 2012), providing an indirect and mostly incomplete measure of forests' net ecosystem exchange of carbon (NEE). This approach requires periodic information on the carbon content of biomass, and involves fundamental assumptions on carbon stocks – especially when reliable data is missing. This is notably true for many developing nations (Grassi et al. 2018, IPCC 2006). Moreover, each of these country estimates is based on different data quality, definitions of forest area, and accounting methods. Though data quality is gradually improving, this suggests a sizable challenge to develop a valid and internationally comparable inventory of global forest carbon fluxes based on indirect stock-based

[2] Results from the simulations of the Dynamic Global Vegetation Model (DGVM) Community Land Model (CLM) version 4.5 (Oleson et al. 2013; Table SI 8 in Grassi et al. 2018);

techniques (Grassi et al. 2018).

This study has four objectives: First, I provide estimates of the annual carbon sequestration of established forests, and the biophysical climate change mitigation potential of AR based on the direct micrometeorological measurement of NEE as provided by FLUXNET (NASA 2015) (section 2). With this direct measurement of above canopy carbon flux no information on carbon stocks is needed to infer NEE. Thus, NEE estimates based on FLUXNET data may provide a more valid picture of forests' carbon sink and their mitigation potential. Second, with this straightforward approach, I infer the forest land share required to meet the 2 °C climate target and three AR scenarios to acquire this goal (section 3; see Appendix A Methods and Materials for details). Third and subsequently, I identify the countries with the largest climate liabilities, and economic capabilities while having the greatest mitigation potential through AR (section 4).

Fourth, for effective policies targeted at enhancing forests and climate change mitigation, knowledge on the key drivers of forest area is essential. However, information on causal relationships of forest gain and loss is sparse, and unconsolidated (Aguilar and Song 2018, Morales-Hidalgo et al. 2015) with a focus on forest loss (Busch and Ferretti-Gallon 2017). Yet, this is only half of the story to be told. Thus, here I identify the major predictors of the forest land share of 98 countries from 1990 to 2015 gathered from the Food and Agriculture Organization of the United Nations (FAO 2018) applying causal inference (section 5). The last section summarizes and discusses the main results, and closes with some concluding remarks.

2 Global and regional forest carbon sink

To quantify the NEE of countries' forests, I utilize the newest available micrometeorological FLUXNET data of 78 measurement towers in forests of 16 countries on five continents from 2000 to 2014 (N=607; Table B.1 in Appendix B Supplementary Figures and Tables). Multiple linear ordinary least squares (OLS) regression identifies annual mean temperature as the main determinant of forests' NEE (u-shaped relationship) in this data (Table B.2, and Figure B.1 in Appendix B). Model predictions on countries' NEE of forests using countries' average temperature taken from the World Bank (2018) show that established forests sequester -8.8 $tCO_2ha^{-1}yr^{-1}$ on average in 2015 (median: -9.2; Appendix A). This is rather close to prior assessments based on indirect measurements of NEE (Sohngen 2010). Portugal has the highest negative NEE with a net absorption of -15.1 $tCO_2ha^{-1}yr^{-1}$, whereas the highest positive NEE is observed for Canada with a net release of 16.3 $tCO_2ha^{-1}yr^{-1}$ (Figure 1a). The forests of almost all countries are net absorbers of carbon, except the boreal forests in Canada, the Russian Federation, and Mongolia that are net sources of carbon. This might be due to diebacks of these boreal forests resulting from insect outbreaks and wildfires due to higher mean temperatures and droughts induced by climate change (Canadell and Raupach 2008). As introspection of Figure 1a reveals, NEE varies by climate forest domain following a u-shaped mean temperature – NEE relationship. The carbon sequestration of boreal forests is lowest with a mean NEE of -1.1 $tCO_2ha^{-1}yr^{-1}$, while it is highest for temperate forests with -12.6 $tCO_2ha^{-1}yr^{-1}$. Tropical forests' NEE lies in-between with an average of -6.0 $tCO_2ha^{-1}yr^{-1}$. This pattern is in line with former research (Brumme et al. 2005).

Multiplying countries' average NEE per hectare by their forest area (FAO 2018, Figure 1b) suggests an overall forest carbon sink of -8.3 $GtCO_2yr^{-1}$ or -1.1 tCO_2yr^{-1} per capita (p.c., UNPD 2017) in 2015. Carbon sequestration is highest in the forests of the United States and Brazil (-3.2 $GtCO_2yr^{-1}$ each), followed by China (-2.0 $GtCO_2yr^{-1}$), Australia (-1.5 $GtCO_2yr^{-1}$) and the Democratic Republic of the Congo (-1.1 $GtCO_2yr^{-1}$). The rest of the world's countries has a net absorption of less than -1.0 $GtCO_2yr^{-1}$ each, and Canada, Mongolia, and the Russian Confederates have a substantial net release of 16.7 $GtCO_2yr^{-1}$ in sum.

The global estimate of this rather simple approach using direct carbon flux measurements of NEE is fairly close to the estimates of two recent studies applying more complicated, indirect, carbon stock-based inventories of NEE (Grassi et al. 2018, Oleson et al. 2013, Pan et al. 2011). Grassi et al. (2018) report a global forest carbon sink of -8.0 $GtCO_2yr^{-1}$ for the Community Land Model (version 4.5; Oleson et al. 2013)[3] and Pan et al. (2011) estimate a sink of -8.8 $GtCO_2yr^{-1}$ based on changes in carbon stocks.

[3] This Dynamic Global Vegetation Model (DGVM) could be considered one of the most elaborate DGVMs as it comprises the most relevant ecological characteristics as compared to other commonly used DGVMs (Table SI 7 in Grassi et al. 2018).

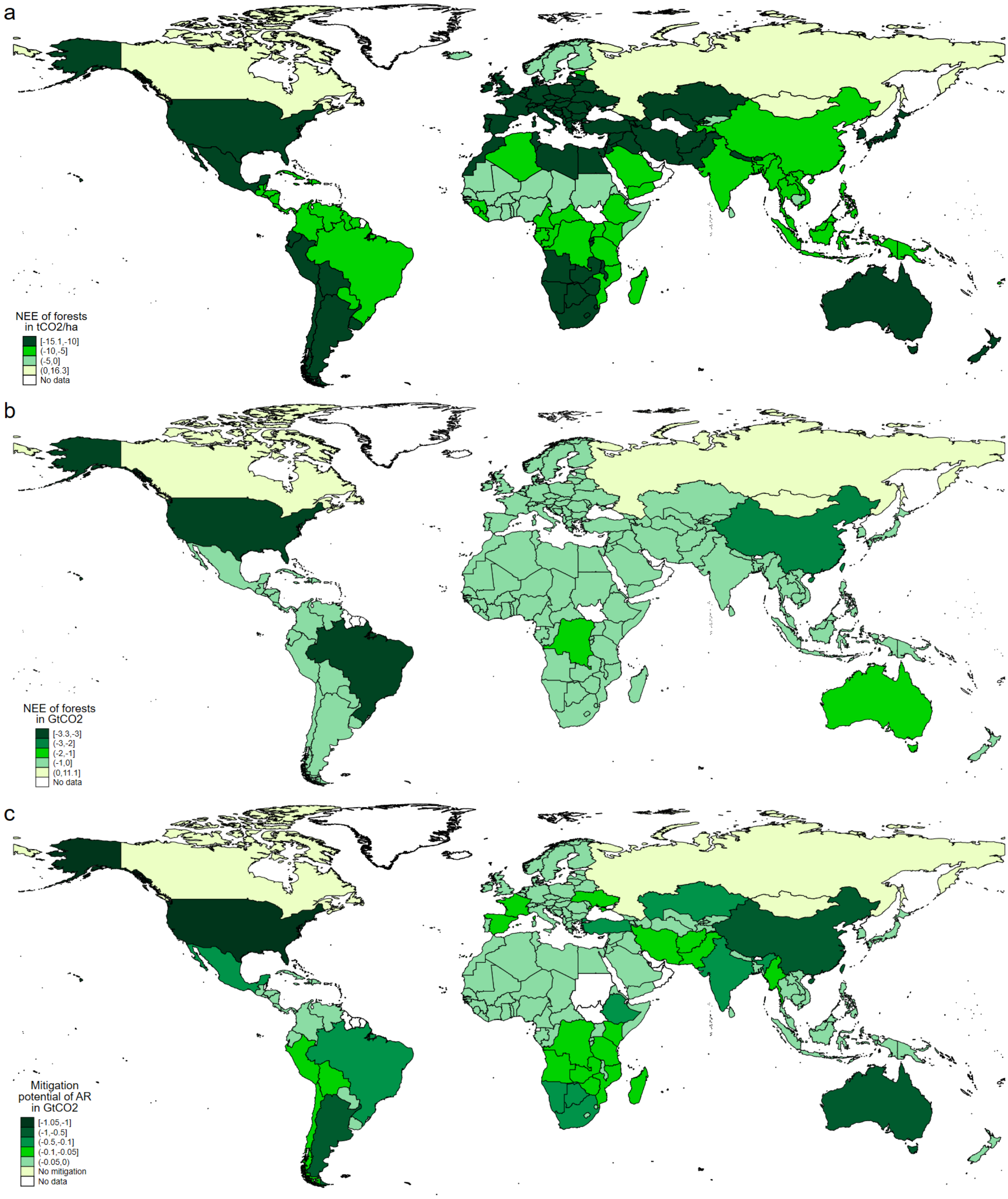

Figure 1 | Net ecosystem exchange (NEE) of CO_2 of countries' forests in 2015. a-c, Data source for the calculation of NEE of CO_2 of countries' forests is FLUXNET (NASA 2015), World Bank (2018) and FAO (2018). Negative numbers indicate net absorption of carbon, positive numbers its net release. **a,** Carbon sequestration in $tCO_2ha^{-1}yr^{-1}$ of forest area (mean = -8.8, median = -9.2, min. (Portugal) = -15.1, max. (Canada) = 16.3). **b,** Countries' overall forest carbon sequestration in $GtCO_2yr^{-1}$ (sum = -8.3 $GtCO_2yr^{-1}$). **c,** Countries' overall NEE potential of afforestation/reforestation (AR) in $GtCO_2yr^{-1}$ based on scenario 3 exceeding the 7.8 $GtCO_2yr^{-1}$ required to meet the 2 °C respectively 3 tCO_2 per capita climate target (sum = -8.0 $GtCO_2yr^{-1}$; see text and Appendix A for details).

