

# State Characteristics & Carbon Emissions

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## Abstract

United States Carbon Dioxide (CO<sub>2</sub>) emissions have increased by nearly 800% since the start of the 1900s, and while they have decreased by approximately 16% since 2007 (down from 6.13 billion metric tons to 5.27 billion metric tons), we still have much work to do if we are going to avoid dangers like an increase in average temperature, according to a 2018 report from the U.S. Global Change Research Program. The methods we can use to mitigate emissions revolve around implementation of greener practices and technology through public and private policy, as well as the collection of individual actions of a given population; and in order for any of this to be done you need a population that is willing to vote on green policies, buy from green businesses, and/or modify their own individual actions. In our research, we want to see if generalized traits around the character of a state's population, like willingness to vote, importance of religion, social capital, etc., contribute to carbon emissions per capita.

Our data is drawn from a wide range of sources (e.g. Pew Research Center, Milken Institute, Environmental Protection Agency, etc.), we start with creating a base model surrounding the IPAT formulation, or Impact = Population x Affluence x Technology, which was proposed in the early 1970s (Ehrlich and Holdren, 1972); and adding our social capital and behavioral variables to the IPAT formulation in order see if they have a significant association with carbon emissions per capita. **We hypothesize that our initial IPAT variables will be statistically significant, and that our social capital and behavioral variables will also be significant predictors of state level carbon emissions.** Results suggest that the IPAT model, while simplistic, does significantly capture over 50% of the variation by itself; the Political Affiliation and Religious Intensity of a state is significantly associated with carbon emissions where emissions decrease with respect to Percent Democratic and increase with being more religious. However, voter turnout, volunteerism, and our community social capital variables were not associated with changes in carbon emissions per capita.

## Literature

An ever increasing population and the increasing consumption of that population have been linked to increased Greenhouse Gas (GHG) emissions (Dietz & Rosa, 1997). Thus, the way in which a population is consuming things like gas and cars, space heating/cooling, household appliances, etc., will have larger and larger impacts on GHG emissions as the population continues to increase (Swim et al., 2011). **An important contributor to GHG emissions, and especially GHG emissions per capita, may be psychosocial, behavioral, and general characteristics of a population.** With certain populations having very different types of people, some more are involved in volunteering, politics, religion, etc., it would be important to look into behavioral variables surrounding social capital that could be evidence that certain behavioral characteristics are associated with preservation of the environment. **Prior research discusses social capital as a possible predictor of environmental degradation, but did not find a significant relationship between social capital and environmental degradation/protection (Grafton and Knowles 2004).**

## Importance

Greenhouse Gases, including Carbon Dioxide, have a major impact on the environment, with the Intergovernmental Panel on Climate Change (and the Environmental Protection Agency) stating that emissions from human activities are the most important driver of climate change. With emissions being driven up by what groups of people do, as well as the practices of entire businesses, part of the method for fixing these issues is to shape the cultural environment we are in, either politically, technologically, or even by social capital. We look at the United States on a state-level view and observe how group behaviors and "cultures" impact Carbon Emissions per capita. Certain models, like IPAT (Impact = Population x Affluence x Technology) have been proposed to give structure in solving environmental impact.

## Limitations

The main limitation is using data by state. There are numerous complexities within states that can obscure certain variables far more than others. A good example of this is in regards to population density. **States like Texas are largely rural with a few cities that are very dense, and thus by looking only at the total state density we are missing the variation across entire areas of states.** This is also true for political affiliation, and since political affiliation and population density are correlated and tied together, **an analysis that focuses on data by county or even satellite data may be more appropriate.**

Another limitation is the lack of capturing data regarding a shift in the costs of carbon emissive activities and practices to other states or even countries. Where energy is actually produced is often different from where it is used, and thus the impact of the production of energy, like from a power plant, should be captured as a control for the variation in statewide energy production. This is true with general consumption too -- the associated costs of a certain activity may be realized elsewhere.

