Ecological Economics 134 (2017) 40–48

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Income Inequality and Carbon Emissions in the United States: A State-level Analysis, 1997–2012

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ARTICLE INFO

Article history:
Received 10 July 2016
Received in revised form 2 December 2016
Accepted 21 December 2016
Available online xxxx

Keywords:
Climate change
Carbon emissions
Income inequality
Ecological economics
Environmental sociology
Sustainability

ABSTRACT

This study investigates the relationship between U.S. state-level CO_2 emissions and two measures of income inequality: the income share of the top 10% and the Gini coefficient. Each of the inequality measures, which focus on unique characteristics of income distributions, is used to evaluate the arguments of different analytical approaches. Results of the longitudinal analysis for the 1997 to 2012 period indicate that state-level emissions are positively associated with the income share of the top 10%, while the effect of the Gini coefficient on emissions is non-significant. The statistically significant relationship between CO_2 emissions and the concentration of income among the top 10% is consistent with analytical approaches that focus on political economy dynamics and Veblen effects, which highlight the potential political and economic power and emulative influence of the wealthy. The null effect of the Gini coefficient is generally inconsistent with the marginal propensity to emit approach, which posits that when incomes become more equally distributed, the poor will increase their consumption of energy and other carbon-intensive products as they move into the middle class.

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1. Introduction

Inequality has become a salient political issue in the United States, following the emergence of Occupy, the publication of Piketty's *Capital in the Twenty-first Century*, and continuing economic distress in many parts of the country. Over this same time period, researchers across various disciplines have begun to pay more attention to the role of inequality in climate change. The bulk of attention has been given to international and global inequalities, such as global North-South differences in historic CO_2 emissions (Chancel and Piketty, 2015; Jorgenson, 2014; Rosa and Dietz, 2012), disproportionate impacts of climate effects (IPCC, 2014; Roberts and Parks, 2006) and power imbalances between nations in the global North and South with respect to climate policy (Ciplet et al., 2015; Dunlap and Brulle, 2015). A relatively unexplored question is the role that income inequality plays as a driver of anthropogenic CO_2 emissions. Does the existence of income inequality itself contribute to the volume of emissions? Are societies with more inequality higher emitters? Or is greater income equality associated with higher levels of emissions because there are more middle-class people with carbon-intensive lifestyles?

To the extent that this question has been addressed, most of the studies have taken their unit of analysis as the nation state, asking how domestic measures of income inequality affect CO_2 emissions across countries and over time (Ravallion et al., 2000; Grunewald et al., 2012; Jorgenson, 2015; Jorgenson et al., 2016). The results of these studies are mixed, with findings differing by group of countries, time periods, and modeling techniques (Borghesi, 2006). This is not surprising, as there are a number of different pathways through which income inequality might affect emissions.

In this study, we shift the analysis of CO_2 emissions and income inequality to a different scale—the sub-national, and more specifically the U.S. state level. We analyze anthropogenic emissions across all 50 U.S. states and the District of Columbia, over the period 1997–2012, asking how the level of income inequality within a state is associated with its CO_2 emissions. To our knowledge, with the exception of a preliminary analysis using a more restricted measure of emissions (Jorgenson et al., 2015), the present study is the first to analyze the relationship between CO_2 emissions and inequality in a longitudinal, U.S. cross-state context.[1] Furthermore, we focus on two measures of income inequality that capture different characteristics of inequality within income distributions: the Gini coefficient and the income share of the top 10%. As we note in the following literature review, each of these measures is well suited for empirically evaluating the arguments of different analytical approaches.

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[1] Jorgenson et al. (2015) conduct a preliminary U.S. state-level analysis of the effect of one measure of income inequality – the Theil index – on CO_2 emissions from just the residential sector. Their estimated models include a limited number of control variables, and the literature review and theoretical discussion are short and relatively narrow in scope.

http://dx.doi.org/10.1016/j.ecolecon.2016.12.016
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2. Literature Review

There are a variety of pathways through which income inequality can potentially affect emissions. The research literature, while relatively small, includes multiple approaches that identify different possibilities. The first approach, attributable originally to Boyce (1994, 2007; Boyce et al., 1999), is a political-economy explanation in which income concentration operates mainly via political influence on environmental policy. Boyce argues that the wealthy reap disproportionate economic benefits from polluting activities, both via their ownership of companies that engage in them and because they are better able to protect themselves from negative impacts. They convert their preference for less environmental protection into influence in the political sphere. Studies in this tradition were originally about environmental policies and outcomes other than greenhouse gases, although there are a few recent analyses which address climate change. A second approach, which we term "propensity to emit," argues that at different levels of income, individuals' or households' propensity to consume carbon-intensive goods varies as consumption patterns change (Borghesi, 2006; Grunewald et al., 2012; Ravallion et al., 2000). For this reason, changes in the income distribution across households yield changes in emissions. A third approach posits that greater concentrations of income at the top of the distribution lead to heightened consumption competition and longer hours of work, which in turn increases energy consumption and emissions (Bowles and Park, 2005; Schor, 1998). This is a kind of Veblen (1934) effect in which the wealthy consume expensive, publicly visible goods and services to gain status. We discuss these three approaches in turn.

The political economy approach developed by Boyce (Boyce, 1994, 2007; Boyce et al., 1999) argues that inequality is likely to be associated with higher levels of energy use (e.g., fossil-fuels), pollution and environmental degradation. Increased fossil-fuel consumption has both global and local consequences, given that it leads to higher levels of CO_2 emissions as well as other pollutants with more localized effects, including increases in the emission of carbon monoxide (CO) and nitrogen oxides (NO_x). While Boyce offers a number of arguments about these relationships, a primary one is that the wealthy prefer more pollution. This is both because they are more likely to be owners of polluting firms and because they consume more goods and services, which are in themselves polluting. Thus, environmental protection is costlier for the wealthy, and the wealthy are better equipped to protect themselves from environmental harms while shifting such burdens onto the poor. Boyce concludes that the wealthy are likely to use their economic power to gain political power, which they use to dominate the policy environment.