3 Forest land share trends and AR scenarios

Before evaluating countries' climate change mitigation potential of AR (Figure 1c), the current forest land share, suitable land for AR as well as competing land uses have to be quantified. The average forest land share as provided by the FAO shrunk from 31.8 % in 1990 to 30.8 % in 2015 (Figure 2), which corresponds to a forest loss of 1.3 Mkm^2 – an area as large as Peru.

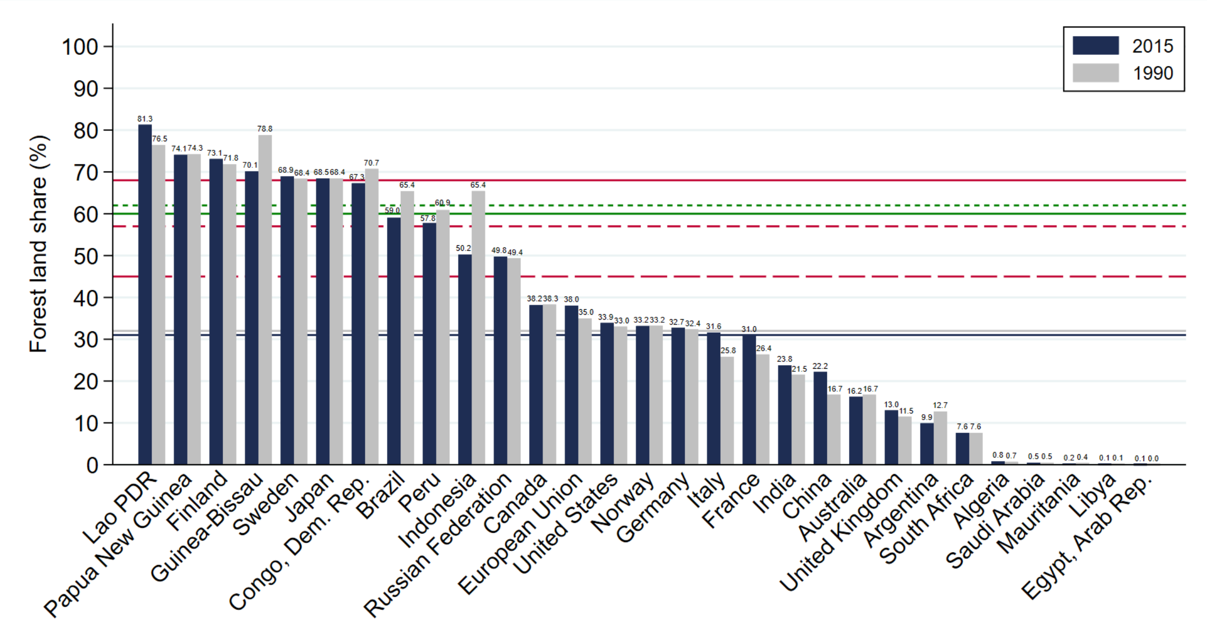

Figure 2 | Forest land share in international comparison 1990 and 2015. Depicted are the top and bottom five countries, top five countries with respect to overall forest area (FAO 2018) by climate domain in 2015, and members of the G7 and BRIICS if not already included. Dark blue solid line = mean 2015; Grey solid line = mean 1990; Scenario 1: Red solid line = required forest share for the 2 °C climate target, red long-dashed line = achievable forest share; Scenario 2: red dashed line = achievable forest share; Scenario 3: Green solid line = required forest share, green short-dashed line = achievable forest share. See text and Appendix A for details.

As Figure 2 shows, European countries like France, Italy, Germany, and Norway resemble the mean of 2015. The forest land share varies strongly: Laos ranks highest with 81.3 % and is followed by Papua New Guinea, Finland, Guinea-Bissau, and Sweden constituting the top five. The bottom five countries with almost no forests are Algeria, Saudi Arabia, Mauritania, Libya, and Egypt. Between 1990 and 2015 Indonesia incurred the greatest loss of almost a quarter and Brazil as top carbon sequestering country lost 10.0 % of its tropical forests. The greatest gain was accomplished by China with a one third increase in forest area while ranking third in overall NEE. For the United States as top carbon absorbing nation, almost no change in forest cover was observed in this period.

Furthermore, Figure 2 presents the required as well as the achievable forest land share of three different AR scenarios to prevent dangerous climate change. The global annual gross carbon budget to fulfil the 2 °C climate target with a probability of at least 66 % is an estimated 30 $GtCO_2$ (IPCC 2014, Friedlingstein et al. 2014, Meinshausen et al. 2009). Assuming an average annual world population of 9.8 billion people until 2100 (UNPD 2017), this goal translates into ~3 t of gross CO_2 emissions per capita (p.c.) and year.

First, scenario 1 is the baseline scenario. It assumes constant production and consumption patterns, constant other carbon sinks, and a further required emissions reduction of 1.0 tCO_2yr^{-1} p.c. after accounting for the overall forest carbon sequestration of 0.8 tCO_2yr^{-1} p.c.. Hence, in scenario 1 the required forest land share to meet the 2 °C respectively the 3 tCO_2 p.c. climate target is 67.8 % (red solid line in Figure 2) to additionally sequester 9.8 $GtCO_2yr^{-1}$ (Appendix A). The red long-dashed line is the forest land share that can be achieved via 100 % AR of all shrub-covered areas and herbaceous vegetation as retrieved from the FAO (2018; 44.8 % forest land share). This is more than one third of the required AR. Second, in scenario 2 a forest land share of up to 57.5 % can be achieved by additionally afforesting and reforesting 44 % of permanent grassland and cropland (FAO 2018), assuming current diets and an average land demand of 2,100 m^2 p.c. (Hallström et al. 2015) for feeding an expected 9.8 billion people per year (red dashed line in Figure 2). This represents more than two thirds of this tremendous AR challenge. Finally, in scenario 3 healthier diets with reduced red and ruminant meat consumption decrease agricultural land demand further by 28.0 % to 1,510 m^2 p.c. and reduce dietary-related emissions by 0.2 tCO_2 yr^{-1} p.c. (Hallström et al. 2015). This yields a required forest land share of 60.0 % to meet the 2°C climate target (green solid line in Figure 2) equivalent to an additional 7.8 $GtCO_2yr^{-1}$ to be sequestered by forests. Thus, in this healthy diet scenario further AR of grassland and cropland results in an attainable 62.0 % of forest land share (8.0 $GtCO_2yr^{-1}$; green short-dashed line in Figure 2).

Consequently, the 2 °C climate target can be met by almost doubling the current forest area whilst safeguarding food security with a healthy diet. This outstanding challenge means 37.9 Mkm^2 more of forest area or an estimated 2.6 trillion additional trees. Approximately, this corresponds to the number of trees lost since the start of human civilization (Crowther et al. 2015). This challenge translates into approximately 260 trees p.c. or one tree p.c. per week for a realisation time of five years.

Realizing the need for large-scale AR, there are promising worldwide projects like ‘Plant for the Planet’, which aims at planting one trillion trees. Since 2007, this project has planted 13.6 billion trees (Plant for the Planet 2019) – 0.5 % of the climate target. In 2017 the World Wildlife Fund, the Wildlife Conservation Society and BirdLife International launched the ‘Trillion Trees’ program aiming at restoring one trillion trees by 2050 (Trillion Trees 2019). Furthermore, the ‘Bonn Challenge’ strives for the restoration of 3.5 Mkm^2 of forests by 2030 (~9.2 % of AR required for the 2 °C target). To date pledges exceed 1.7 Mkm^2 (International Union for Conservation of Nature 2019). To achieve the targets of all three voluntary initiatives together would account for the vast majority of the required AR (86 %). 260 trees per capita seems a relatively low number. However, the need for fast and forceful AR is high leaving this venture an ambitious challenge.

4 Liabilities, AR potentials, and capabilities

Given that call, who is in charge of action? Being the country with the highest negative NEE of established forests (Figure 1b), and the world's second largest carbon emitter (Janssens-Maenhout et al. 2017), the United States of America rank highest in the climate change mitigation potential of countries through AR (NEE = -1.0 $GtCO_2yr^{-1}$; Figure 1c). Figure 1c also demonstrates that the world's largest carbon emitter and third largest carbon absorber in forests, China, has the second highest AR potential (-0.8 $GtCO_2yr^{-1}$). This offers a great opportunity for the United States, and China, accounting for almost half of the global carbon emissions and having to bear one of the highest domestic social costs of carbon emissions (Ricke et al. 2018), to take their responsibility for climate change mitigation seriously. Together with Australia, Argentina, and Brazil they form the top five countries with respect to mitigation potential through AR, accounting for almost half of its total.

The radar plots in Figure 3 provide a more comprehensive picture of the countries' climate change liabilities, forests' mitigation contributions, AR potentials, and economic capabilities for action in worldwide comparison. One group of countries at the top of the ranking of the sum score of these characteristics is formed by those ranking highest in mitigation potential of AR, while being among the largest emitters of CO_2 (p.c.) and the wealthiest nations (Figure 3a-c,e-j,n). These countries are Japan, Spain, France, Australia, the United States, Argentina, Italy, Germany, Brazil, and the United Kingdom. Hence, these states could take over their responsibility for climate change mitigation relatively easily via large-scale domestic AR activities. Figure 2 indicates that the forest land share of three of these countries, France, Italy, and the United Kingdom, grew between 1990 and 2015, while Brazil, and Argentina experienced forest loss.

Another group of nations is both liable of global warming and has high AR potential, but to some extent lacks economic strength to implement large-scale measures. Countries like China, Peru, South Africa, Indonesia, and India fall into this group (Figure 3k-m,o,p). Indonesia and Peru reflect this, since these countries lost forests between 1990 and 2015 (Figure 2). By contrast, China, and India gained forest in this period probably due to large-scale AR programs. These nations and poor countries with little climate responsibility but large AR potential like the Democratic Republic of the Congo (Figure 3t) need multilateral financial assistance, foremost from wealthy, climate-responsible states, to unfold their AR potential. This applies to countries, which additionally have relatively low or no AR mitigation potential like South Korea, Sweden, Canada, and the Russian Federation (Figure 3d, q-s). This could be a worthwhile enhancement of the REDD+ (Reducing Emissions from Deforestation and Forest Degradation) framework.