## Methods and Assumptions

Our focus is on the simple I=PAT equation that can serve as a backbone for our regression. I=PAT is discussed in *Human Behavioral Contributions to Climate Change (Swim, Clayton, Howard)*, and is a model from the 1970s for measuring impact by looking at Population (P), Affluence (consuming and spending practices), and Technology (T). We use two index variables that capture the technological nature of businesses and labor within a state, so as to see if a more technologically-inclined state will reduce carbon emissions. Thus, we use these two variables as proxies for an actual variable for Technology. The first variable, Technology Concentration and Dynamism, is from data involving the business climate of a state. Things like "Percent of Businesses in High-Tech NAICS Codes", "Number of Technology Fast 500 Companies", "Average Yearly Growth of High-Tech Industries", etc. The second variable, Technology and Science Workforce, is from data around the labor intensity of different science and technology related professions; essentially measuring the level of technological affiliation in a workforce. It is important to note that in the typical IPAT formulation, Technology is meant to be positively correlated with environmental degradation -- we instead look for a variable we hypothesize as negatively correlated, thus we have a difference with the IPAT model (although not crucial).

We have aggregate data by state, with the purpose of observing if the different aggregate behaviors/characteristics have measurable impacts on carbon emissions per capita. While this is inherently limiting, as the issue of climate change is far more granular than state-level, we believe it's a proper method for getting a picture of how different practices and people in different states impact climate change.

After aggregating our data from a wide selection of sources by state, we proceed to run our base regression. With logged carbon emissions per capita as the dependent variable, we had Population Density (population per square mile), GDP Per Capita (dollars), and Technology Concentration and Dynamism, as our independent variables. We use this as our base model to introduce other variables on their own. We then made a final regression that holds all of our important variables and controls.

## Results

Independent Variables	IPAT (1)	Social Capital Index (2)	Full (3)	Swap Tech Variables (4)	
GDP per capita	0.000015 (0.000062)	0.000014 (0.000007)	0.000021 (0.000056)	0.000025 (0.000008)	Significant at 5% Level
Population Density	-0.00085 (0.00023)	-0.00084 (0.00025)	-0.00047 (0.0002)	-0.00046 (0.00029)	Significant at 10% Level
Technology Concentration and Dynamism	-0.016 (0.0027)	-0.016 (0.0028)	-0.014 (0.0022)	-	Not Significant
Technology Science and Workforce	-	-	-	-0.0169 (0.00697)	
Social Capital Index	-	0.0138 (0.0815)	-	-	
Percent "Very Religious"	-	-	0.0104 (0.0059)	0.0109 (0.0076)	
Volunteer Rate (2018)	-	-	-0.0138 (0.0101)	-0.0032 (0.0139)	
Voter Turnout	-	-	0.0086 (0.0093)	0.0036 (0.0119)	
Percent Democratic	-	-	-0.035 (0.0089)	-0.0363 (0.0115)	
Intercept	3.029 (0.319)	3.049470774 (0.343100280)	3.318 (0.985)	3.2496 (1.273)	
Observations	50	50	50	50	
R-Squared	0.5572	0.5575	0.7432	0.5764	

The first regression depicted in the above table is used as our base regression to pull our other variables in to. It involves the I=PAT formula and we wanted to test to see if such a formula, while simplistic, is still useful. **On its own, it can explain ~55.7% of the variation in our data.** As we **increase the GDP per capita by \$1000, we have an associated increase in carbon emissions per capita by ~1.46%, all else equal**, which is very large considering the median GDP per capita is around \$47,000 (a ~98.1% increase). This coincides with the current literature on consumption and carbon emissions. **Population density**, however, is **associated with a decrease of .085% in carbon emissions per capita for an additional person per square mile, all else equal**. This goes against the current literature, however the reasoning, we believe, has to do with population density being a factor that should be investigated at a more granular level than the state (this is further discussed in Limitations). Lastly we can see that our **technology index** variable for business within a state **is associated with a decrease in carbon emissions** (a 1 point increase in the index variable is associated with a 1.61% decrease in carbon emissions per capita, all else equal)

In our second and third regressions the additional social capital and behavioral variables have been added. We can observe the extreme **insignificance of the Social Capital Index**, when added to the IPAT formula, indicating that we are in agreement with prior research on the lack of an associated effect from a generalized level of social capital on environmental protection. **We fail to reject the hypothesis that Social Capital has no effect on carbon emissions per capita.**

Looking to our third regression, however, where we break down some of the variables associated with social capital, like political affiliation and intensity (voter turnout), religious strength/intensity, volunteerism, etc., to observe if these other behavioral/character traits have some impact, we only get **percent of the population that are very religious** and **political affiliation** as significantly impacting carbon emissions per capita, with the former just barely not meeting significance at the 5% level (p value of .0505). A population consisting more of strongly religious people and/or republican voters is associated with an increase in carbon emissions per capita.

