

Income Inequality and Residential Carbon Emissions in the United States: A Preliminary Analysis¹

Andrew K. Jorgenson

Department of Sociology,
Boston College, Boston, United States

Juliet B. Schor

Department of Sociology,
Boston College, Boston, United States

Xiaorui Huang

Department of Sociology,
Boston College, Boston, United States

Jared Fitzgerald

Department of Sociology,
Boston College, Boston, United States

Abstract

The authors investigate the relationship between U.S. state-level residential carbon emissions and income inequality for the 1990–2012 period. Results of the analysis indicate a positive association between emissions and income inequality—measured as the Theil index—and these findings hold across a variety of model estimation techniques and net of the effects of other established human drivers of emissions. The authors conclude by underscoring the need for more research on the effects of income inequality on carbon emissions and other related environmental outcomes.

Keywords: climate change, income inequality, carbon emissions

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Introduction

Much research in the structural human ecology tradition focuses on the human drivers of greenhouse gas emissions. The majority of this research—to date—considers how population, affluence, and related factors explain growth in and variation between national-level emissions. Without doubt, population and affluence are primary drivers of national-level carbon emissions, methane emissions, and other greenhouse gases (e.g., Dietz, 2015; Dietz & Jorgenson, 2013; Jorgenson & Birkholz, 2010; Jorgenson & Clark, 2012; Knight & Schor, 2014; Rosa & Dietz, 2012; Rosa, York, & Dietz, 2004; Shandra et al., 2004; York, Rosa, & Dietz, 2003).

Research that further broadens structural human ecology has considered how various forms of international inequality also shape uneven levels of and growth in national-level emissions and related outcomes. This research consistently shows that types of international inequalities tied to asymmetrical global production and trade networks as well as coercive forms of international power (e.g., military power) contribute to many environmental problems, including anthropogenic carbon emissions (e.g., Burns, Davis, & Kick, 1997; Clark, Jorgenson, & Kentor, 2010; Grimes & Kentor, 2003; Jorgenson, 2012). Overall, these bodies of international research enhance our collective understanding of the human dimensions of global climate change and other environmental problems (Rosa et al., 2015).

With the growing availability of data, in recent years researchers have begun to investigate the human drivers of carbon emissions at smaller scales, such as at the U.S. state and county levels (e.g., Clement & Schultz, 2011; Dietz et al., 2015; Elliott & Clement, 2014). Many of the findings are consistent with the results of the comparative international research, especially the commonly observed impacts of population size, affluence, and urbanization. While it is recognized that comparative international research is important for a variety of substantive and practical reasons (Rosa et al., 2015), the assessment of society/nature relationships at smaller scales allows for further theoretical testing as well as the execution of research with perhaps more actionable policy implications (Rudel, 2005), especially considering the gridlock in international negotiations on climate change (Ciplet, 2015; Roberts & Parks, 2007).

A key issue that is absent from these streams of structural human ecology at all scales is research on greenhouse gas emissions and income inequality. Climate change and growth in income inequality are two of the most pressing problems of the current era. The former, if it continues unchecked, will not only undermine established ways of living, but also create catastrophic impacts on both natural and human systems (Intergovernmental Panel on Climate Change,

2014). The latter not only increases poverty and undermines well-being, but has become so pronounced in some nations that it threatens their basic economic functioning (Piketty, 2014). If income inequality was found to contribute to environmental problems such as carbon emissions, and thus climate change, policies to reduce income inequality could be promoted as both ecologically and socially beneficial (Jorgenson, 2015).

This preliminary study seeks to help remedy this absence by assessing the relationship between carbon emissions and income inequality at the U.S. state level.² In particular, we conduct a state-level longitudinal analysis of the effects of income inequality on residential carbon emissions for the 1990–2012 period. We employ the STIRPAT approach, a foundational tool in the structural human ecology tradition, in our analysis. The results suggest that income inequality, measured by the Theil index, increases residential carbon emissions in the United States, and these findings hold net of the effects of other well-established drivers of anthropogenic emissions.

Brief literature review

There are relatively few research findings on the relationship between carbon emissions and income inequality, and they mostly originate in the discipline of economics. We briefly summarize portions of this literature.