Boyce identifies a "power-weighted social decision rule" in which those with more economic power, and thus political power, have a larger influence on policy outcomes and use that power to prevent environmental protection. It is worth noting that these dynamics can be occurring even under the standard assumption that the environment is a normal good, that is, people want to consume more "environmental amenities" and by extension "environmental policy," as their income rises. Boyce's hypothesized effects operate alongside the increasing demand for "the environment" as income rises.

Using data from across the U.S. states, Boyce and collaborators (Boyce et al., 1999) estimated a model in which income inequality predicts political power, political power predicts environmental policies, and environmental policies predict environmental stress and subsequently public health outcomes. Environmental sociologists have similarly argued that reducing environmental harms may first require a shift toward greater political and economic equality (Ciplet et al., 2015; Downey, 2015; Roberts and Parks, 2006).

In the second approach, which focuses on the marginal propensity to emit (MPE), there is not a single hypothesis, although Ravallion et al. (2000) find that higher levels of within-country inequality are associated with lower emissions. Thus, they argue, there is a conflict between distributional policies to enhance equality and climate policy to reduce emissions. One argument is that the MPE declines with income, an empirical finding from previous research (Ravallion et al., 2000, citing Holtz-Eakin and Selden, 1995; Schmalensee et al., 1998; Heil and Selden, 1999). However, Ravallion et al. (2000) identify a variety of possible effects operating in different directions such that the relationship between within-country inequality and emissions is theoretically ambiguous. These include the factors identified by Boyce as well as an Ostrom-type effect on the ability to cooperate to achieve policy outcomes (see also Heerink et al., 2001).

In these studies, it is generally argued that consumption demand is the key factor determining MPE. However, this approach does not consider one class of Keynesian effects. In a Keynesian model, lower-income households have a higher marginal propensity to consume than higher-income households, so increases in inequality that lower incomes for the poor should reduce emissions. Accordingly, there is an additional mechanism by which higher inequality may reduce emissions, which is that the poor have a higher propensity to consume.

Finally, the relationship may not be linear. If there are three classes of households—poor, middle class, and wealthy—the propensity to consume and emit may rise and then fall, which would make the relationship between inequality and emissions curvilinear. This is partly supported by the results of Grunewald et al. (2012), who find that the inequality-emissions link varies with the level of inequality. In high inequality countries, reductions in inequality yield lower emissions; in low inequality countries, less inequality yields higher emissions.

The third approach argues that higher inequality leads to more consumption competition (Schor, 1998), which in turn increases emissions. There are two pathways for this effect. The first, a Veblen effect, is that inequality induces status consumption as households increase their spending to keep up with the visible lifestyles of high-income households. (Veblen, 1934; Schor, 1998). Second, growth in inequality has been shown to increase working hours (Bowles and Park, 2005), and cross-national research suggests that longer working hours are drivers of energy consumption and CO_2 emissions via both their impacts on economic growth and on households' consumption choices (Fitzgerald et al., 2015; Knight et al., 2013).

In addition to these approaches to inequality and emissions, there is a growing body of research that investigates how CO_2 emissions are distributed across households. While these studies do not explicitly test for the impact of inequality, a main finding in this research is that higher income households emit more CO_2 than lower income households. For example, Pattison et al. (2014) find that counties in the U.S. with the highest average household incomes have greater consumption-based CO_2 emissions but lower production-based emissions than less affluent counties. They conclude that rich communities are able to avoid some of the consequences of their carbon-intensive consumption by shifting carbon-intensive industrial activities into poorer areas, which is similar to arguments in the international inequality literatures within environmental sociology and ecological economics on the outsourcing of environmental harms from wealthier nations to poorer nations (Dunlap and Brulle, 2015; Martinez-Alier and Muradian, 2015). Weber and Matthews (2008) also find large differences by income, with the highest expenditure households emitting 10 times that of the lowest (see also Boyce and Riddle, 2009; Kunke and Kammen, 2011).

In this study of U.S. state-level emissions, we explore these questions by focusing on two measures of income inequality: the income share of the top 10% and the Gini coefficient. We suggest the former is a more appropriate measure for capturing political economy and Veblen effects than the Gini coefficient, because the potential effect of the top 10% measure depends on the economic and political power and the emulative pull of the wealthy. By contrast, the Gini coefficient does not directly capture the location in the distribution where inequality is occurring, and variation in Gini coefficients can be due to differences between low and middle income households. For the MPE approach, the Gini coefficient remains relevant, although as noted, that approach does not yield clear theoretical predictions.

3. Methods

3.1. Sample

The dataset contains annual observations from 1997 to 2012 for all 50 U.S. states as well as the District of Columbia. These are the years in which comparable data suitable for longitudinal analyses are currently available for the dependent variable and the key independent variables. This yields an overall sample of 816 observations.

3.2. Model Estimation Techniques

To estimate the majority of reported models, we use a time-series cross-sectional Prais-Winsten regression model with panel-corrected standard errors, allowing for disturbances that are heteroskedastic and contemporaneously correlated across panels (Beck and Katz, 1995). We correct for AR(1) disturbances (i.e., first-order autocorrelation) within panels, and since we have no theoretical basis for assuming the process is panel specific, we treat the AR(1) process as common to all panels. We control for both year-specific and state-specific effects, the equivalent of a two-way fixed effects model (Allison, 2008). We note that this technique controls out between-state variation in favor of estimating within-state effects, a common approach in panel analyses of the human drivers of emissions (Rosa and Dietz, 2012; Marquart-Pyatt et al., 2015).

