Carbon Emissions, Minimum Wage, and Income Inequality

Introduction

This paper seeks to explore the relationship between income and income inequality, and carbon emissions. It aims to analyze how consumption-based carbon emissions are affected by changes in income inequality in all U.S. states. The study hypothesizes that income inequality and carbon emissions are positively correlated; abating income inequality by improving economic outcomes for low income communities in the US would lead to a reduction in carbon emissions.

Often, distressing over the environmental impact of one's activities is a privilege that the poorest communities do not enjoy. People who work multiple minimum wage jobs to support their families do not have the capacity to consider how their choices could translate into environmental degradation.[1] Improving economic opportunities would allow individuals residing in low-income communities to make smarter - more sustainable / eco-conscious - decisions as such decisions tend to be costlier or have a large initial capital requirement associated with them.

This paper examines residential carbon emissions in US states as a proxy for consumption-based carbon emissions as the independent variable, against income inequality measured by the Theil index, and minimum wage rate at the state level.

Consumption-based Carbon Emissions

Carbon dioxide is one of the most abundant greenhouse gases in the atmosphere, and it also stays in the atmosphere longer than any other greenhouse gas. According to the US National Oceanic and Atmospheric Administration, CO2 is responsible for about 2/3rds of the total energy imbalance that is causing Earth's temperature to rise.[2] One of the major contributors to rising carbon dioxide concentrations is fossil fuel consumption. Through fossil fuel consumption, each year we produce more carbon dioxide than natural processes can remove. As the rate of production increases more than the rate of carbon sequestration, the annual net growth of CO2 in our atmosphere keeps rising exponentially. This demands an extensive analysis of the anthropogenic activities that contribute to this increasingly worrying problem.

Carbon emissions can broadly be classified into two groups based on the activities through which they are released into the atmosphere: production-based carbon emissions and consumption-based carbon emissions. Production-based carbon emissions include emissions that arise from manufacturing / production activities, including those for goods and services that are exported or consumed by residents of a different county. The consumption-based approach examines the direct emissions from goods and services, such as from raw materials, manufacturing, and distribution,

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[1] Lux, Travis. "Life Raft." "So You've Got Climate Anxiety. Here's What You Can Do About It." from New Orleans Public Radio, December 1, 2020, Britt Wray, https://www.wwno.org/coastal-desk/2020-12-01/life-raft-so-youve-got-climate-anxiety-heres-what-you-can-do-with-it

[2] Lindsey, R. (n.d.). Climate change: Atmospheric carbon dioxide. Climate Change: Atmospheric Carbon Dioxide | NOAA Climate.gov. Retrieved December 20, 2021, from https://www.climate.gov/news-features/understanding-climate/climate-change-atmospheric-carbon-dioxide

and allocates this to the final consumer rather than to the producer of those emissions.[3] The few studies that explore the relationship between carbon emissions and income inequality/affluence focus on production-side emissions. However, to capture the true relationship between income-inequality and carbon emissions, it is essential to analyze consumption-based emissions. When analyzing carbon emissions against income inequality, it is important to investigate consumption activities rather than production-side for two main reasons: 1) wealth and power and 2) accumulation of carbon-intensive industries.

In exploring income inequality, the emphasis is always placed on economic opportunities. Rarely are the systematic structures that dictate our relationships with each other examined to understand their impact on our relationship with nature. In his lecture titled '*Inequality and the Environment*', UMass Economist James K. Boyce accentuates the role of wealth and power in our relationship with the environment. He discusses the 'power-weighted social decision rule', according to which, "a society's decision about whether, when, and where to degrade (or protect) the environment are shaped by the preferences and relative power of those who win and lose from that decision."[4] This relative power to influence environmental decisions exists in both the market (purchasing power) and the state (political power).