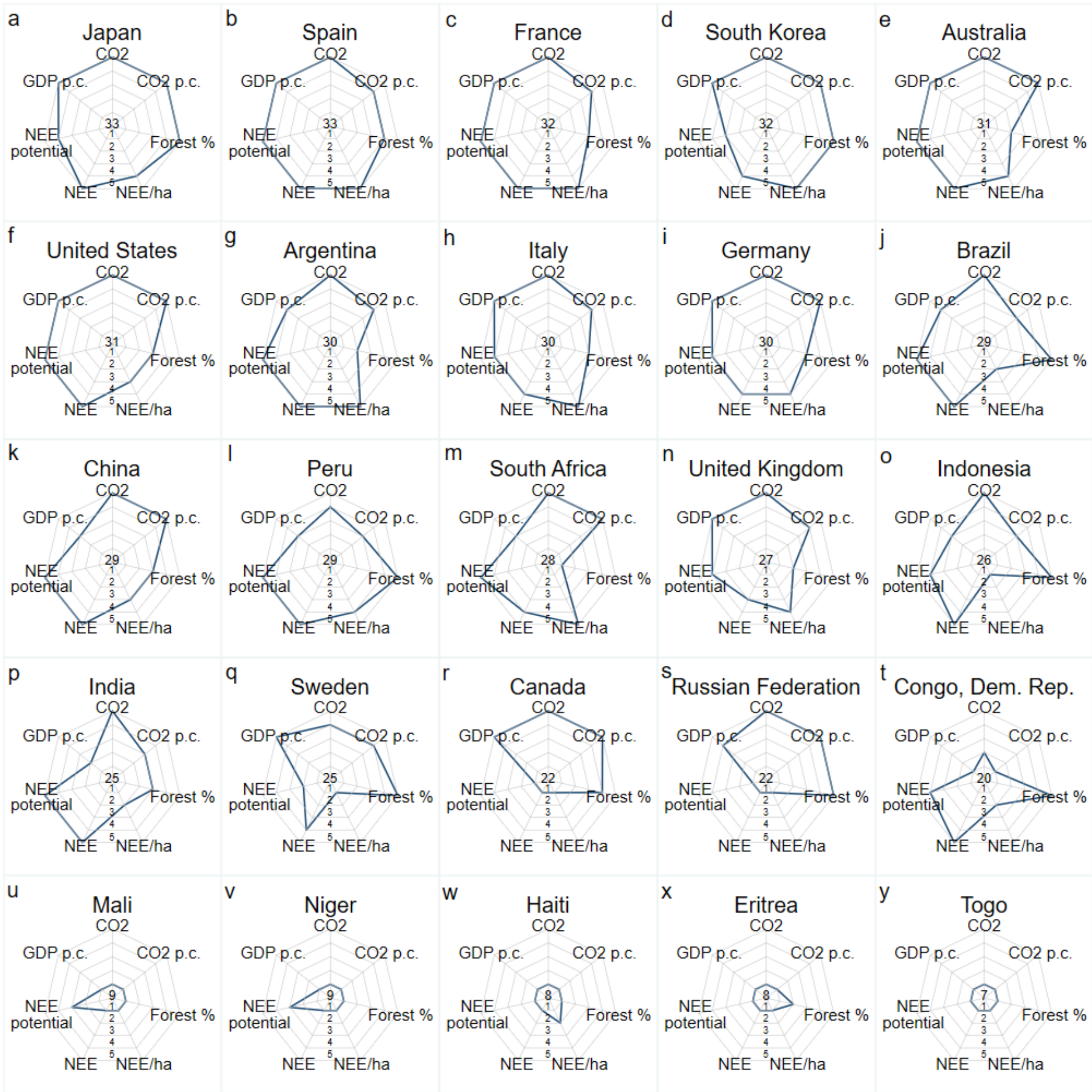

Figure 3 | Country ranking of climate responsibility, forests' mitigation contribution and potential, and economic capabilities in 2015. a-y, Radar plots of countries' relative performance with regard to climate responsibility (CO_2, and CO_2 per capita (p.c.) emissions (Janssens-Maenhout et al. 2017)), forests' mitigation contribution (forest land share (%; FAO 2018), net ecosystem exchange (NEE) per ha, and national NEE), forests' mitigation potential (NEE potential)), and economic capabilities (gross domestic product (GDP) p.c. (IMF 2018)). The numbers 1 to 5 on the spokes of the radars indicate the quintile the country ranks (1 = lowest, 5 = highest). The numbers in the centre of each radar represent the sum of quintiles of each country. Presented are the top and bottom five countries with respect to this sum, the top five countries of overall forest area by climatic forest domain and members of the G7 and BRIICS. The full country ranking of the sum score and all included variables can be obtained from Table B.4 in Appendix B.

5 Predictors of national forest land share

Nonetheless, the plea for international cooperation and referring to climate change responsibility is not enough. For effective policies targeted at the enhancement of forests, profound knowledge on the key drivers of national forest area is crucial. Previous research has focused on determinants of forest loss with different regional and temporal cover and a focus on satellite-derived data in recent years (Busch and Ferretti-Gallon 2017, Leblois et al. 2017). However, these studies are agnostic about AR and forest regrowth, as some authors critically remark themselves (DeFries et al. 2010). Focusing on forest loss only shines light on half of the story to be told. Hence, causal information on the predictors of national forest land share analysing panel data of many countries by means of causal inference is still sparse and unconsolidated (Aguilar and Song 2018, Morales-Hidalgo et al. 2015).

Aguilar and Song (2018), and Morales-Hidalgo et al. (2015) are the only two studies regressing changes in national forest area as provided by the FAO on changes in countries' socioeconomic characteristics utilizing fixed effects (FE) panel regression models. Morales-Hidalgo et al. (2015) is the first study regressing national forest area between 1990 and 2015 gathered from the FAO on a few socio-economic and political indicators applying causal inference. The results of their country and year FE panel regression models (Table 6 in Morales-Hidalgo et al. 2015) suggest that population growth reduces forest area, whereas GDP p.c. and protected areas increase it. Nonetheless, the results of Morales-Hidalgo et al. (2015) could be biased by omitting other substantial drivers of forest land share. Aguilar and Song (2018) is the only study analysing the ratio between national forest area and land area (i.e. forest land share) ensuring comparability of changes in forest cover between countries irrespective of their total land area. In their FE models, Aguilar and Song (2018) include agricultural land area, 10-year lagged GDP growth rate, GNI p.c., population growth rate, population density, share of rural population, rate of secondary school enrolment, its 15-year lagged values, and the squares of all these characteristics as independent variables. The results of their beta-logistic generalized linear mixed models with ratio response indicate that all of the considered covariates are substantially related to forest land share (Table 3 in Aguilar and Song 2018). However, FE models including both levels and lags of the same characteristics produce biased results, if the causal effects emerge immediately (Vaisey and Miles 2017), as it is the case in Aguilar and Song (2018). Furthermore, the results of Aguilar and Song (2018) could be biased by omitting important confounding variables.

To improve, consolidate and expand previous studies, here I regress the forest land share of 98 countries from 1990 to 2015 as provided by the FAO on socio-economic, political, and ecological characteristics applying country and year FE regression models (Brüderl and Ludwig 2015; Appendix A). The 98 countries analysed (Table B.7) have high or sufficient quality of forest area data (tiers 3 and 2; FAO 2016) and comprise around 89 % of global forest area in 2015 (Keenan et al. 2015). All other countries, which have unreliable data solely based on expert estimates (tier 1) are excluded from the analysis. First, one of the best-documented drivers of deforestation is agricultural expansion (Jorgenson 2006). As model 1 of Figure 4 shows, a 1 % within-country increase in agricultural land share on average leads to a 0.2 % within-country decrease in the forest land share. Population growth explains this effect, as it disappears when population size is included in the regression (model 2). Population growth of 1 % yields deforestation of 0.27 %. This suggests that agricultural expansion allows population growth, which in turn exerts pressure on forests because of land demands for housing, mobility, and other resources.[4]

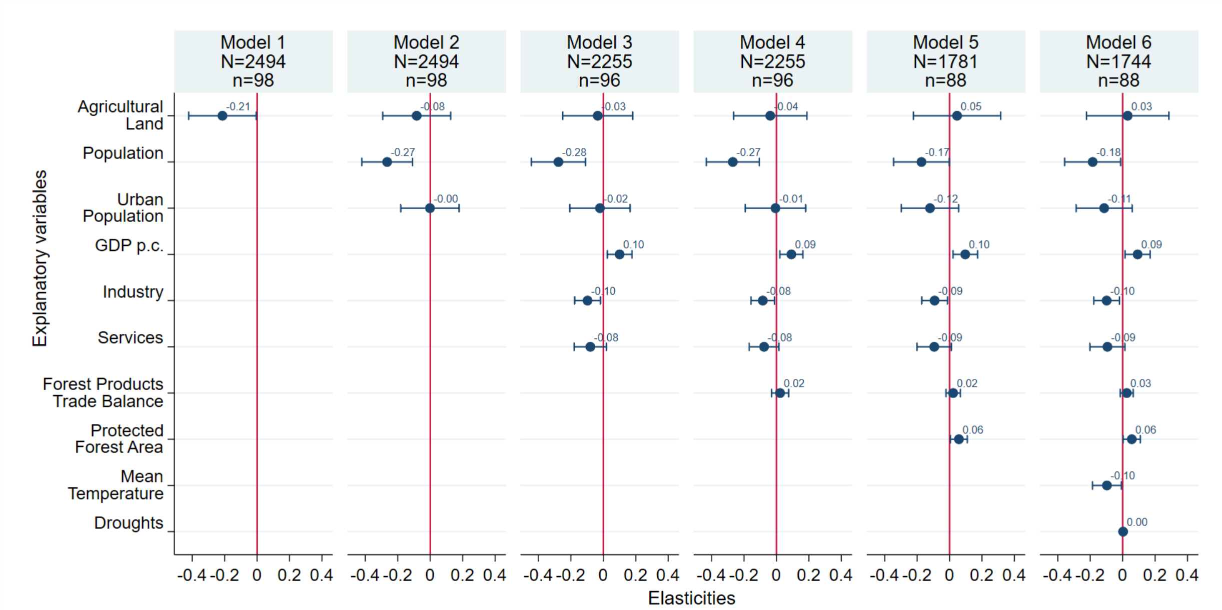

Figure 4 | Predictors of national forest land share. Coefficient plots of unstandardized regression coefficients (dark blue filled circles) of country and year fixed effects regressions of national forest land share on various successively included predictors (models 1-6) including 95 % confidence intervals (dark blue bars; see Table B.5 in Appendix B for details). All six models contain dummy variables for each year to control for overall time-trends. All variables are included by taking their natural logarithm allowing the estimation of elasticities. 'n' refers to the number of countries, and 'N' to the number of observations (number of countries (n) times the number of years). Table B.6 in Appendix B describes all variables and Table B.7 lists all countries included in the models.