Ravallion et al. (2000) hypothesize that when the relationship between household income and emissions is concave, the wealthy emit less than the poor for each dollar of additional income, so that a redistribution of income from the wealthy to the poor will result in increased emissions. They posit that consumption demand is the key factor determining the increase of emissions induced by an increase in disposable income, i.e., the marginal propensity to emit. However, this is only one of the possible mechanisms at work. In a Keynesian model, lower-income households consume more than higher-income households for each dollar of additional income (i.e., the marginal propensity to consume declines with income). In that case, reductions in inequality that result in greater income for the poor yield a higher level of overall consumption demand and thus emissions.

In contrast, James Boyce's (1994, 2003, 2008) "power-weighted social decision rule" suggests that when the beneficiaries of environmental degradation are more powerful than those who bear the costs, the overall level of environmental degradation will be greater. Since the wealthy benefit more from environmental

² While the focus for this preliminary study is on U.S. state-level emissions, in other research in progress we are investigating the relationship between carbon emissions and domestic inequality cross-nationally.

degradation as both consumers and producers, and the poor benefit less and are more vulnerable to harmful consequences, higher levels of income inequality are likely to lead to increased carbon emissions and other environmental harms because the interests of the wealthy are protected in the political sphere (see also Cushing et al., 2015). In a similar vein, Pattison et al. (2014) find that counties in the U.S. with the highest average household incomes have greater consumption-based carbon emissions but lower production-based emissions than less affluent counties. Pattison et al. (2014) conclude that wealthier communities are able to avoid some of the consequences of their carbon-intensive consumption by shifting carbon-intensive industrial activities into poorer areas.

Others have suggested that domestic inequality undermines environmental protection by reducing social cohesion and cooperation. By eroding social trust, income inequality may inhibit pro-environmental collective actions and socially responsible behaviors, thereby leading to growth in emissions (Cushing et al., 2015; Ostrom, 2008; Wilkinson & Pickett, 2010). Related to this, Knight and Rosa (2011) demonstrate that countries with higher levels of social trust achieve greater subjective human well-being with less environmental impact.

Another approach argues that rising income inequality can increase status-based consumption of goods and fossil fuels as individuals spend more and more to emulate the standards set by the “overconsuming” wealthier members of society in what we may call a Veblen effect (Schor, 1998; Veblen, 1934). Average working hours have also been shown to increase with rising income inequality (Bowles & Park, 2005), and recent cross-national research indicates that longer working hours are associated with greater environmental impacts, including growth in energy consumption and carbon emissions (Fitzgerald, Jorgenson, & Clark, 2015; Knight, Rosa, & Schor, 2013).

Vona and Patriarca (2011) find that in wealthy countries, growth in income inequality reduces the development and diffusion of environmentally beneficial consumer products because it creates a larger gap between what wealthy early adopters are willing to pay and what the less wealthy can afford. And research by Jorgenson, Rice, and Clark (2010) shows that in developing nations, growth in fossil fuel consumption is positively associated with overall urbanization (the percent of the population residing in urban areas), but negatively associated with growth in urban slum prevalence (the percent of the population residing in urban slum conditions). Jorgenson et al. (2010) conclude that these divergent relationships are partly attributed to the differences in average incomes between urban slum residents and non-slum urban residents as well as the broader structural inequalities that inhibit access for urban slum residents to energy and other resources for household consumption.

In this study, we explore a particular type of inequality—namely, high-income concentration at the top of the distribution. We hypothesize that where there is more income concentrated at the top, emissions will be higher for (at least) two reasons. First, there will be a stronger political economy effect in which the wealthy use their political power to avoid carbon-control measures. Second, high-income concentration leads to stronger Veblen effects in which high-income households compete for status via the “over-consumption” of goods and services which require high energy use (Schor, 1998; Ehrhardt-Martinez & Schor, 2015). Veblen identified houses and transportation, both of which are highly energy intensive, as two of the three major areas of status competition (Veblen, 1934). High-income households today compete via the purchase of large homes (Dwyer, 2007; Frank, 2010), which in turn yields low population density and high residential energy use. In transportation, wealthy households purchase powerful motorized vehicles (autos, boats, and airplanes) and engage in frequent long-distance travel. In addition, this portion of the distribution engages in high consumption overall. More generally, this approach is in some ways similar to that of Chakravarty et al. (2009) who emphasize the strong intra-national differences in carbon intensity, with emissions highly concentrated at the top of the income and wealth distribution.

Data and methods

The dataset

Our dataset contains annual observations from 1990 to 2012 for all 50 U.S. states, as well as the District of Columbia (i.e., 23 annual observations per case). This yields an overall sample of 1,173 observations, and a perfectly balanced panel dataset.