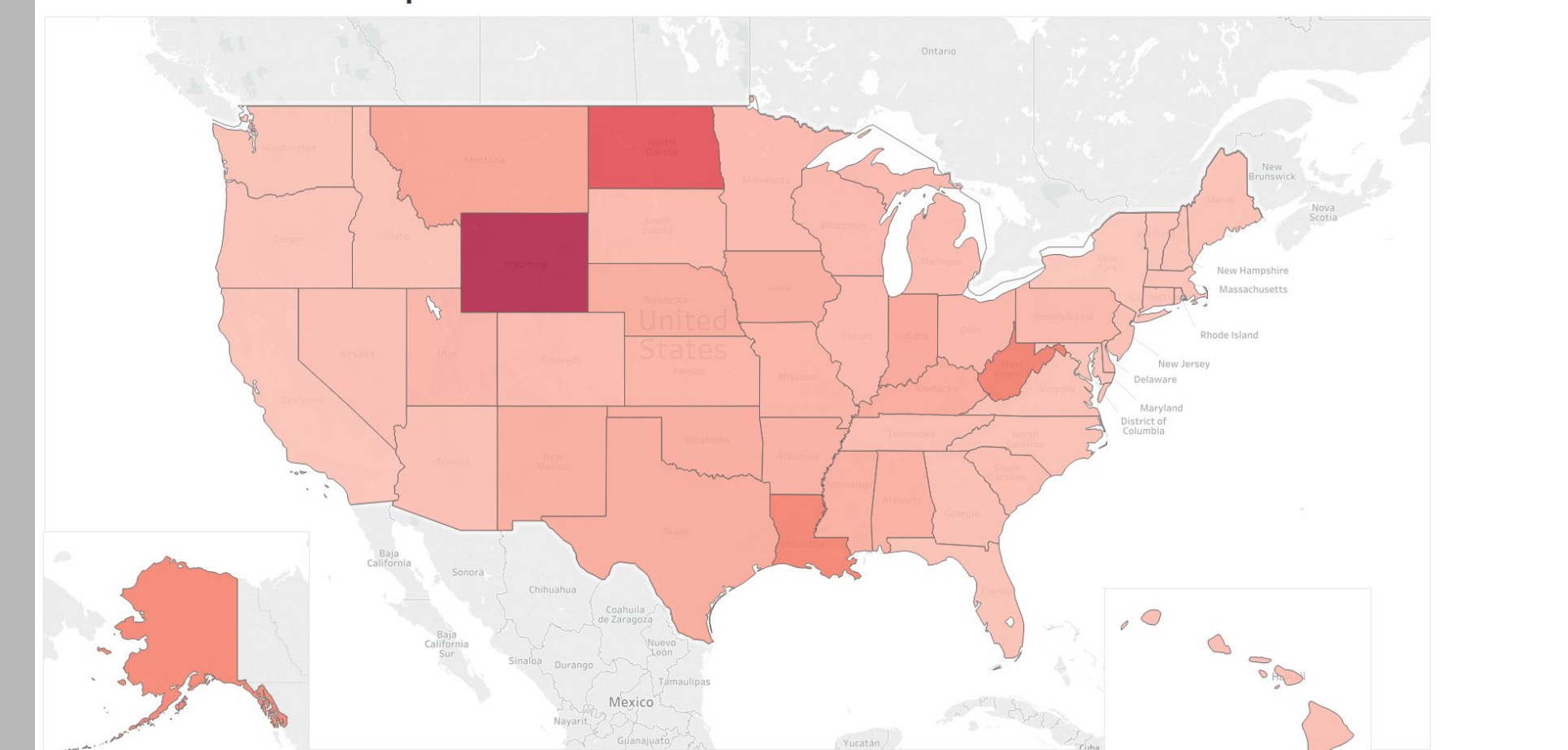
Our 4th regression involves swapping out the two tech index variables to show that, while till significant, we lose a lot of our R<sup>2</sup> value (loss of 16.7% variation explained) by working with the labor/workforce tech index. This tells us that the association of better technology with lower carbon emissions is predominantly associated with the business sector, as opposed to the relevant technologically-focused workforce of a population.