Second, it has often been hypothesized that urbanization slows deforestation and promotes AR, because the per capita land demand of cities is assumed to be lower as compared to rural areas (Jorgenson 2006). However, the models 2-6 of Figure 4 reveal that increasing rates of the population living in urban areas are not substantially related to countries' forest area.

Third, the direction of the impact of growing wealth on forest cover is widely discussed in the literature (e.g. Jorgenson 2006). There has been widespread consent that deforestation activities prevail at low and middle levels of gross domestic product (GDP) p.c. and AR activities outweigh deforestation at higher levels of GDP p.c.

[4] Moreover, in the FE regression of population (N=2504, n=98), the elasticity of agricultural land is 0.49 (p < 0.001). Together with the results of the models 1 and 2 of Figure 4, this suggests that population growth mediates the relationship between agricultural expansion and forest loss.

following a trajectory referred to as the environmental Kuznets curve (EKC; Aguilar and Song 2018). However, the empirical evidence for a forest EKC is mixed and the two most recent and elaborate studies found evidence for a clear positive relationship between GDP and forest cover invalidating the forest EKC hypothesis (Aguilar and Song 2018, Morales-Hidalgo et al. 2015). Models 3-6 of Figure 4 highlight this as well: Economic growth of 1 % increases forest land share by 0.1 % irrespective of economic structure and wealth levels.[5] Hence, this supports the notion that wealth at least to some extent leads to more awareness for the ecosystem services of forests and the need to protect them.

In addition to that and extending prior studies, economic structural change could affect forest transition net of GDP growth. An increasing GDP share of the industry sector might introduce pressure on forestlands because of relatively high land requirements of industrial production sites and higher returns for industrial production than for forest products. As models 3-6 of Figure 4 indicate, there is some evidence in favour of this argument, because a 1 % increase in the GDP share of the industry sector yields a 0.1 % decrease in forest land share. In turn, expansion of the service sector could release pressure from forests, as services are presumed to have less land demand. However, in the data there is no support for this notion, since a 1 % increase in the GDP share of the service sector is also related to a 0.1 % decline in forest cover. Yet, this effect is not statistically significant at the $p = 0.05$ level.

Furthermore, the model is enhanced by including an indicator of foreign trade in forest products. It has been a common concern that forest products trade could be one of the reasons for deforestation especially in poor countries with tropical forests

[5] The partial residual plot for GDP of a penalized splines FE regression (Ruppert et al. 2003) adequately modelling non-linearities confirms this, too (Figure B.2 in Appendix B).

and few alternatives of employment to timber logging or farming. By contrast, one can argue that foreign trade of forest products could be an incentive for forest conservation, when the net return of forestry investments and sustainable forest management is greater than the net return for forest clearing for agricultural production (Burgess 1993). However, models 4-6 of Figure 4 demonstrate that increases in exports of forest products relative to their imports do not substantially alter countries' forest area.

Moreover, policies for forest protection may contribute to stop deforestation and forest degradation, and foster AR activities with the aim of enhancing the global forest carbon sink, conserving biodiversity, and safeguarding other ecosystem services of forests. These goals are part of manifold international initiatives and agreements on forest protection. Designating and managing protected areas has been a primary strategy to achieve these goals (Morales-Hidalgo et al. 2015). Hence, protected forest area serves as an indicator for a country's willingness to sustain the ecosystem services of forests and to commit to AR activities. As models 5 and 6 of Figure 4 reveal, a 1 % increase in protected forest area is associated with forest growth of 0.06 %. This effect is statistically significant, but rather small. This is in line with the results of Moral-Hidalgo et al. (2015).

Finally, climate change itself might harm forest ecosystems leading to forest degradation and forest loss. Long-term case studies of tree mortality indicate that higher mean temperature and droughts increase tree mortality and the frequency of wildfires (Canadell and Raupach 2008, Young et al. 2017, Martin 2015). However, it is still unclear whether this also applies to forest loss on a global scale. As model 6 of Figure 4 shows, a 1 % increase in countries' mean air temperature reduces their forest area on average by 0.1 %, while severe drought events do not affect forest cover immediately and ceteris paribus. This suggests that global warming contributes to forest loss, even though the effect is rather small.

6 Discussion and Conclusion

Altogether, this study suggests that dangerous climate change could be prevented solely by AR, as forests' biophysical climate change mitigation potential safeguarding food security with healthy diets (scenario 3) exceeds the required additional carbon uptake for the 2 °C target. For this, the study estimates countries' carbon sequestration of forests based on the direct micrometeorological measurement of NEE, average temperature and forest area. This straightforward, direct carbon flux-based method provides estimates that are comparable to the most recent studies applying more complicated, indirect carbon stock-based inventories of NEE. The direct approach followed here might provide a more valid picture given the outlined shortcomings of indirect carbon stock-based inventories. However, the direct approach rests on the assumption that countries' average temperature is a valuable approximation of the mean climatic conditions of their forests. Moreover, uncertainties stem from data gaps on the NEE of tropical forest biomes, as Figure B.1 in Appendix B demonstrates. Further uncertainties may arise from varying tree density, age, species, species richness and the health of forests (Hawes 2018). Hence, further validation of these initial findings is needed. This includes the establishment of additional and more precise FLUXNET measurement towers especially in tropical forests to close data gaps, and to increase accuracy and spatial resolution of model predictions.

Furthermore, the analysis identifies future regional hotspots for the AR potential. The United States, China, Australia, Argentina, and Brazil are the top five countries with respect to mitigation potential through AR, accounting for almost half of its total.

However, to unfold the AR potential effectively, it is vital to establish a global mandatory carbon certificate market incorporating the forest carbon sink of countries and private forest owners. This generates financial incentives to restore and sustain forest biomes (Sohngen 2010). Enriching voluntary initiatives like REDD+ with countries' AR potentials, climate-liabilities, and economic capabilities might be a valuable starting point for that.

Evenly important, the analysis of the major drivers of countries' forest land share highlights that curbing agricultural expansion and population growth may be a focus for AR policies. Moreover, forests' vulnerability to global warming points to the necessity to plant the right trees in the right places. Therefore, sustainable regional forest management needs to identify the tree species most resilient to temperature increases, and enhance the biodiversity of forests (Huang et al. 2018, Liang et al. 2017). Together with growing wealth, the expansion of protected forest areas is a suitable way to amplify the forest carbon sink, conserve biodiversity, and safeguard other vital ecosystem services provided by forests.

Nevertheless, biophysical, social, and economic challenges alongside large-scale AR might jeopardize its potential benefits (e.g. Canadell and Raupach 2008, Smith et al. 2016, Fuss et al. 2018), and contest the feasibility of the three presented AR scenarios. In general, all three presented AR scenarios a priori exclude land cover types that are, by themselves, biophysically unsuitable for near-term and cost-efficient AR (i. e. artificial surfaces, permanent snow and glaciers, terrestrial barren land, and sparsely natural vegetated areas). In addition, all scenarios safeguard food supply for 10 billion people. However, the feasibility of all three scenarios more or less depends on the socio-economic pressure exerted on the land designated to be afforested/reforested. Griscom et al. (2017) report that almost half of the existing AR potential could be cost-effectively realized below US$100 tCO_2^{-1} (the estimated social cost of 1 tCO_2 emitted within the 2 °C climate target). More than 10 % of the AR potential are achievable at low cost (<US$10 tCO_2^{-1}). At least part of scenario 1, the AR of shrub-covered and herbaceous vegetation, might be reachable at low cost. However, costs are expected to be higher for the AR of agricultural land (permanent grassland and cropland; scenarios 2 and 3). Agricultural expansion and increases in population density increase the opportunity costs of not clearing forests and the costs of AR, and decrease forest cover (as shown in this study). Near-term costs might be even higher, when a large-scale diet transition away from red and ruminant meat is demanded to free up additional land for AR (scenario 3). Yet, meat reduced diets are regarded as 'win-win diets' fostering both public health and the environment in the long-run (Willett et al. 2019). Moreover, and as this study demonstrates, the growing wealth of nations decreases the relative costs of AR and conveys forest protection and AR. Nonetheless, well-tailored AR policies have to account for possible trade-offs between climate change mitigation through AR and benefits for the local population. Here, agroforestry and policies targeted at the promotion of timber as building material whilst substituting carbon-intensive concrete and steel could be especially beneficial, and may substantially promote climate change mitigation (Oliver et al. 2014, Tollefson 2017).

All told, permanent carbon storage is a prerequisite to outpace the burning of fossil carbon and reduce the CO_2 concentration in the atmosphere. Hence, it is vital to combine sustainably managed, large-scale AR activities with technologies for permanent carbon storage like bioenergy with carbon capture and storage (BECCS) at the end of the trees' life cycle for effective climate change mitigation (Fuss et al. 2018, Smith et al. 2016). What is more, abating emissions and applying other negative emissions technologies are valuable in order to hedge the impact of potential side effects of one mitigation option like AR (Minx et al. 2018, Sohngen 2010, Fuss 2010) to keep up with the need for fast and forceful action to prevent dangerous climate change.

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Appendices

A. Methods and Materials

Global and regional forest carbon sink

To assess the net ecosystem exchange of carbon (NEE) of countries' forests I use the newest available direct measurements of NEE of 78 micrometeorological measurement towers located in forests of 16 countries from 2000-2014 provided by FLUXNET (NASA 2015). See Table B.1 in Appendix B for an overview of the analysed tower sites. FLUXNET sites collect data on the exchanges of CO_2 between forests and the atmosphere, precipitation and air temperature at least in a 30 minutes interval. Table B.3 provides a summary of the descriptive statistics. The tower sites use eddy covariance methods to measure forests' NEE. The unique dataset utilized here, 'FLUXNET2015', provides standardized values for these characteristics and underwent several quality control tests and gap-filling (Pastorello et al. 2017).