To estimate the few reported models that include time-invariant control variables, we use generalized least squares random effects regression (Cameron and Trivedi, 2009). The random effects models also include a correction for first-order autocorrelation (i.e., AR[1] correction) as well as year-specific intercepts.

All non-binary variables are transformed into base 10 logarithmic form (labeled "LG" in Tables 1–4), an established approach in research on the drivers of anthropogenic emissions (Rosa and Dietz, 2012). For such variables, the regression models estimate elasticity coefficients where the coefficient for the independent variable is the estimated net percent change in the dependent variable associated with a 1% increase in the independent variable (York et al., 2003).

3.3. Dependent Variable

The dependent variable is annual CO_2 emissions from fossil fuel combustion, measured in millions of metric tons. This measure includes emissions from the commercial, industrial, residential, transportation, and electric power sectors. We obtained these emissions data from the United States Environmental Protection Agency's (EPA) "State Energy CO_2 Emissions" online database (https://www3.epa.gov/statelocalclimate/resources/state_energyco2inv.html, accessed July 2, 2015). These state-level measures of CO_2 emissions are analogous to country-level measures of "production-based emissions", rather than "consumption-based emissions", which are trade-adjusted measures that account for the emissions generated in the processes of production, which are then attributed to the consuming rather than producing country using input-output analysis techniques. Like prior cross-national studies (e.g., Knight and Schor, 2014), we would prefer to analyze both production-based and consumption-based measures of state-level CO_2 emissions, but to the best of our knowledge the latter are currently unavailable in longitudinal form for U.S. states and the District of Columbia.

3.4. Key Independent Variables

In this study we focus on two measures of income inequality: the Gini coefficient and the income share of the top 10%. We obtained the Gini coefficient data from the "U.S. State-Level Income Inequality" database, hosted by Mark Frank, Professor of Economics at Sam Houston State University (http://www.shsu.edu/~eco_mwf/inequality.html, accessed July 15, 2015). The values of estimated Gini coefficients can range from zero (perfect equality) to 1 (perfect inequality). Thus, we added a constant of one to each score before transformation into logarithmic form.

We gathered the income share of the top 10% data from the World Wealth and Income Database (WWID), which were developed by Mark Frank and colleagues (http://www.wid.world/#Database:, accessed July 16, 2015). These data are measured in percentages. The inequality measures are constructed from individual tax filing data

Table 1
Descriptive statistics.

	Mean	Standard deviation	Minimum	Maximum
CO_2 emissions	112.412	113.784	2.710	712.940
Gini coefficient	0.593	0.036	0.520	0.760
Income share of top 10%	43.627	4.905	33.560	62.260
Population size	5,765,477.941	6,426,923.470	480,000.000	38,000,000.000
GDP per capita	41,646.320	15,576.883	25,224.000	151,257.000
Percent of population in urban areas	73.084	14.984	37.992	100.000
Manufacturing as percent of GDP	13.204	6.086	0.210	30.590
Fossil-fuel production	998,037.747	1,982,492.732	0.000	13,339,833.000
State environmentalism	51.900	21.610	6.500	90.000
Midwest census region	0.235	0.424	0.000	1.000
South census region	0.314	0.464	0.000	1.000
West census region	0.255	0.436	0.000	1.000
Northeast census region	0.196	0.397	0.000	1.000
CO_2 emissions (LG)	1.855	0.453	0.433	2.853
Gini coefficient (LG)	0.202	0.010	0.182	0.245
Income share of top 10% (LG)	1.637	0.047	1.525	1.794
Population size (LG)	6.543	0.449	5.681	7.580
GDP per capita (LG)	4.602	0.110	4.401	5.180
Percent of population in urban areas (LG)	1.854	0.096	1.580	2.000
Manufacturing as percent of GDP (LG)	1.099	0.245	0.080	1.500
Fossil-fuel production (LG)	3.663	2.756	0.000	7.125
State environmentalism (LG)	1.660	0.247	0.813	1.954

Notes: all continuous variables are reported in both original values and base 10 logarithmic form (labeled "LG"); 816 total observations for each variable except State Environmentalism (800 total observations).

Table 2
Pairwise correlations.

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
CO_2 emissions (LG)	1.												
Gini coefficient (LG)	2.	0.126											
Income share of top 10% (LG)	3.	0.219	0.629										
Population size (LG)	4.	0.856	0.173	0.411									
GDP per capita (LG)	5.	−0.281	0.183	0.290	−0.139								
Percent of population in urban areas (LG)	6.	0.218	0.209	0.431	0.417	0.525							
Manufacturing as percent of GDP (LG)	7.	0.463	−0.237	−0.114	0.404	−0.615	−0.313						
Fossil-fuel production (LG)	8.	0.512	0.147	−0.049	0.208	−0.247	−0.028	0.069					
State environmentalism (LG)	9.	−0.053	−0.111	0.287	0.274	0.128	0.200	0.149	−0.458				
Midwest census region	10.	0.151	−0.231	−0.335	0.053	−0.070	−0.066	0.296	0.053	0.140			
South census region	11.	0.249	0.105	0.057	0.210	−0.108	−0.180	0.044	0.172	−0.188	−0.375		
West census region	12.	−0.151	0.115	−0.029	−0.193	0.024	0.254	−0.329	0.187	−0.363	−0.324	−0.395	
Northeast census region	13.	−0.287	−0.002	0.324	−0.090	0.175	0.003	−0.006	−0.462	0.465	−0.274	−0.334	−0.289

Notes: all continuous variables are in base 10 logarithmic form (labeled "LG"); 816 total observations for each variable except State Environmentalism (800 total observations).

available from the Internal Revenue Service. For in-depth information on the creation of the income inequality measures, see Frank et al. (2015).