## Data and Variables

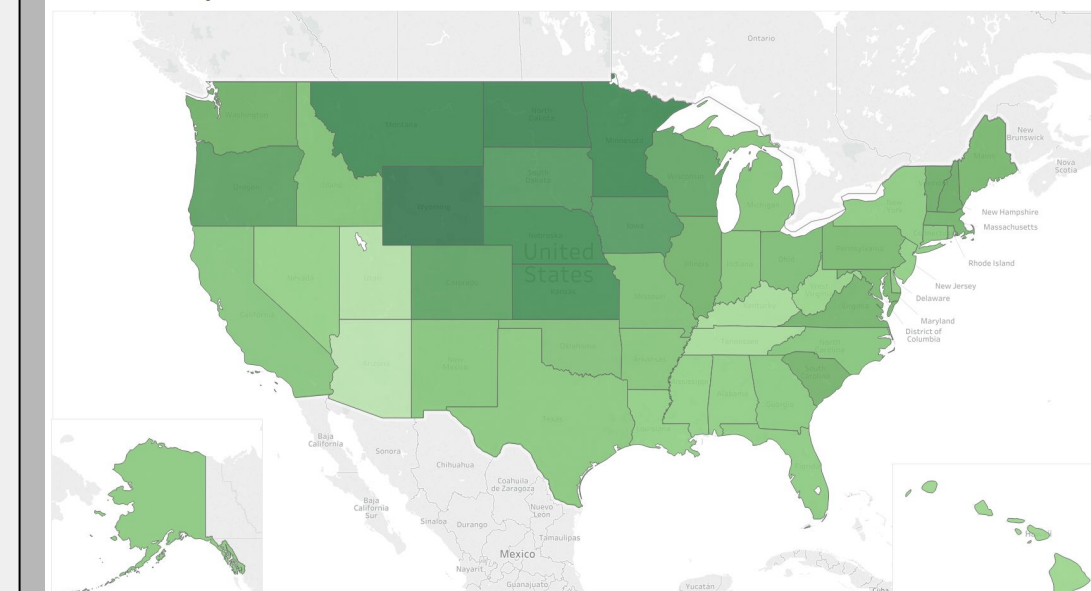
Independent Variable	Source and year	Min	Mean	Median	Max
Logged Carbon Emissions Per Capita and Energy Usage data by state	U.S. Energy Information Administration (EIA) (2017)	2.088	2.831	2.746	4.66
Social Capital Index	Journal of Socio-Economics (2006)	-1.391	0.0517	-0.248	3.338
Religious Intensity and Percent Very Religious	Pew Research Center, Fact Tank (2016)	33	54.67	54.67	77
Population (2018) and Land Area (2017) and Population Density	State Symbols USA (2017)	1.29	201.71	107	1200.77
Technology Concentration and Dynamism	Milken Institute, State Tech and Science Index (2018)	9.78	49.47	52.34	92.22
GDP Per Capita	Bureau of Economics (2017)	31633	48272	46874	67705