To infer the NEE of countries' forests from these 78 FLUXNET sites I apply a straightforward approach consisting of three steps: Firstly, I regress their annual NEE on several site characteristics (average temperature, average temperature squared, precipitation, latitude, and elevation) controlling for overall time-trends by including dummy variables of the years observed. While primarily interested in the variation between the forest sites, the inclusion of the 607 site-years available for this model minimize the influence of a specific observation period stemming from annual variation in climatic and other conditions. Therefore, all standard errors are clustered by tower site to ensure robustness with respect to heteroscedasticity and autocorrelation. The results of this linear ordinary least squares (OLS) regression model (Table B.2) indicate that only average temperature substantially relates to NEE. As Figure B.1 shows, the temperature – NEE relationship of forests follows a u-shaped pattern. Forests with an annual mean temperature of -5 to 0 °C are net emitters of carbon, whereas the carbon sequestration of forests is highest in climatic domains with an average of about 15 °C. Even higher temperatures are associated with lower sequestration. Note that uncertainty between 15 and 26 °C is relatively high, because of a rather limited number of tower sites in this climatic forest domain. The reported regression results of Table B.2 were tested for robustness: First, the model was rerun excluding one measurement tower each time from the regression. Second, all parameters were tested for linearity including a penalized splines fixed effects (FE) regression model (Ruppert et al. 2003). Furthermore, the robustness of standard errors was investigated via non-parametric bootstrapping. None of these checks had any substantial influence on the estimates. In addition, the robustness of all estimates with respect to model specification was assessed using the procedure suggested by Young and Holsteen (2017). The potential influence of omitted variables was examined using the method suggested by Frank (2000). Also these checks detected no fundamental deviations from the reported results. The analyses were conducted using the statistical software package STATA 15.1.

Secondly, I predict the mean annual sequestration between the years 2000 and 2014 (t) of country *i*'s forests in tons CO_2 per hectare (y_i) from model 1 of Table B.2 according to the following formula:

$$y_i = \frac{1}{T}\sum_{t=1}^{T}(\beta_0 + \beta_1 a_{it} + \beta_2 a_{it}^2 + \beta_3 b_i + \gamma_t) \quad \text{(Eq. A.1).}$$

β_0 represents the model intercept. a_{it} stands for the average air temperature of country *i* in year *t*, β_1 for the regression coefficient of the sites' average temperature, and β_2 for the coefficient of its square. b_i denotes country *i*'s centroid's latitude, and β_3 the regression coefficient for the forest sites' latitude. γ_t represents the regression coefficient for year *t*. With β_0=5.60, β_1=-2.20, β_2=0.07, β_3=-0.06 from model 1 of Table B.2 follows:

$$y_i = \frac{1}{T}\sum_{t=1}^{T}(5.60 - 2.20 a_{it} + 0.07 a_{it}^2 - 0.06 b_i + \beta_t) \quad \text{(Eq. A.2).}$$

Data for a_{it} is taken from the Climate Change Knowledge Portal of the World Bank (2018; Table B.6), and from the Country Geography Database of Portland State University (2018) for b_i. Computation of Eq. A.2 yields a global average of -8.8 $tCO_2ha^{-1}yr^{-1}$ (median = -9.2, sd. = 4.8, min. = -15.1, max. = 16.3) sequestered by forests in 2015. With roughly 2.7 trillion trees (Crowther et al. 2015) in the 40.0 Mkm^2 (FAO 2018) of forests worldwide, this translates into a mean of -8.8 $kgCO_2yr^{-1}$ per tree (tropical forests (latitude 0° to <25° North (N) or South (S)): -8.4, temperate forests (25° to <50° N or S): -17.3, boreal forests (≥50° N): -1.9) as weighted by the share of trees by forest type (tropical: 0.48, temperate: 0.24, boreal: 0.27; Crowther et al. 2015).

Thirdly, simply multiplying countries' average NEE per hectare by their forest area gathered from the FAO (2018) gives countries' forest carbon sink. Summing up yields an estimate for the global forest carbon sequestration of -8.3 $GtCO_2yr^{-1}$ or -1.1 tCO_2yr^{-1} per capita (p.c.; UNPD 2017).

Afforestation/reforestation (AR) scenarios

To prevent dangerous climate change, the required and achievable forest land share of three different AR scenarios are developed. The basis for these scenarios is the 2 °C target and the associated remaining carbon budget until 2100. With the Paris Climate Agreement, the world community has agreed upon the limitation of global warming to well below 2 °C relative to preindustrial levels (UNFCCC 2015). A maximum of 2 °C of warming until 2100 may provide a relatively safe operating space for humanity and prevent dangerous climate change alongside a lock-in of a 'Hothouse Earth' pathway with potentially hazardous consequences for ecosystems and human socio-economic systems (IPCC 2014, Steffen et al. 2018, Fischer et al. 2018, Rockström et al. 2009). Yet, humanity allegedly has already committed to 1.3 °C of warming (Mauritsen and Pincus 2017). Hence, limiting global warming to 1.5 °C and presumably providing an even safer operating space (IPCC 2018) seems out of reach (Raftery et al. 2017). Global CO_2 emissions of fossil fuel use and industrial processes have risen to 35.8 $GtCO_2$ or 4.8 tCO_2 per capita (p.c.) in 2016 (Janssens-Maenhout et al. 2017). This surpasses the global annual gross carbon budget (an estimated 30 $GtCO_2$) to fulfil the 2 °C target with a probability of at least 66 % (IPCC 2014, Friedlingstein et al. 2014, Meinshausen et al. 2009). Assuming an average annual world population of 9.8 billion people until 2100 (UNPD 2017) this goal translates into ~3 t of gross CO_2 emissions p.c. and year.

Scenario 1 is the baseline assuming business-as-usual production and consumption patterns, constant other carbon sinks, further required emission reductions of 1.0 tCO_2yr^{-1} p.c. after accounting for the overall forest carbon sequestration of 0.8 tCO_2yr^{-1} p.c. with an expected average population of 9.8 billion people per year until 2100. Hence, the required additional absorption by forests for the 2 °C respectively the 3 t p.c. target is 9.8 $GtCO_2yr^{-1}$. Assuming similar carbon sequestration of established forests and afforested/reforested land, simple solution of the rule of three and addition to the existing forest area (40.0 Mkm^2) delivers a required forest area of 88.0 Mkm^2. With a global land area of 129.7 Mkm^2 (FAO 2018) this corresponds to a forest land share of 67.8 % necessary to reach the 2 °C target with AR activities alone. This implicitly assumes similar tree density, species, species richness and forest health of afforested/reforested land and established forests. To quantify the land area suitable for AR, land unsuitable for near-term and cost-efficient AR was excluded. These land cover types are artificial surfaces (including urban and associated areas), permanent snow and glaciers, terrestrial barren land, and sparsely natural vegetated areas as quantified by the FAO (2018). 100 % AR of all shrub-covered areas and herbaceous vegetation (18.1 Mkm^2) result in an achievable 44.8 % of forest land share in this scenario.

S*cenario 2* further assumes current diets and an associated demand of agricultural land of 2,100 m^2 p.c. (Hallström et al. 2015). As there are 3,770 m^2 p.c. of agricultural land currently available, 44 % of permanent grassland and cropland (FAO 2018) can be additionally afforested/reforested (16.4 Mkm^2) for feeding an expected 9.8 billion people per year. Hence, a forest land share of 57.5 % can be realized in scenario 2 (77.6 Mkm^2). This accounts for more than two thirds of the AR climate target outlined in scenario 1.

To achieve the AR target fully, further reduction in the demand for agricultural land is required. In *scenario 3* healthier diets with reduced red and ruminant meat consumption further decrease agricultural land demand by 28.0 % to 1,510 m^2 p.c. while dietary-related emissions decrease by 0.2 tCO_2yr^{-1} p.c. (Table 1 in Hallström et al. 2015). Hence, this reduction in carbon emissions implies a global reduction of the required carbon uptake by forests of 2.0 $GtCO_2yr^{-1}$ to 7.8 $GtCO_2yr^{-1}$. This resembles a required forest land share of 60.0 % or 77.9 Mkm^2 of forest area. Via a further 28.0 % AR of permanent grassland and cropland a forest land share of 62.0 % or 80.4 Mkm^2 of forest area can be achieved to additionally sequester 8.0 $GtCO_2yr^{-1}$.

Predictors of national forest land share

Compared to cross-sectional regression models, the FE panel model has the advantage of exploiting the longitudinal structure of the data as it only includes within-country variation. Hence, the FE model is not biased by cross-sectional unobserved heterogeneity (Brüderl and Ludwig 2015, Wooldridge 2010). If the strict exogeneity assumption ($r\,(\boldsymbol{x}_{it}, \varepsilon_{it})$ = 0) holds, FE models adequately estimate unbiased causal effects (Vaisey and Miles 2017). The model can be written as

$$y_{it} - \bar{y}_i = (\boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_i)\boldsymbol{\beta} + \boldsymbol{Z}_t\boldsymbol{\gamma} + \varepsilon_{it} - \bar{\varepsilon}_i \qquad \text{(Eq. A.3).}$$

Here, y_{it} denotes the forest land share of country *i* in year *t*. $\bar{y}_i$ represents country *i*'s mean of the whole observation period. $\boldsymbol{x}_{it}$ stands for the vector of all exogenous variables for country *i* at time *t*, and $\bar{\boldsymbol{x}}_i$ for the average of the time observed. The model further comprises a vector of dummy variables (***Z***) for every year to control period effects for all countries (time FE). A country's time varying stochastic error term is represented by ε_{it}. All metric variables are included by taking their natural logarithm, which allows the estimation of elasticities. All standard errors are clustered by country and year, and are therefore robust with respect to heteroscedasticity and autocorrelation. The reported regression results of Figure 4 were tested for robustness analogous to the results of the analysis for the FLUXNET data as already explained above. Furthermore, all six models were recalculated using the total forest land area as dependent variable instead of forest land share. None of these checks detected any substantial deviations from the results reported in Figure 4.

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Data availability: All data used in this article is publicly available at the referenced webpages.