3.5. Control Variables

We include population size, measured in the number of persons, which we obtained from the United States Census Bureau database for state-level population estimates (https://www.census.gov/popest/data/intercensal/index.html, accessed July 10, 2015). We also include Gross Domestic Product (GDP) per capita by state (reported in chained 2007 dollars), which we gathered from the United States Department of Commerce Bureau of Economic Analysis database (http://www.bea.gov/itable/, accessed July 10, 2015). Population size and GDP per capita are included in all estimated models. Consistent with past research on anthropogenic emissions (Dietz, 2015; Jorgenson and Clark, 2012; Lamb et al., 2014; Rosa and Dietz, 2012; York et al., 2003), we anticipate that both population size and GDP per capita will exhibit positive effects of state-level CO_2 emissions.

Many of our reported models include state-level measures of the percent of the population in urban areas, manufacturing as a percent of GDP, and total fossil-fuel production (coal, natural gas, and crude oil) in billions of British thermal units (Btu). The urban data are obtained from United States Census (https://www.census.gov, accessed July 10, 2015), and are only available each decade. Using the measures for 2000 and 2010, we interpolated values for all other years in the dataset.[2]

Scholars have highlighted how urbanization could be more or less carbon-intensive (Jorgenson et al., 2014). For example, Rees and Wackernagel (1996) argue that the organization of urban areas—which use extensive amounts of energy and other natural resources—are environmentally unsustainable. In contrast, some bodies of research underscore ecologically beneficial aspects of urbanization, such as energy efficiencies associated with higher population concentration (Dodman, 2009). Of particular relevance for the current study, the relative size of urban populations has been found to be a significant predictor of increased energy consumption and CO_2 emissions in recent U.S. state-level analyses (Clement and Schultz, 2011).

The manufacturing data are gathered from the United States Department of Commerce "Bureau of Economic Analysis" database (http://www.bea.gov/index.htm, accessed September 21, 2015). The fossil-fuel production data are obtained from the United States Energy Information Administration (EIA) "State Energy Data System" database (http://www.eia.gov/state/seds/seds-data-complete.cfm?sid=US#Production, accessed February 5, 2016). The EIA database provides production measures for each of the three fossil-fuels individually, which we summed to create the total measures. Conventional wisdom would suggest that both the relative size of a state's manufacturing sector and its level of fossil-fuel production could increase overall state-level emissions, and both have been found in past comparative-international research to be significant predictors of national-level emissions (Dunlap and Brulle, 2015; Rosa and Dietz, 2012). Thus, we consider them to be important control variables in our state-level study.

We include Dietz et al.'s (2015) measure of state environmentalism in the random effects models. These data measure pro-environmental voting by states' Congressional delegations. Dietz et al. create an average of House and Senate scores that are based on the League of Conservation Voters' rating (ranging from 0 to 100) for each member of Congress based on her or his votes on environmental issues as identified by the League for the 1990 to 2005 period. Dietz et al. (2015) find that state-level carbon emissions are negatively associated with their measure of state environmentalism. While these measures cover a fifteen-year period, they are technically time-invariant and perfectly correlated with the state-specific fixed effects. The District of Columbia is not included in these measures and thus excluded from the dataset for the estimated models that include the state environmentalism measure.

In the final random effects model we include dummy variables for Census Region, which consist of Midwest Census Region, South Census Region, West Census Region, and Northeast Census Region.

Table 3
Fixed effects longitudinal models of the effect of income inequality on CO_2 emissions in all 50 U.S. states and District of Columbia, 1997 to 2012.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gini coefficient (LG)	0.163	0.117			−0.040	−0.071
	(0.335)	(0.289)			(0.351)	(0.300)
Income share of top 10% (LG)			0.134*	0.120*	0.138*	0.125*
			(0.061)	(0.056)	(0.066)	(0.060)
Population size (LG)	0.511**	0.427**	0.512**	0.432**	0.512**	0.432**
	(0.107)	(0.120)	(0.097)	(0.109)	(0.097)	(0.109)
GDP per capita (LG)	0.257**	0.231**	0.248**	0.228**	0.247**	0.226**
	(0.062)	(0.064)	(0.062)	(0.064)	(0.063)	(0.065)
Percent of population in urban areas (LG)		0.954**		0.913**		0.916**
		(0.296)		(0.285)		(0.281)
Manufacturing as percent of GDP (LG)		−0.005		−0.010		−0.010
		(0.019)		(0.019)		(0.019)
Fossil-fuel production (LG)		0.003		0.003		0.003
		(0.003)		(0.003)		(0.003)
R^2	0.996	0.996	0.996	0.996	0.996	0.996
rho	0.591	0.595	0.561	0.571	0.561	0.569

Notes: estimated with Prais-Winsten regression; 16 annual observations for 51 cases in all models; 816 total observations in all models; coefficients flagged for statistical significance; **−< 0.01 *−< 0.05 (two-tailed tests of statistical significance); panel-corrected standard errors in parentheses; models includes AR(1) correction (labeled as "rho"); models include unreported case-specific and year-specific intercepts (two-way fixed effects); all continuous variables are in base 10 logarithmic form (labeled "LG").

[2] We acknowledge the limitations with these urban measures and recognize that there are a variety of techniques for missing data imputation, each of which has relative strengths and weaknesses. We therefore report estimated models that include urbanization as well as estimated models that do not.

3.6. Descriptive Statistics and Bivariate Analysis

Table 1 provides descriptive statistics (in both regular and base 10 logarithmic form for all non-binary variables), and Table 2 reports pairwise correlations for the variables included in the regression models. As noted in Table 2, for the analyzed longitudinal data (yearly point estimates from 1997 to 2012, all non-binary variables in base 10 logarithmic form), state-level CO_2 emissions is positively associated at 0.126 with the Gini coefficient and 0.219 with the income share of the top 10%.