Model estimation techniques

We employ multiple model estimation techniques to assess the effect of income inequality on residential carbon emissions. Doing so allows for evaluating empirical relationships across a range of model specifications, each of which has its relative strengths and weaknesses (Allison, 2009). We first estimate random effects models, using the “xtreg” suite of commands in Stata version 13 software (“xtreg re”).³ One of the advantages of random effects models is the ability to include time invariant predictor variables (e.g., census region). We then estimate

3 We note that the Hausman test comparing the “xtreg” fixed effects model and random effects model is non-significant. Nonetheless, the estimated standard errors for the fixed effects model are generally larger than the random effects model, leading to more conservative hypothesis testing.

fixed effects models, first with the within estimator in Stata (“xtreg fe”), and then with Prais-Winsten regression with panel corrected standard errors (xi:xtpcse). The fixed effects models and random effects models also include unreported year-specific intercepts.

All continuous variables are in logarithmic form (base 10), a well-established approach in structural human ecology, and commonly referred to as STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology; see stirpat.msu.edu/; York, Rosa, & Dietz, 2003). Given that the variables are in logarithmic form, STIRPAT is by design an elasticity model. The coefficient for each continuous independent variable in such a model is the estimated percentage change in the dependent variable associated with a 1% increase in the independent variable, controlling for all other factors in the model.

Dependent variable

Our dependent variable is residential carbon dioxide emissions from fossil fuel combustion, measured in million metric tons CO₂ (MMTCO₂). We obtained these publicly available data from the United States Environmental Protection Agency (EPA), which provides state-level emissions data for various sectors, including residential, commercial, industrial, transportation, and electric power, as well as for all sectors combined (epa.gov/statelocalclimate/resources/state_energyco2inv.html, accessed July 1, 2015). The EPA bases the state-level emissions estimates on energy consumption data from the EIA's State Energy Consumption, Price, and Expenditure Estimates (SEDS), released Spring 2014 (www.eia.doe.gov/emeu/states/seds.html).

Independent variables

Our measure of income inequality is the Theil index for household income inequality (Theil, 1967), which we obtain from Mark Frank's U.S. State-Level Income Inequality Database (www.shsu.edu/~eco_mwf/inequality.html, accessed July 3, 2015). The steps used in the creation of these inequality measures are provided in great detail in the Appendix in Frank (2014). The Theil index measures the discrepancies between the distribution of income and the distribution of population between groups. It compares the income and population distribution structures by summing across groups the weighted logarithm of the ratio between each group's income and population shares. When this ratio is one for a particular group, then that group's contribution to income inequality is zero (Conceicao & Ferreira, 2000). An important property of the Theil index is its sensitivity to income transfers from the poor to the rich within a given population, which differentiates it from other common measures of income inequality, including the Gini coefficient. The Theil index tends to be

highly correlated with more simple measures that quantify the percentage of all income or wealth owned by those in the top 1%, top 5%, and top 10%, while the Gini coefficient tends to be only moderately correlated with such measures (Frank, 2014).

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 (www.census.gov/popest/data/intercensal/index.html, accessed July 1, 2015). We also include Gross Domestic Product (GDP) per capita by state, which we obtained from the United States Department of Commerce Bureau of Economic Analysis database (www.bea.gov/itable/, accessed July 1, 2015).

We note that there is a discontinuity in the time series of GDP by state at 1997, where annual estimates prior to that year are calculated using one classification system (and reported in chained 1997 dollars), while annual estimates from 1997 to the present (and reported in chained 2007 dollars) are calculated using a different classification system (for more information, see www.bea.gov/regional/docs/product/). Thus, caution must be used when merging data from these two different panels into one overall dataset. We suggest that these differences are partially accounted for by the inclusion of year-specific fixed effects in all reported models, and we prefer to include these measures as a merged dataset to allow for greater temporal depth in our analysis of the residential emissions and income inequality relationship. In a sensitivity analysis available upon request, we restricted the overall dataset to 1997–2012, and the results of interest are substantively consistent with the findings reported below in Table 2.

In the random effects models we also include dummy variables for Census Region, which consist of South Census Region (Alabama, Arkansas, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, West Virginia), Midwest Census Region (Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Wisconsin), Northeast Census Region (Connecticut, Delaware, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont), and West Census Region (Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, Oregon, Washington, Wyoming).

Table 1 provides the descriptive statistics and bivariate correlations for the dependent variable and the independent variables. As a reminder, all continuous variables are in logarithmic form (base 10).