B. Supplementary Figures and Tables

Country	Tower site code	Reference paper	Country	Tower site code	Reference Paper	Country	Tower site code	Reference paper
Belgium	BE-Vie	Aubinet et al. (2001)	French Guyana	GF-Guy	Bonal et al. (2008)	United States	US-Blo	Falge et al. (2002)
Brazil	BR-Sa1	Hayek et al. (2018)	Germany	DE-Hai	Knohl et al. (2003)		US-GBT	Zeller and Nikolov (2000)
	BR-Sa3	Saleska et al. (2003)		DE-Lkb	Lindauer et al. (2014)		US-GLE	Frank et al. (2014)
Canada	CA-Gro	McCaughey et al. (2006)		DE-Lnf	Anthoni et al. (2004)		US-Ha1	Barford et al. (2001)
	CA-NS1	Goulden et al. (2006)		DE-Obe	Bernhofer et al. (2008)		US-KS1	Dore et al. (2003)
	CA-NS2	Bond-Lamberty et al. (2004)		DE-Tha	Grünwald and Bernhofer (2007)		US-Me1	Irvine et al. (2007)
	CA-NS3	Bond-Lamberty et al. (2004)	Ghana	GH-Ank	Chiti et al. (2010)		US-Me2	Law et al. (2004)
	CA-NS4	Schmidt et al. (2011)	Italy	IT-CA1	Sabbatini et al. (2016)		US-Me3	Sun et al. (2004)
	CA-NS5	Bond-Lamberty et al. (2004)		IT-CA3	Sabbatini et al. (2016)		US-Me4	Law et al. (2004)
	CA-Oas	Chen et al. (2003)		IT-Cp2	Fares et al. (2014)		US-Me5	Law et al. (2004)
	CA-Obs	Chen et al. (2003)		IT-Cpz	Garbulsky et al. (2008)		US-Me6	Ruehr et al. (2012)
	CA-Qfo	Bergeron et al. (2007)		IT-Isp	Ferréa et al. (2012)		US-MMS	Baldocchi et al. (2005)
	CA-SF1	Amiro et al. (2006)		IT-La2	Marcolla et al. (2003)		US-Oho	Chu et al. (2016)
	CA-TP1	Arain and Restrepo-Coupe (2005)		IT-Lav	Marcolla et al. (2003)		US-PFa	Desai et al. (2008)
	CA-TP2	Arain and Restrepo-Coupe (2005)		IT-PT1	Migliavacca et al. (2009)		US-Prr	Kobayashi et al. (2014)
	CA-TP3	Arain and Restrepo-Coupe (2005)		IT-Ren	Montagnani et al. (2009)		US-Syv	Desai et al. (2005)
	CA-TP4	Arain and Restrepo-Coupe (2005)		IT-Ro1	Rey et al. (2002)		US-UMd	Gough et al. (2013)
	CA-TPD	Schmidt et al. (2011)		IT-Ro2	Tedeschi et al. (2006)		US-WCr	Desai et al. (2005)
Czech Republic	CZ-BK1	Acosta et al. (2013)		IT-SR2	Gruening et al. (2013)		US-Wi0	Desai et al. (2008)
Denmark	DK-Sor	Pilegaard et al. (2011)		IT-SRo	Chiesi et al. (2005)		US-Wi1	Desai et al. (2008)
Finland	FI-Hyy	Suni et al. (2003)	Netherlands	NL-Loo	Moors (2012)		US-Wi2	Desai et al. (2008)
	FI-Let	Koskinen et al. (2014)	Panama	PA-SPn	Wolf et al. (2011)		US-Wi3	Desai et al. (2008)
	FI-Sod	Thum et al. (2007)	Russian Federation	RU-Fyo	Kurbatova et al. (2008)		US-Wi4	Desai et al. (2008)
France	FR-Fon	Delpierre et al. (2016)		RU-SkP	Maximov (2012)		US-Wi5	Schmidt et al. (2011)
	FR-LBr	Berbigier et al. (2001)	Switzerland	CH-Dav	Zielis et al. (2014)		US-Wi8	Desai et al. (2008)
	FR-Pue	Rambal et al. (2004)		CH-Lae	Etzold et al. (2011)		US-Wi9	Schmidt et al. (2011)

Table B.1 | FLUXNET micrometeorological measurement towers in forests included in the regression analysis by country (NASA 2015).

Model	(1)
Dependent variable	NEE
Average temperature	-2.20***
	(0.46)
Average temperature squared	0.07**
	(0.03)
Precipitation	-0.00
	(0.00)
Latitude	-0.06
	(0.29)
Elevation	-0.00
	(0.00)
2000 (reference)	
2001	3.80
	(2.60)
2002	-1.21
	(3.38)
2003	-1.77
	(3.98)
2004	-2.15
	(3.69)
2005	-1.42
	(3.65)
2006	-0.10
	(3.62)
2007	-3.53
	(3.84)
2008	-1.75
	(3.73)
2009	-1.45
	(4.02)
2010	0.34
	(3.83)
2011	-1.63
	(3.90)
2012	-1.24
	(3.90)
2013	-0.93
	(3.80)
2014	-2.46
	(3.92)
Constant	5.60
	(19.49)
n x T	607
n	78
adjusted R^2	0.15

Table B.2 | Linear OLS regression of net ecosystem exchange. NEE = net ecosystem exchange in $tCO_2ha^{-1}yr^{-1}$. ** = p < 0.01, *** = p < 0.001. Unstandardized regression coefficients with standard errors in brackets. All standard errors are clustered by tower site, and robust with respect to heteroscedasticity and autocorrelation. Years covered: 2000-2014. Table B.3 gives a descriptive overview of all variables in model 1. Table B.1 lists all 78 micrometeorological measurement towers of FLUXNET in forests included in model 1.

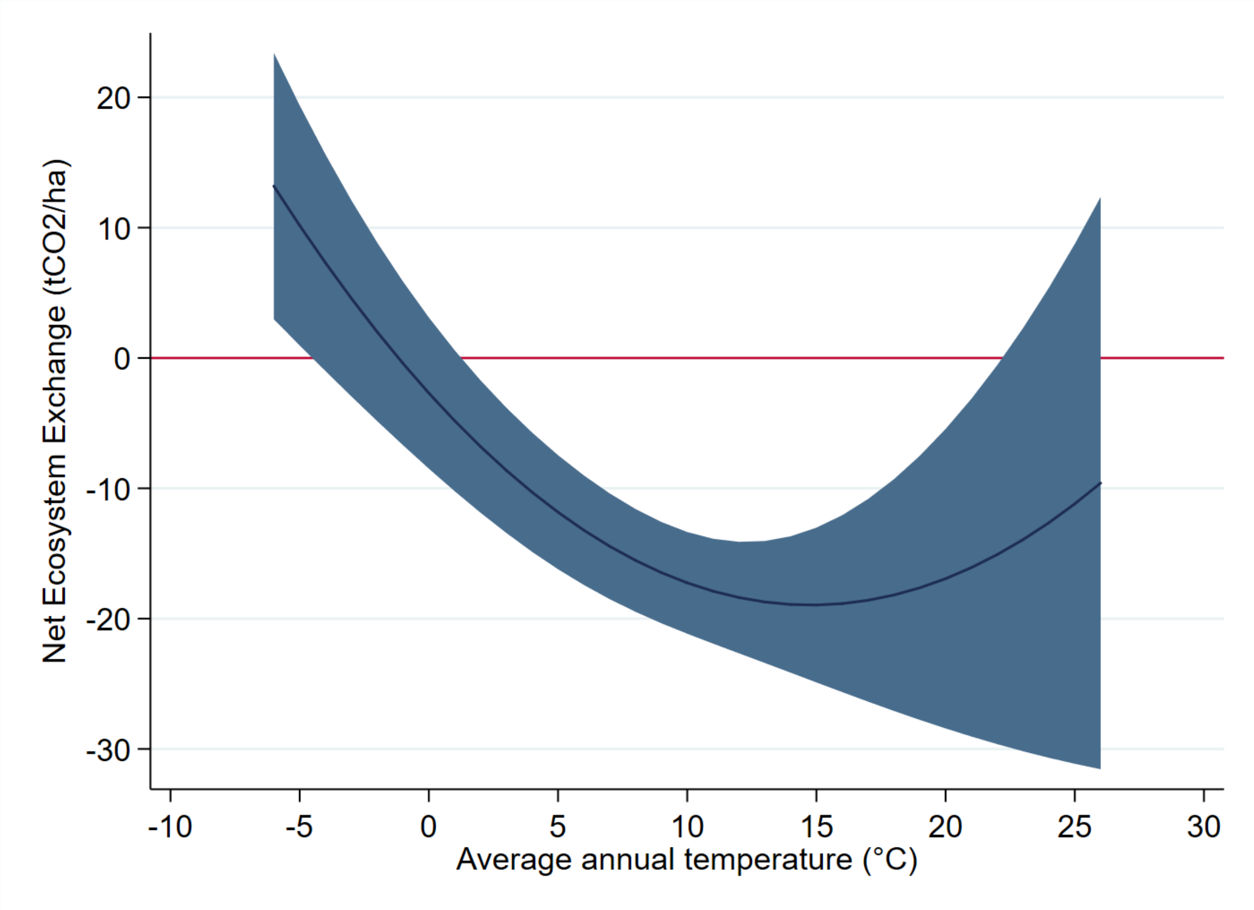

Figure B.1 | Predicted values of net ecosystem exchange (NEE) by annual average temperature. NEE of CO_2 as predicted by the OLS regression model presented in Table B.2 (dark blue line) with 95% confidence intervals (blue area). Negative numbers on the y-axis indicate net absorption of CO_2 by forests, positive numbers net CO_2 release.

Variable	mean	within ($\bar{x}_i$)			between ($x_{it} - \bar{x}_i + \bar{\bar{x}}$)			N (nxT)	n	Description
		sd	min.	max.	sd	min.	max.			
Net ecosystem exchange	-13.98	6.28	-41.86	13.55	15.52	-67.40	10.21	674	94	Net ecosystem exchange (NEE) of CO_2. NEE is the sum of Gross Primary Productivity (GPP, i.e. biomass stored) and ecosystem respiration (release of CO_2 from soil and plant). Negative numbers indicate net absorption, positive numbers net release of CO_2. Unit: t per ha.
Average temperature	8.87	0.73	6.52	11.21	7.42	-4.62	25.89	693	94	Average annual air temperature derived from daily averages. Unit: °C.
Precipitation	0.92	0.19	0.19	1.59	0.56	0.16	3.11	693	94	Annual precipitation. Sum of daily data. Unit: 1000 mm.
Latitude	44.39	0	44.39	44.39	12.93	2.9	67.4	693	94	In degrees north or south from equator.
Elevation	527.62	0	527.62	527.62	596.38	1	3197	625	78	Elevation of site. Unit: m above sea level.