To provide better context of the bivariate associations across the U.S. states and District of Columbia, Fig. 1 is a scatterplot of the association between percent change from 1997 to 2012 in CO_2 emissions and percent change from 1997 to 2012 in the Gini coefficient. Similarly, Fig. 2 is a scatterplot of the association between percent change in emissions and percent change in the income share of the top 10%. Values of the 3 change scores for all states and the District of Columbia are provided in the Appendix A. For these measures, percent change in state-level emissions are positively correlated with percent change in the Gini coefficient at 0.195, and positively correlated at 0.220 with percent change in the income share of the top 10%.

According to Fig. 1, and for example, Wyoming is a state that experienced relatively large percent increases in both emissions and the Gini coefficient, while Alaska experienced the greatest percent decrease in the Gini coefficient, and a modest decrease in emissions as well. Turning to Fig. 2, Arkansas and North Dakota experienced relatively large percent increases in both CO_2 emissions and the income share of the top 10%, while relative to other states, Delaware and Maryland experienced notable percent decreases in both emissions and income share among the top 10%.

4. Results

Table 3 provides the estimates for six fixed effects models of CO_2 emissions in all 50 U.S. States and the District of Columbia, from 1997 to 2012. We note that the close to perfect R-squared statistic for these models is largely due to the case-specific and year-specific intercepts, which by themselves explain the majority of variation in the outcome. Models 1 and 3 each consist of one of the two income inequality measures as well as the controls for population size and GDP per capita. The inequality measure in Model 1 is the Gini coefficient, and in Model 3 it is the income share of the top 10%. The estimated effect of the Gini coefficient in Model 1 is non-significant, while in Model 3 the effect of income share of the top 10% is positive and statistically significant. For the latter, a 1% increase in the income share of the top 10% is associated with a 0.134% increase in emissions. As expected, the effects of population size and GDP per capita are positive and statistically significant.

Models 2 and 4 expand Models 1 and 3, and include the other three time-variant controls: percent of the population in urban areas, manufacturing as a percent of GDP, and fossil-fuel production. With the inclusion of the additional measures, the estimated effect of the Gini coefficient remains non-significant, while the estimated effect of income share of the top 10% on CO_2 emissions remains statistically significant, but slightly decreases in value (elasticity coefficient = 0.120). Population size and GDP per capita continue to have positive effects on emissions. The effect of percent of population in urban areas on CO_2 emissions is positive and statistically significant in both models, while the estimated effects of the other two additional controls are non-significant. The null finding for the manufacturing measure, we suspect, is at least partly due to the analysis of CO_2 emissions from the commercial, industrial, residential, transportation, and electric power sectors combined. The state-level measures of fossil-fuel production are relatively time-invariant and thus highly correlated with the case-specific fixed effects, which could explain their non-significant effect in both models.

Model 5 includes both of the income inequality measures as well as population size and GDP per capita, while Model 6 adds the other three time-variant controls. The findings of interest remain the same: the effect of the income share of the top 10% is positive and statistically significant in both models (elasticity coefficient = 0.138 in Model 5 and 0.125 in Model 6), while the effect of the Gini coefficient continues to be non-significant. The findings concerning the control variables are consistent with the prior four models. Overall, the results reported in Table 3 suggest that the relationship between state-level CO_2 emissions and the Gini coefficient is non-significant, while the effect of income share of the top 10% on emissions is positive and nontrivial in magnitude. Based on the point estimates for the elasticity coefficients from these models, a 1% increase in the income share of the top 10% is associated with between a 0.120 and a 0.138% increase in CO_2 emissions, net of the various time-variant controls and the two-way fixed effects. Using the emissions data for the year 2012, this range of elasticity coefficients suggests that a 1% increase in the income share of the top 10% is associated with between 812,325.4 and 934,174.4 metric tons of additional CO_2 emissions for Texas (the largest state-level emitter), between 89,175.2 and 102,551.9 metric tons of additional emissions for South Carolina (the median level of emissions in 2012 compared to the other states and the District of Columbia), and between 3251.3 and 3738.4 metric tons of additional CO_2 emissions for the District of Columbia (lowest level of emissions in 2012 compared to the 50 US states).

Table 4 reports the findings for the random effects analysis, labeled as Model 7 and Model 8. The two estimated models include all the time-variant predictors as well as the time-invariant measure of state environmentalism. Model 8 also includes the census region dummy variables, where the Northeast census region is the reference category. The results of interest are consistent with the fixed effects analysis reported in Table 3: the estimated effect of the Gini coefficient on CO_2 emissions is non-significant, while the elasticity coefficient for the effect of income share of the top 10% is positive and statistically significant. In Model 7, a 1% increase in the income share of the top 10% is associated with a 0.097% increase in emissions, while in Model 8, a 1% increase in this

Table 4
Random effects longitudinal models of the effect of income inequality on CO_2 emissions in all 50 U.S. states, 1997 to 2012.

	Model 7	Model 8
Gini coefficient (LG)	−0.126	−0.106
	(0.222)	(0.220)
Income share of top 10% (LG)	0.097*	0.101*
	(0.042)	(0.042)
Population size (LG)	0.823**	0.735**
	(0.043)	(0.047)
GDP per capita (LG)	0.238**	0.252**
	(0.065)	(0.065)
Percent of population in urban areas (LG)	−0.030	0.286
	(0.178)	(0.191)
Manufacturing as percent of GDP (LG)	0.004	−0.005
	(0.021)	(0.021)
Fossil-fuel production (LG)	0.010**	0.009**
	(0.003)	(0.003)
State environmentalism (LG)	−0.455**	−0.426**
	(0.077)	(0.088)
Midwest census region		0.222**
		(0.054)
South census region		0.196**
		(0.059)
West census region		0.001
		(0.061)
R^2	0.842	0.874
rho	0.736	0.736

Notes: estimated with GLS random effects regression; 16 annual observations for 50 cases (excludes District of Columbia); 800 total observations; coefficients flagged for statistical significance; ** —<0.01 * —<0.05 (two-tailed tests of statistical significance); standard errors in parentheses; models includes AR(1) correction (labeled as "rho"); models include unreported year-specific intercepts; all continuous variables are in base 10 logarithmic form (labeled "LG"); Northeast Census Region is reference category in Model 8.

