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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**	.84**	0.61*	0.63*	0.62*	0.65*
	(.30)	(.30)	(0.26)	(0.27)	(0.27)	(0.28)
GDP p. c.	.39**	.38**	0.42**	0.41**	0.38*	0.37
	(.14)	(.14)	(0.14)	(0.14)	(0.16)	(0.17)
Income Gini Coefficient	−.15	−.15	0.03	−0.00	0.07	0.03
	(.18)	(.18)	(0.14)	(0.14)	(0.21)	(0.26)
Wealth Inequality * 2001		−.08		−0.03***		0.62*
		(.04)		(0.01)		(0.28)
Wealth Inequality * 2002		−.17***		−0.03***		0.61
		(.05)		(0.01)		(0.28)
Wealth Inequality * 2003		.03		0.02		0.66*
		(.04)		(0.01)		(0.28)
Wealth Inequality * 2004		−.09*		−0.02*		0.63
		(.04)		(0.01)		(0.28)
Wealth Inequality * 2005		−.08*		−0.01		0.64
		(.04)		(0.01)		(0.30)
Wealth Inequality * 2006		−.12**		0.03**		0.68
		(.04)		(0.01)		(0.31)
Wealth Inequality * 2007		−.06		0.00		0.65
		(.05)		(0.01)		(0.30)
Wealth Inequality * 2008		−.03		0.02		0.67
		(.05)		(0.02)		(0.31)
Wealth Inequality * 2009		−.10*		0.01		0.66
		(.04)		(0.01)		(0.30)
Wealth Inequality * 2010		−.01		0.03		0.68
		(.04)		(0.01)		(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*	0.57	0.09	0.44	0.36	0.15
	(0.27)	(0.28)	(0.24)	(0.36)	(0.37)	(0.27)
GDP p. c.	0.38*	0.43*	0.71**	0.25	0.25	0.51**
	(0.16)	(0.17)	(0.18)	(0.21)	(0.20)	(0.16)
Income Gini Coefficient	0.07	−0.01	−0.02	−0.01	−0.07	−0.10
	(0.21)	(0.20)	(0.26)	(0.17)	(0.17)	(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**	0.12**	0.08	−0.04
	(0.05)	(0.04)	(0.05)	(0.03)
Wealth Share of Top 10%	0.32	0.25	0.24	−0.09
	(0.24)	(0.19)	(0.29)	(0.19)
GDP p. c.	0.42*	0.38**	0.39*	0.55**
	(0.15)	(0.10)	(0.16)	(0.15)
Income Gini Coefficient	0.00	0.24	−0.09	0.16
	(0.22)	(0.13)	(0.20)	(0.15)
GDP p. c. squared		−0.01		−0.04
		(0.03)		(0.05)
Fossil Fuel Energy Consumption		0.54***		0.67***
		(0.13)		(0.14)
Trade Balance		−0.46***		−0.07
		(0.09)		(0.12)
Industry		−0.19		0.17
		(0.30)		(0.25)
Services		−0.96		0.01
		(0.56)		(0.49)
Electricity Production from Non-fossil Sources		−0.08*		−0.06*
		(0.03)		(0.02)
International Environmental Agreements		0.05		−0.01
		(0.07)		(0.07)
Energy Prices		−0.06		−0.06
		(0.03)		(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*	0.12*	0.37	0.34	0.90*	0.72*
	(0.06)	(0.06)	(0.20)	(0.19)	(0.31)	(0.30)
Population	0.51**	0.43**	0.59***	0.54***	0.54*	0.51*
	(0.10)	(0.11)	(0.10)	(0.11)	(0.19)	(0.20)
GDP p. c.	0.25**	0.23**	0.26***	0.24***	0.28**	0.27**
	(0.06)	(0.06)	(0.05)	(0.05)	(0.09)	(0.08)
Urban Population		0.91**		0.79**		0.74
		(0.29)		(0.27)		(0.39)
Fossil Fuel Production		0.00		0.02**		0.02
		(0.00)		(0.01)		(0.01)
Manufacturing		−0.01		−0.16		−0.28
		(0.02)		(0.17)		(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*	0.50	0.34	0.36
	(0.30)	(0.31)	(0.25)	(0.26)
GDP p. c.	0.39**	0.45***	0.48***	0.48***
	(0.10)	(0.11)	(0.12)	(0.12)
GDP p. c. squared		−0.50***	−0.52***	−0.36*
		(0.07)	(0.08)	(0.14)
Fossil Fuel Production p.c.			0.09	0.08
			(0.06)	(0.06)
Manufacturing			−0.72**	−0.69**
			(0.21)	(0.22)
Renewable Energy Production			0.24	0.23
			(0.14)	(0.13)
Energy Prices			−0.30**	−0.38**
			(0.10)	(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

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