Table B.3 | Variable description of FLUXNET data of micrometeorological measurement towers in forests. Data source is FLUXNET, a global network of micrometeorological tower sites with long-term measurement. FLUXNET is operated by the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC) of the National Aeronautics and Space Administration (NASA) of the United States. Years covered: 2000-2014.

Rank	Country	Sum score of quintiles	CO_2 emissions	CO_2 p.c. emissions	Forest land share	NEE per ha	NEE	NEE potential	GDP p.c.
1	Japan	33	5	5	5	4	5	4	5
2	Spain	33	5	4	4	5	5	5	5
3	South Korea	32	5	5	5	5	4	3	5
4	France	32	5	4	3	5	5	5	5
5	United States	31	5	5	3	3	5	5	5
6	Australia	31	5	5	2	4	5	5	5
7	Mexico	30	5	4	3	4	5	5	4
8	Argentina	30	5	4	2	5	5	5	4
9	Italy	30	5	4	3	5	4	4	5
10	Germany	30	5	5	3	4	4	4	5
11	Turkey	30	5	4	2	5	5	5	4
12	Brazil	29	5	3	5	2	5	5	4
13	Peru	29	4	3	5	4	5	5	3
14	New Zealand	29	3	5	4	4	4	4	5
15	China	29	5	5	3	3	5	5	3
16	Poland	29	5	5	3	4	4	4	4
17	Iran, Islamic Rep.	29	5	5	1	5	4	5	4
18	Venezuela, RB	29	5	4	5	2	5	4	4
19	South Africa	28	5	5	1	5	4	5	3
20	Turkmenistan	28	4	5	2	5	4	4	4
21	Malaysia	28	5	5	5	2	4	3	4
22	Belarus	28	4	4	4	4	4	4	4
23	Czech Republic	28	4	5	4	4	3	3	5
24	Greece	28	4	4	3	5	4	4	4
25	Bulgaria	28	4	5	4	5	3	3	4
26	United Kingdom	27	5	4	2	4	3	4	5
27	Portugal	27	4	4	4	5	3	3	4
28	Chile	27	4	4	3	3	5	4	4
29	Serbia	27	5	5	3	5	3	3	3
30	Bolivia	27	3	3	5	4	5	5	2
31	Romania	27	4	4	3	4	4	4	4
32	Indonesia	26	5	3	5	1	5	4	3
33	Finland	26	4	5	5	1	4	2	5
34	Austria	26	4	5	4	3	3	2	5
35	Hungary	26	4	4	3	5	3	3	4
36	Belgium	26	4	5	3	5	2	2	5
37	Kazakhstan	26	5	5	1	3	3	5	4
38	Ukraine	26	5	4	2	4	4	5	2
39	Colombia	26	4	3	5	2	5	4	3
40	Slovenia	25	3	5	5	4	2	1	5
41	Thailand	25	5	4	3	1	4	4	4
42	Croatia	25	3	4	4	5	3	2	4
43	India	25	5	3	3	2	5	5	2
44	Vietnam	25	5	3	5	2	4	4	2
45	Sweden	25	4	4	5	1	4	2	5
46	Morocco	25	4	3	2	5	4	4	3
47	Slovak Republic	25	3	5	4	4	2	2	5
48	Bosnia and Herzegovina	24	3	5	4	4	3	2	3
49	Angola	24	3	2	4	3	5	5	2
50	Netherlands	24	4	5	2	5	1	2	5
51	Ecuador	24	3	3	5	3	4	3	3
52	Ireland	24	3	5	2	4	2	3	5
53	Estonia	24	3	5	5	3	2	1	5
54	Latvia	23	2	4	5	3	3	2	4
55	Zambia	23	2	1	5	3	5	5	2
56	Zimbabwe	23	3	2	4	3	5	5	1
57	Norway	23	4	5	3	1	3	2	5
58	Botswana	23	2	3	2	3	4	5	4
59	Uruguay	23	2	3	2	5	3	4	4
60	Azerbaijan	23	3	4	2	5	2	3	4
61	Myanmar	23	3	1	4	3	5	5	2
62	Uzbekistan	22	4	3	1	5	3	4	2
63	Paraguay	22	2	2	4	3	4	4	3
64	Russian Federation	22	5	5	5	1	1	1	4
65	Namibia	22	1	3	2	4	4	5	3
66	Lithuania	22	3	4	4	3	2	2	4
67	Syrian Arab Republic	22	4	3	1	5	1	3	5
68	Denmark	22	3	4	2	4	2	2	5
69	Lao PDR	22	1	2	5	3	5	4	2
70	Canada	22	5	5	4	1	1	1	5
71	Tanzania	22	2	1	5	3	5	5	1
72	Iraq	21	4	4	1	4	2	3	3

Table B.4 | Full country ranking of climate responsibility, forests' mitigation contribution and potential, and economic capabilities in 2015.

Rank	Country	Sum score of quintiles	CO_2 emissions	CO_2 p.c. emissions	Forest land share	NEE per ha	NEE	NEE potential	GDP p.c.
73	Congo, Rep.	21	2	2	5	2	5	3	2
74	Israel	21	4	5	1	4	1	1	5
75	Switzerland	21	3	4	3	3	2	1	5
76	Gabon	21	2	3	5	2	4	1	4
77	Algeria	21	4	4	1	3	2	4	3
78	Congo, Dem. Rep.	20	2	1	5	2	5	4	1
79	Cameroon	20	3	2	4	2	4	3	2
80	Panama	20	2	3	5	2	3	1	4
81	Georgia	20	2	3	4	3	3	2	3
82	Lebanon	20	3	4	2	5	1	1	4
83	Saudi Arabia	20	5	5	1	2	1	1	5
84	Pakistan	20	4	2	1	4	2	5	2
85	Central African Republic	20	1	1	4	2	4	3	5
86	Macedonia, FYR	20	2	4	4	4	2	1	3
87	Cuba	20	3	3	3	2	2	2	5
88	Papua New Guinea	20	2	2	5	2	5	2	2
89	Mozambique	20	2	1	5	2	5	4	1
90	Albania	19	1	3	3	5	2	2	3
91	Dominican Republic	19	3	3	4	3	2	1	3
92	Tunisia	19	3	3	1	4	2	3	3
93	Philippines	19	4	2	3	2	3	3	2
94	Egypt, Arab Rep.	19	5	3	1	3	1	3	3
95	Nepal	18	2	1	3	5	3	3	1
96	Ethiopia	18	2	1	2	3	4	5	1
97	Costa Rica	18	2	3	5	2	2	1	3
98	Libya	18	4	5	1	3	1	2	2
99	Honduras	17	2	2	4	2	3	2	2
100	Bangladesh	17	4	2	2	2	2	3	2
101	Nigeria	17	4	2	1	1	3	4	2
102	Kenya	17	3	2	1	2	3	5	1
103	Ghana	17	3	2	4	1	3	2	2
104	Afghanistan	17	2	1	1	5	2	5	1
105	Cambodia	17	2	2	5	1	3	2	2
106	Somalia	17	1	1	2	1	3	4	5
107	Guatemala	17	3	2	3	2	3	2	2
108	Moldova	17	2	3	2	5	1	2	2
109	Cote d'Ivoire	16	2	2	3	1	3	3	2
110	Jordan	16	3	3	1	4	1	1	3
111	Swaziland	16	1	2	4	4	1	1	3
112	Madagascar	16	1	1	2	3	4	4	1
113	Jamaica	15	2	3	3	2	1	1	3
114	Malawi	15	1	1	3	3	3	3	1
115	Sri Lanka	15	3	2	3	1	2	1	3
116	Nicaragua	15	2	2	3	2	2	2	2
117	Uganda	14	2	1	2	2	2	4	1
118	Mongolia	14	3	4	1	1	1	1	3
119	Burundi	14	1	1	2	3	1	1	5
120	Liberia	14	1	1	4	2	3	2	1
121	Senegal	14	2	2	4	1	2	2	1
122	Armenia	14	1	3	2	3	1	1	3
123	Yemen, Rep.	13	3	2	1	3	1	2	1
124	Lesotho	13	1	1	1	5	1	2	2
125	Guinea	13	1	1	3	1	3	3	1
126	Benin	13	2	2	4	1	2	1	1
127	El Salvador	13	2	2	2	2	1	1	3
128	Kyrgyz Republic	12	2	2	1	1	1	3	2
129	Rwanda	11	1	1	2	4	1	1	1
130	Guinea-Bissau	11	1	1	5	1	1	1	1
131	Chad	11	1	1	1	1	2	4	1
132	Sierra Leone	11	1	1	4	1	2	1	1
133	Tajikistan	11	1	2	1	2	1	3	1
134	Gambia, The	11	1	1	5	1	1	1	1
135	Burkina Faso	10	1	1	2	1	2	2	1
136	Mauritania	10	1	2	1	1	1	2	2
137	Niger	9	1	1	1	1	1	3	1
138	Mali	9	1	1	1	1	1	3	1
139	Haiti	8	1	1	1	2	1	1	1
140	Eritrea	8	1	1	2	1	1	1	1
141	Togo	7	1	1	1	1	1	1	1

Table B.4, continued | Full country ranking of climate responsibility, forests' mitigation contribution and potential, and economic capabilities in 2015. p.c. = per capita, NEE = net ecosystem exchange, GDP = gross domestic product. Numbers represent the quintiles the countries rank if not indicated otherwise. Data sources: CO_2 emissions: EDGAR – Emissions Database for Global Atmospheric Research; forest land share: FAO – Food and Agriculture Organization of the UN; NEE: own calculations based on FLUXNET data; GDP: IMF – International Monetary Fund.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Forest land share			
Agricultural land	-0.21*	-0.08	-0.03	-0.04	0.05	0.03
	(0.10)	(0.10)	(0.10)	(0.11)	(0.13)	(0.12)
Population		-0.27**	-0.28**	-0.27**	-0.17*	-0.18*
		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Urban population		-0.00	-0.02	-0.01	-0.12	-0.11
		(0.09)	(0.09)	(0.09)	(0.09)	(0.08)
GDP per capita			0.10*	0.09*	0.10*	0.09*
			(0.04)	(0.03)	(0.04)	(0.04)
Industry			-0.10*	-0.08*	-0.09*	-0.10*
			(0.04)	(0.04)	(0.04)	(0.04)
Services			-0.08	-0.08⁺	-0.09⁺	-0.09⁺
			(0.05)	(0.04)	(0.05)	(0.05)
Forest products trade balance				0.02	0.02	0.03
				(0.03)	(0.02)	(0.02)
Protected forest area					0.06*	0.06*
					(0.03)	(0.03)
Mean temperature						-0.10*
						(0.04)
Droughts						0.00
						(0.00)
n x T	2494	2494	2255	2255	1781	1744
n	98	98	96	96	88	88
adjusted R^2 within	0.06	0.15	0.22	0.20	0.27	0.28

Table B.5 | Country and time fixed effects regressions of forest land share. ⁺ = p < 0.10, * = p < 0.05, ** = p < 0.01. Unstandardized regression coefficients with standard errors in brackets. All six models include the years 1990-2015 and contain dummy variables for each year in order to control for overall time-trends. All standard errors are clustered by country and year, and robust with respect to heteroscedasticity and autocorrelation.