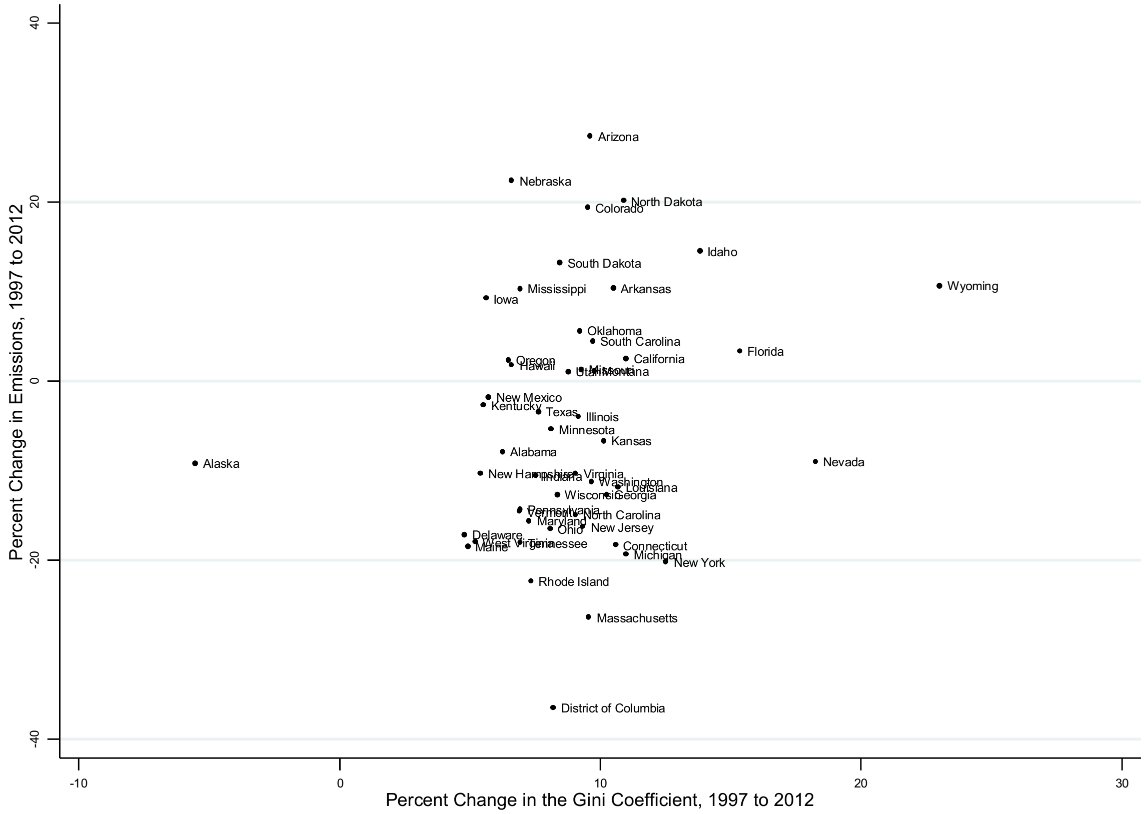

Fig. 1. Scatterplot of the association between CO_2 emissions and the Gini coefficient (both measured as percent change scores for 1997 to 2012).

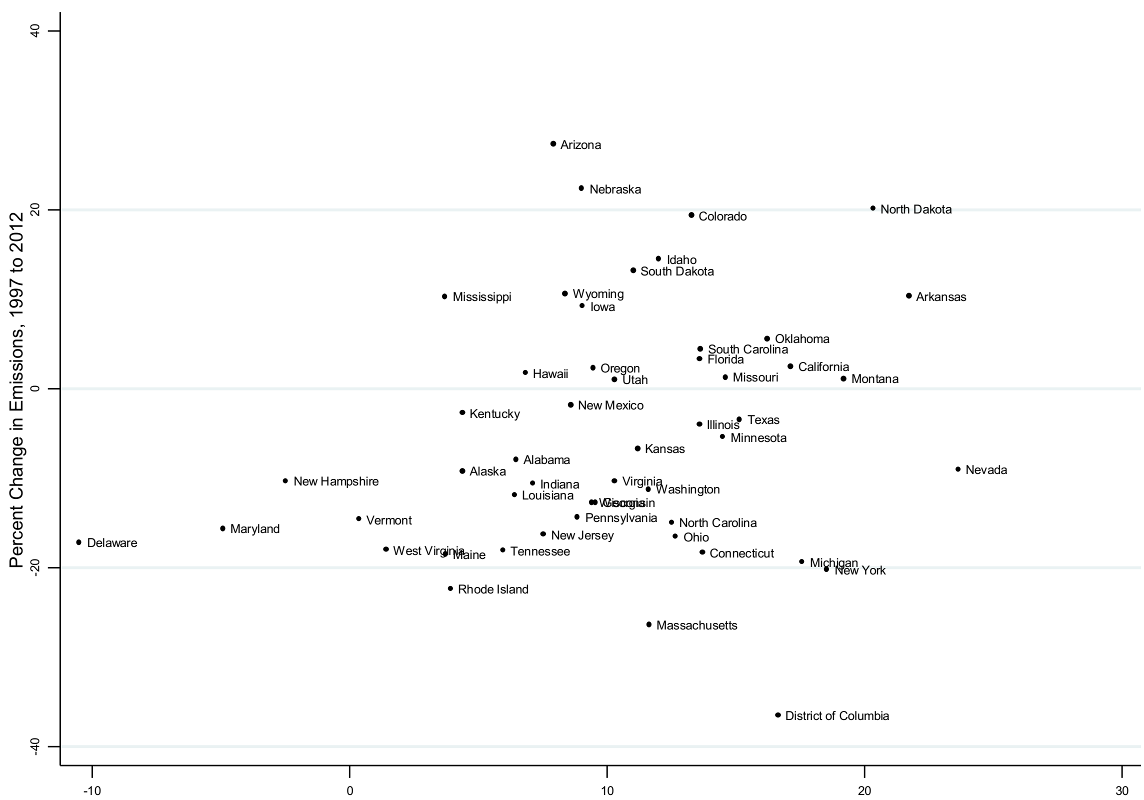

Fig. 2. Scatterplot of the association between CO_2 emissions and the income share of the top 10% (both measured as percent change scores for 1997 to 2012).

measure of income inequality is associated with a 0.101% increase in CO_2 emissions.