## Descriptive Statistics

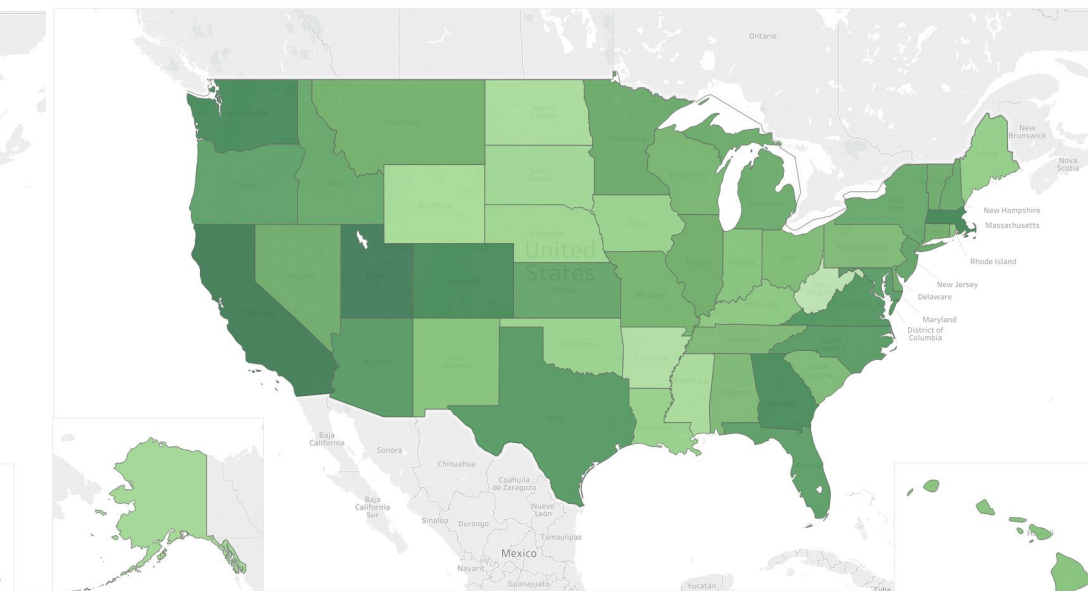
Emissions Per Capita



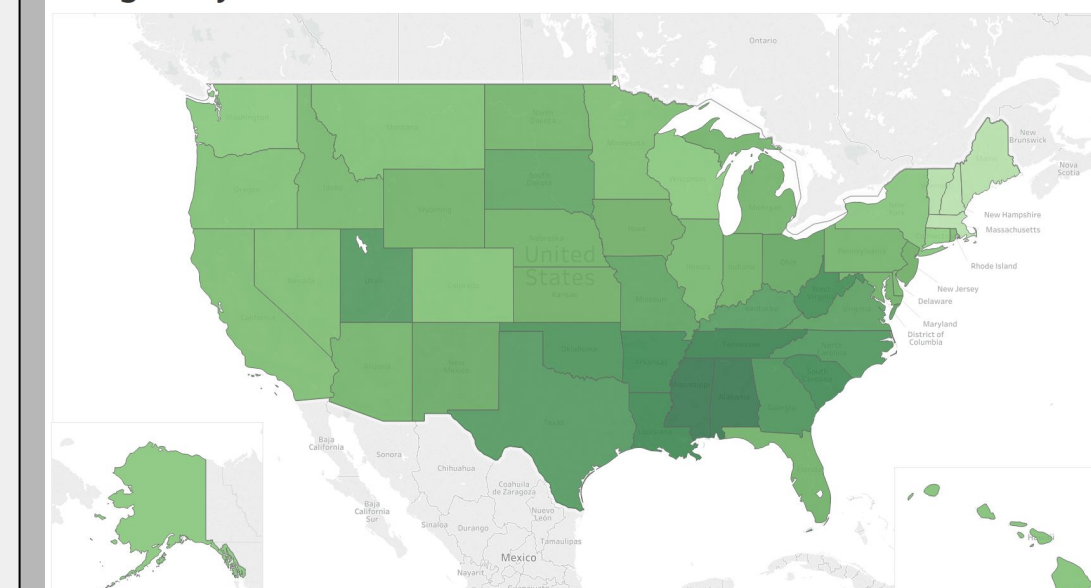
Social Capital Index



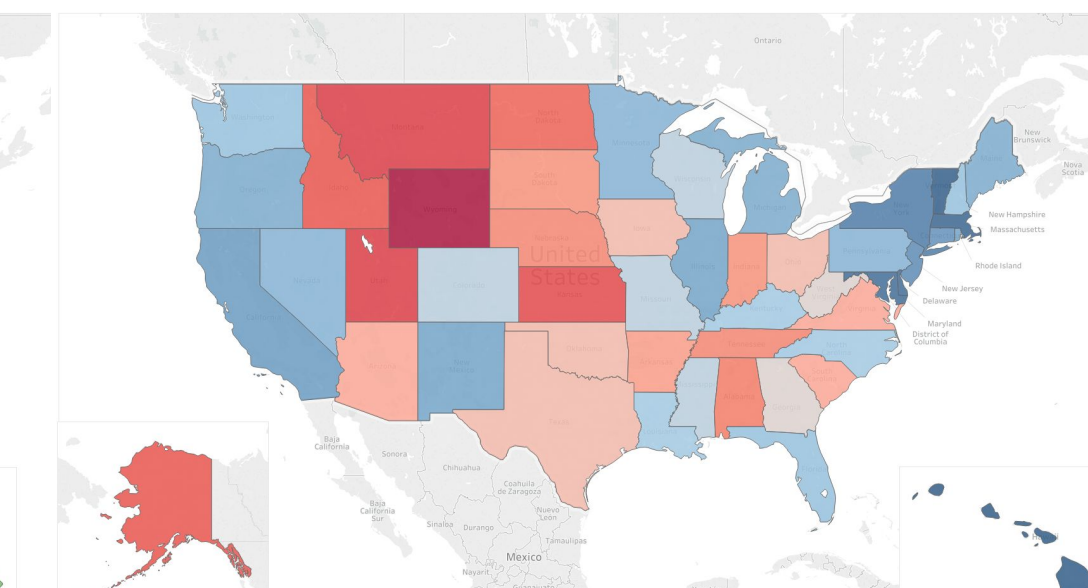
Technology Index



Religiosity



Percent Democratic



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