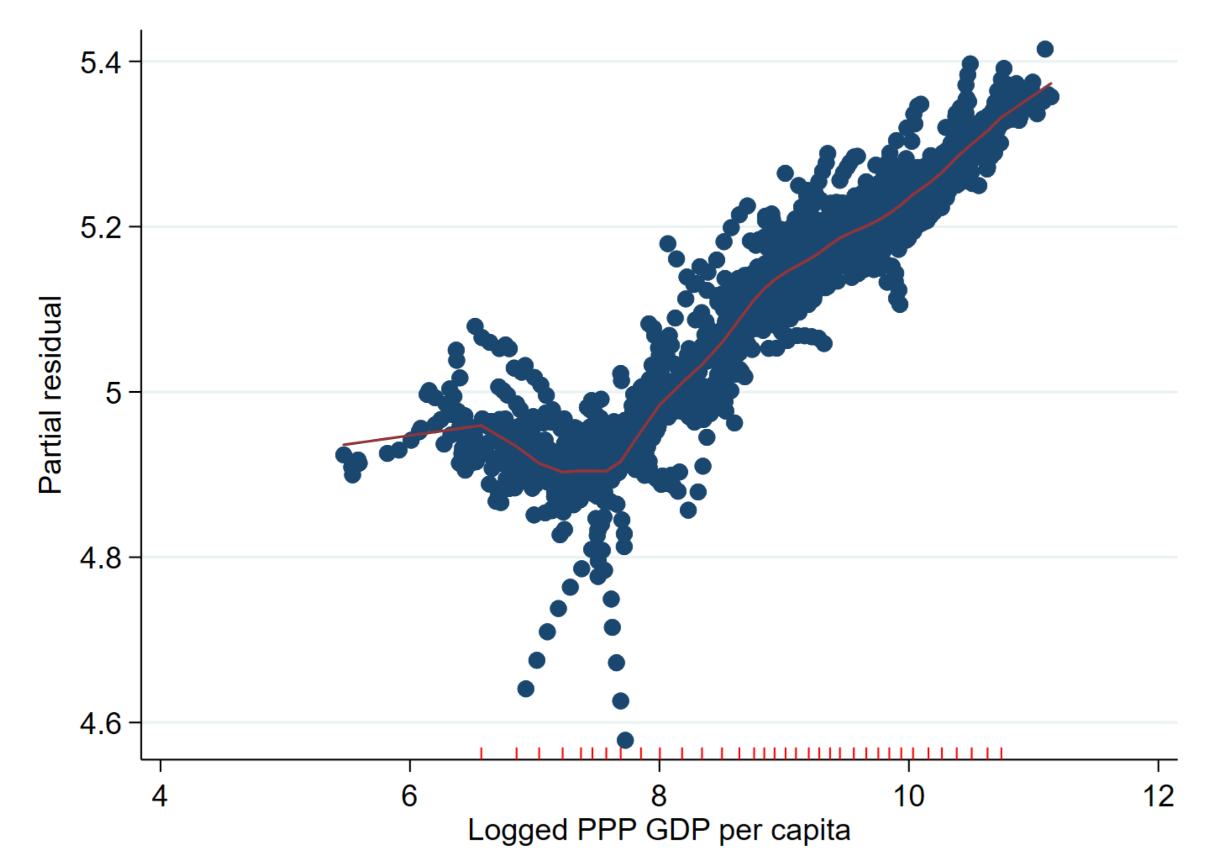

Figure B.2 | Partial residual plot for GDP p.c. of model 6 in Figure 4 and Table B.5. Partial residual for every country year (blue filled circles) and the smoothed mean (red curve) as calculated from the fixed effects regression with penalized splines (Ruppert et al. 2003) for logged GDP per capita. Red ticks on the x-axis represent knots. The plot demonstrates that the effect of GDP growth on forest land share growth is almost flat for poor countries with logged PPP GDP p.c. of less than ca. 8.0, and positive and virtually linear for richer countries. Thus, the effect is positive and linear for the vast majority of observations.

Variable	mean	within ($\bar{x}_i$)			between ($x_{it} - \bar{x}_i + \bar{\bar{x}}$)			N (nxT)	n	Description	Data Source
		sd	min.	max.	sd	min.	max.				
Forest land share	32.77	2.02	18.34	50.01	23.83	0	98.60	4690	181	Forest is determined both by the presence of trees and the absence of other predominant land uses. Forest area is land under natural or planted stands of trees of at least 5 meters in situ or with the potential of growth to this height, with an area of more than 0.5ha and width of more than 20m, and a canopy cover of at least 10%, whether productive or not, and excludes tree stands in agricultural production systems and trees in urban parks and gardens. Unit: % of land area.	FAO
Agricultural land	40.37	2.87	19.71	57.93	21.12	0.53	84.40	4650	182	Agricultural land refers to the share of land area that is arable, under permanent crops, and under permanent pastures. Unit: % of land area.	FAO
Population	34.12	12.17	-191.34	249.11	127.76	0.02	1272.37	4754	183	Total population. Unit: 1 million.	UNPD, WB
Urban population	52.83	3.37	39.20	69.73	23.32	8.93	100	4806	185	Urban population refers to people living in urban areas as defined by national statistical offices. Unit: % of total population.	UNPD, FAO, WB
GDP p. c.	11.29	4.85	-16.87	47.98	11.75	0.54	62.31	4384	177	Gross domestic product (GDP) per capita (p.c.) based on purchasing power parity (PPP). PPP GDP is GDP converted to international dollars using PPP rates. Unit: 1000 international dollars.	IMF
Industry, value added	28.17	4.50	-5.59	60.52	11.04	7.20	75.96	4092	174	Industry corresponds to the International Standard Industrial Classification (ISIC) divisions 10-45. The origin of value added is determined by the ISIC, revision 3. Unit: % of GDP.	WB
Services, value added	55.57	5.41	22.75	99.17	13.46	22.77	82.07	4075	173	Services correspond to ISIC divisions 50-99. The industrial origin of value added is determined by the ISIC, revision 3. Unit: % of GDP.	WB
Forest products trade balance	0.16	1.53	-24.07	27.69	2.03	-2.09	24.27	4171	174	Forest products trade balance is the ratio of exports to imports of forest goods as share of GDP.	FAO
Protected forest area	37.40	34.56	-640.36	469.28	142.59	0	1630.39	3289	149	Protected forest area is designated primarily for conservation of biological diversity and natural and associated cultural resources. Protection and maintenance is managed through legal or other effective means. Unit: km^2.	FAO
Mean temperature	18.98	0.49	15.61	21.29	8.21	-5.97	28.90	4225	169	Mean annual air temperature derived from quality controlled monthly observational data from thousands of weather stations worldwide. Unit: °C.	WB
Droughts	0.20	0.36	-0.60	1.16	0.24	0	1	1963	160	Dummy, 1, if a drought occurred at least once a year. A drought is classified if at least one of the following criteria is met: 10 or more people dead, 100 or more people affected, declaration of a state of emergency, call for international assistance.	CRED

Table B.6 | Drivers of national forest land share: variable description. CRED = Centre for Research on the Epidemiology of Disasters, FAO = Food and Agriculture Organization of the United Nations, IMF = International Monetary Fund, UNPD = United Nations Population Division, WB = World Bank; All variables in the models are included by taking the natural logarithm allowing for the estimation of elasticities. Years covered: 1990-2015.

Algeria*#	Hungary*#	Peru*#
Argentina*#	India*#	Philippines*#
Australia*#	Indonesia*#	Poland*#
Austria*#	Iran, Islamic Rep.*#	Portugal*#
Bangladesh*#	Ireland*#	Romania*#
Belarus*#	Israel	Russian Federation*#
Belgium*#	Italy*#	Senegal*#
Brazil*#	Jamaica*#	Serbia*#
Bulgaria*#	Japan*	Slovak Republic*#
Burkina Faso*#	Kenya*#	Slovenia*#
Cambodia*#	Lao PDR*	South Africa*#
Cameroon*#	Latvia*#	South Korea*#
Canada*#	Lebanon*#	Spain*#
Chile*#	Liberia	Sri Lanka*
China*#	Lithuania*#	Swaziland*#
Colombia*#	Malawi*#	Sweden*#
Congo, Rep.*#	Malaysia*#	Switzerland*#
Costa Rica*	Mali*#	Tajikistan*#
Croatia*#	Mexico*#	Tanzania*#
Czech Republic*#	Mongolia*#	Thailand*#
Denmark*#	Morocco*#	Tunisia*#
Dominican Republic*	Mozambique*#	Turkey*#
Ecuador*#	Myanmar*#	Uganda*#
Estonia*#	Namibia*#	Ukraine*#
Ethiopia*	Nepal*#	United Kingdom*
Finland*#	Netherlands*#	United States*#
France*	New Zealand*#	Uruguay*#
Gabon*#	Nicaragua*#	Uzbekistan*#
Gambia, The*#	Niger*#	Venezuela, RB*#
Georgia*#	Norway*#	Vietnam*#
Germany*#	Panama*#	Zambia*#
Ghana*#	Papua New Guinea*#	Zimbabwe*#
Guatemala*#	Paraguay*#	

Table B.7 | Countries included in the analyses. All 98 countries are full members of the United Nations, have sufficient quality of forest area data (tier 2 and 3; FAO 2016) and are included in the models 1, and 2 of Table B.5. Due to missing values in the further added variables, the models 3 and 4 include the 96 countries indicated by '*', and for the models 5 and 6 of Table B.5 the 88 countries marked by '#'.

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Bern, 13. Juni 2019

Sebastian Mader