Turning briefly to the controls, the results indicate that CO_2 emissions are negatively associated with state environmentalism. In Model 8, the dummy variables for the Midwest and South census regions are positive and statistically significant, suggesting regional variation. The effect of fossil-fuel production is positive and statistically significant in both models, while the effect of urban population is non-significant, which contrasts with the results of the fixed effects analysis in Table 3 and could be the result of heterogeneity bias in the random effects models. The effects of all other time-variant controls are consistent with the fixed effects model estimates.

In additional fixed effects models and random effects models we included quadratics for both income inequality measures, a standard approach to testing for curvilinear relationships. Both quadratics yielded non-significant effects on emissions, the main effect of the Gini coefficient remained non-significant, while the main effect of income share of the top 10% continued to be positive and statistically significant. In other analysis, using robust regression, a relatively conservative approach that down-weights the influence of outliers in residuals (Hamilton, 1992), we estimated logged and differenced models (also known as relative change models) of change in emissions from 1997 to 2012 on change in both inequality measures from 1997 to 2012, while controlling for change in population size and change in GDP per capita. The results indicate that the estimated effect of change in the income share of the top 10% (from 1997 to 2012) on change in CO_2 emissions (from 1997 to 2012) is positive and statistically significant (estimated coefficient = 0.606, $p < 0.05$), while the estimated effect of change in the Gini coefficient (from 1997 to 2012) is non-significant. Based on these findings, a 1% increase in the income share of the top 10% from 1997 to 2012 is associated with a 0.606% increase in emissions. These results suggest that the positive association between state-level emissions and the income share of the top 10% also occurs over relatively longer periods of time, and in general, the estimated longer-term effect of the income share of the top 10% on CO_2 emissions appears to be relatively larger than the shorter-term effects reported in Tables 3 and 4.

At the request of an anonymous reviewer, we estimated two-way fixed effects longitudinal models of emissions that include alternative measures of income inequality: the income share of the top 5% and the income share of the top 1%. These two variables, which we obtained from the same source as the other two income inequality measures, are highly correlated with the income share of the top 10%. For the analyzed sample, the Pearson's correlation coefficient for income share of top 10% and top 5% is 0.981, and the Pearson's correlation coefficient for income share of top 10% and top 1% is 0.925. Table 5 reports the findings for these models, which we structured similarly to the models reported in Table 3.

According to Models 9 through 11, the effect of income share of the top 5% on state-level emissions is positive and statistically significant, while Models 12 through 14 suggest the same for the income share of the top 1%. Based on the estimated elasticity coefficients for these models, a 1% increase in the income share of the top 5% is associated with between a 0.088 and a 0.096% increase in CO_2 emissions, while a 1% increase in the income share of the top 1% is associated with between a 0.062 and a 0.069% increase in state-level emissions. The effect of the Gini coefficient remains non-significant when including these two alternative inequality measures, and the estimated effects of all other controls are consistent with the findings from the fixed effects models reported in Table 3.

Table 5
Fixed effects longitudinal models of the effect of income inequality on CO_2 emissions in all 50 U.S. states and District of Columbia, 1997 to 2012.

	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Income share of top 5% (LG)	0.096*	0.088*	0.092*			
	(0.047)	(0.044)	(0.046)			
Income share of top 1% (LG)				0.069*	0.062*	0.066*
				(0.030)	(0.028)	(0.030)
Gini coefficient (LG)			−0.059			−0.090
			(0.300)			(0.301)
Population size (LG)	0.519**	0.436**	0.437**	0.524**	0.441**	0.442**
	(0.098)	(0.110)	(0.110)	(0.097)	(0.110)	(0.110)
GDP per capita (LG)	0.239**	0.218**	0.216**	0.232**	0.212**	0.208**
	(0.062)	(0.065)	(0.066)	(0.062)	(0.065)	(0.066)
Percent of population in urban areas (LG)		0.928**	0.931**		0.924**	0.929**
		(0.287)	(0.284)		(0.287)	(0.283)
Manufacturing as percent of GDP (LG)		−0.009	−0.008		−0.008	−0.008
		(0.019)	(0.019)		(0.019)	(0.019)
Fossil-fuel production (LG)		0.003	0.003		0.003	0.003
		(0.003)	(0.003)		(0.003)	(0.003)
R^2	0.996	0.996	0.996	0.996	0.996	0.996
rho	0.564	0.572	0.570	0.562	0.572	0.569

Notes: estimated with Prais-Winsten regression; 16 annual observations for 51 cases in all models; 816 total observations in all models; coefficients flagged for statistical significance; ** —<0.01 * —<0.05 (two-tailed tests of statistical significance); panel-corrected standard errors in parentheses; models includes AR(1) correction (labeled as "rho"); models include unreported case-specific and year-specific intercepts (two-way fixed effects); all continuous variables are in base 10 logarithmic form (labeled "LG").