Table 1. Descriptive statistics and correlations

	Mean	Std. Dev.		1.	2.	3.	4.	5.	6.	7.
Residential CO ₂ Emissions	0.736	0.361	1.							
Theil Index	0.246	0.043	2.	0.222						
Population Size	6.526	0.448	3.	0.804	0.252					
GDP Per Capita	4.549	0.135	4.	0.023	0.587	-0.074				
South Census Region	0.313	0.464	5.	-0.133	-0.046	0.210	-0.088			
Midwest Census Region	0.235	0.424	6.	0.258	-0.193	0.061	-0.063	-0.375		
Northeast Census Region	0.196	0.397	7.	0.198	0.203	-0.082	0.141	-0.333	-0.273	
West Census Region	0.254	0.436	8.	-0.291	0.052	-0.207	0.026	-0.395	-0.324	-0.288

Notes:

- 1,173 total observations;
- all continuous variables are in base 10 logarithmic form;
- West Census Region is reference category in analysis reported in Table 2

Results

The findings for the analysis are provided in Table 2. RE Model 1 includes the Theil index, population size, GDP per capita, and the unreported period-specific intercepts. RE Model 2 also includes the measures for census region. The fixed effects models include the same predictors as the first random effects model. FE Model 1 is based on the “xtreg” within estimator, and FE Model 2 is based on Prais-Winsten regression with panel-corrected standard errors and unreported dummy variable case-specific fixed effects.

Across all four reported models, the effect of the Theil index on residential carbon emissions is positive and statistically significant. The elasticity coefficient for the Theil index is slightly larger in the fixed effects models (.143) than in the random effects models (.137 and .133), and in FE Model 2 the p-value for its coefficient is slightly above the standard benchmark of .05 with a value of .057 (two-tailed test). These results indicate that a 1% increase in the Theil index leads to between a .133% and .143% increase in residential carbon emissions, net of the effects of population size, level of economic development, and both the time-specific and state-specific fixed effects.

Table 2. Longitudinal models of the effects of income inequality on residential CO₂ emissions in all 50 U.S. states and Washington, DC, 1990–2012

	RE Model 1	RE Model 2	FE Model 1	FE Model 2
Theil Index	0.137** (0.058)	0.133** (0.059)	0.143** (0.059)	0.143* (0.075)
Population Size	0.792*** (0.032)	0.780*** (0.030)	0.835*** (0.037)	0.835*** (0.066)
GDP Per Capita	0.177*** (0.043)	0.177*** (0.043)	0.170*** (0.044)	0.170*** (0.059)
South Census Region		-0.119** (0.058)		
Midwest Census Region		0.191*** (0.062)		
Northeast Census Region		0.251*** (0.065)		
R-square	0.666	0.826	0.665	0.995

Notes:

- RE denotes random effects; FE denotes fixed effects;
- 1,173 total observations; *p<.075, **p<.05, ***p<.01 (two-tailed tests); standard errors in parentheses;
- p-value for Theil Index coefficient is .057 in FE Model 2;
- all continuous variables are in base 10 logarithmic form; all models include unreported period-specific intercepts;
- West Census Region is reference category in RE Model 2;
- FE Model 1 is estimated with the “xtreg” within estimator in Stata;
- FE Model 2 is estimated with Prais-Winsten regression with panel-corrected standard errors;
- FE Model 2 includes unreported dummy variable fixed effects for each case;
- Hausman test for FE Model 1 and RE Model 1 is nonsignificant.

As expected, the estimated effects of population size and GDP per capita are positive and statistically significant across the four models. In the second random effects model, all census region dummy variables exhibit statistically significant effects on emissions as well. We note that the close to perfect R-square statistic for FE Model 2 is largely due to the use of dummy variables for the case-specific fixed effects.

Conclusion

This study makes a modest contribution to structural human ecology research on the causes of anthropogenic greenhouse gas emissions, with a broader goal of bringing greater attention to and facilitating additional research on the environmental impacts of income inequality at multiple scales, a surprisingly

understudied and overlooked topic. The results of our preliminary analysis suggest a positive relationship between state-level residential carbon emissions and income inequality, measured as the Theil index, in the United States, net of the effects of other well-established human drivers of emissions. For us, the next logical steps in this research involve evaluating the effects of other income inequality measures on state-level and national-level carbon emissions, such as the widely used Gini coefficient, which captures different properties of income distributions than the Theil index.

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