5. Conclusion

This study contributes to multidisciplinary research on the human dimensions of climate change by analyzing the associations between CO_2 emissions and different types of income inequality at the U.S. state level. Global and international inequalities of various types have been widely studied. However, there is limited research on income inequality and CO_2 emissions, and it has been primarily conducted at the nation state level, focusing on how income inequality across nations influences national-level emissions. While potentially illuminating, cross-national research might overlook heterogeneity within nations, including the association between income inequality and CO_2 emissions. Thus, the present study advances climate change research by investigating if and how multiple characteristics of income inequality are associated with emissions, and the analysis is conducted at a sub-national level, providing a more nuanced view of these socio-environmental relationships.

The results of the longitudinal analysis indicate that a higher concentration of income among the top 10% (as well as the top 5% and the top 1%) is positively associated with U.S. state-level emissions, while the Gini coefficient's effect of CO_2 emissions is not significantly different than zero. Our findings concerning the concentration of income among the top of the distribution are consistent with analytical approaches that focus on political economy dynamics and Veblen effects, which highlight the potential economic and political power and the emulative influence of the wealthy. The null effects of the Gini coefficient are generally inconsistent with the marginal propensity to emit approach, which suggests that when incomes become more equally distributed, the poor will increase their consumption of energy and other products as they move into the middle class, leading to an overall increase in anthropogenic emissions. These results hold across multiple model specifications, and net of the effects of other established economic, demographic, and political drivers of CO_2 emissions.

Given the urgency of reducing carbon emissions, policy approaches that combine equality-enhancing effects with direct reductions in emissions are promising. Prior research on cap-and-dividend programs, which combine an emissions cap with permit auctioning and per capita revenue disbursement, suggests they are a more progressive policy than carbon taxes or cap-and-trade schemes which do not explicitly reimburse lower-income households. According to Boyce and Riddle (2009), with a \$200 per ton carbon tax and no dividend, income loss among the bottom quintile of households is estimated at 10.2%, or twice the loss for the top quintile. By contrast, with a dividend, the top quintile loses 2.4% and the bottom gains 14.8%. If the findings for our present study are valid, a cap-and-dividend scheme would have a second pathway for emissions reductions, namely the impact of reduced inequality. However, because cap-and-dividend schemes would likely have more impact on the Gini coefficient than the income share of the top 10%, the additional emissions reductions are likely to be modest. Larger impacts on emissions may come from measures targeted at concentrations at the top of the distribution, such as wealth taxes, a financial transactions tax, and steeply progressive income taxes.

We conclude by suggesting future steps in this research area. First, given the findings for our study, it is important to conduct analyses that more closely identify the specific pathways through which inequality affects emissions. Second, future analyses should investigate the relationship between income inequality and CO_2 emissions at sub-national levels within other large nations, such as the province level within China and the state level within Brazil. Third, a related set of issues to consider is if and how recessions might influence the relationship between CO_2 emissions and income inequality, and the extent to which this might differ between nations and between sub-national units. Finally, future research on other environmental outcomes, such as land cover change and industrial water pollution, should investigate the effects of income inequality as well.[3] We hope this study will encourage other scholars to join us in pursuing such future empirical investigations.

Appendix A. Percent Change Scores (1997 to 2012) for CO_2 Emissions and Both Income Inequality Measures

	Percent change in CO_2 emissions	Percent change in the income share of the top 10%	Percent change in the Gini coefficient		Percent change in CO_2 emissions	Percent change in the income share of the top 10%	Percent change in the Gini coefficient
Alabama	−7.896	6.464	6.256	Montana	1.138	19.202	9.779
Alaska	−9.197	4.372	−5.539	Nebraska	22.419	9.026	6.605
Arizona	27.402	7.904	9.611	Nevada	−9.034	23.650	18.263
Arkansas	10.379	21.723	10.499	New Hampshire	−10.326	−2.468	5.405
California	2.525	17.132	10.985	New Jersey	−16.294	7.528	9.336
Colorado	19.400	13.275	9.521	New Mexico	−1.790	8.585	5.714
Connecticut	−18.336	13.699	10.577	New York	−20.206	18.544	12.516
Delaware	−17.168	−10.491	4.784	North Carolina	−14.934	12.526	9.038
District of Columbia	−36.497	16.634	8.188	North Dakota	20.148	20.337	10.889
Florida	3.346	13.604	15.356	Ohio	−16.560	12.671	8.075
Georgia	−12.686	9.546	10.247	Oklahoma	5.635	16.232	9.215
Hawaii	1.758	6.837	6.605	Oregon	2.387	9.469	6.485
Idaho	14.530	12.016	13.822	Pennsylvania	−14.335	8.855	6.918
Illinois	−3.987	13.592	9.164	Rhode Island	−22.347	3.925	7.343
Indiana	−10.605	7.114	7.502	South Carolina	4.508	13.628	9.722
Iowa	9.269	9.060	5.616	South Dakota	13.248	11.018	8.445
Kansas	−6.655	11.187	10.137	Tennessee	−18.069	5.963	6.919
Kentucky	−2.715	4.380	5.512	Texas	−3.409	15.160	7.625
Louisiana	−11.856	6.409	10.680	Utah	1.069	10.298	8.768
Maine	−18.489	3.722	4.914	Vermont	−14.587	0.360	6.892
Maryland	−15.589	−4.917	7.276	Virginia	−10.329	10.304	9.063
Massachusetts	−26.404	11.635	9.555	Washington	−11.212	11.608	9.653
Michigan	−19.393	17.586	10.985	West Virginia	−17.994	1.412	5.199
Minnesota	−5.396	14.505	8.112	Wisconsin	−12.697	9.413	8.355
Mississippi	10.357	3.714	6.931	Wyoming	10.674	8.375	23.013
Missouri	1.334	14.611	9.260				

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[3] Other cross-national and U.S. sub-national research has focused on the relationship between biodiversity loss and one measure of income inequality – the Gini coefficient (e.g., Holland et al., 2009; Mikkelson et al., 2007). We thank an anonymous reviewer for bringing this to our attention.

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