In their study exploring the impact of affluence on carbon emissions at the county level in the US, Patison et al. find that wealthier neighborhoods are able to avoid the consequences of their carbon-intensive consumption by establishing carbon-intensive industries exclusively in the lower-income counties.[5] Consequently, environmental costs stemming from production activities are disproportionately imposed on communities with less wealth and power. Investigating income inequality against production-based carbon emission would, thus, fail to capture the effects of inequalities on carbon emissions. This study seeks to explore how carbon emissions from residential/consumption activities relate to the differences in income/wealth in the US. By analyzing consumption-based emissions, the study aims to understand how income and economic opportunities could be utilized to control the growingly unmanageable CO2 emissions.

Income Inequality and Minimum Wage

'Changes in income inequality' in itself is a convoluted phenomenon; simply investigating changes as a whole would fail to capture the multitudes of nuances in American income inequality. In exploring income inequality against consumption-based carbon emissions, this paper seeks to examine how an absolute change (negative and positive) in income inequality affects carbon emissions, and how negative/positive changes affect carbon emissions.

[3] *Consumption-based GHG emissions of C40 cities*. (n.d.). Retrieved October 11, 2021, from https://www.c40.org/researches/consumption-based-emissions

[4] Boyce, J. (2017, March 28). *Inequality and the environment - peri*. Leontief Prize Lecture. Retrieved October 11, 2021, from https://peri.umass.edu/images/BoyceInequality_and_the_Environment_-_Leontief_lecture.pdf., pg 93

[5] Jorgenson, Andrew K., et al. "Income Inequality and Residential Carbon Emissions in the United States: A Preliminary Analysis." Human Ecology Review, vol. 22, no. 1, [Society for Human Ecology, ANU Press], 2015, pp. 93, http://www.jstor.org/stable/24875150.

A positive change in income inequality could refer to either an increase in economic opportunities for people at the lower end of the income scale, or a restriction/reduction in wealth and income amassing capabilities for people on the higher end of the income scale. Similarly, a negative change could have two connotations: deterioration in economic opportunities for people on the lower end of the scale, and/or removal of restrictions on the ability to amass wealth and income for people on the higher end of the scale. In the context of this paper, a positive/negative change refers to the first scenario: a change in income and economic opportunities for the poor.

The study explores minimum wage rate to analyze how changes in the wage rate could be attributed to changes in income inequality, and in turn, affect consumption-based carbon emissions. People on the lower end of the income scale are the ones most affected by the minimum wage rate, and thus, examining this relationship will allow us to draw interesting conclusions.

Data Description

The paper combines multiple datasets in order to explore the relationship between carbon emissions, income inequality, and minimum wage rate in the US. All three datasets capture most of the key aspects of the relationship between income and income inequality, and carbon emissions.

For the dependent variable, carbon emissions, the paper utilizes a publicly available dataset from the United States Energy Information Administration (EIA). It contains data on residential carbon-emissions, used as a proxy for consumption-based carbon emissions, for all US states and the District of Columbia from 1980 to 2018. The emissions are measured in million metric tons of carbon dioxide (MMTCO2). The data is collected and compiled by the EIA through the State Energy Data System (SEDS). The dataset contains 51 rows over 40 columns: one for state and the rest for years. In cleaning this dataset, I dropped two columns: Percent, Absolute. The Percent column contained the percentage change in carbon emissions from 1980 to 2018. The Absolute column contained the absolute change in carbon emissions from 1980 to 2018. I am interested in analyzing emissions over time and thus, the two columns were not useful in my analysis. Next, I changed the data from a wide to a long format for ease in analysis. The transformed dataset has three columns: state, year, and emissions.

For data on income inequality, the study utilizes a publicly available dataset compiled by economist Mark W. Frank. The dataset contains a panel of annual, US state-level income inequality measures constructed using tax filing data available from the Internal Revenue Service. It contains three measures of income inequality: Atkinson Index, Gini Coefficient, and Theil Index, from 1917-2018. Additionally, it also contains a column for Relative Mean Deviation. For the purposes of this study, I chose to work with the Theil Index. The Theil Index measures "an entropic distance between the current standing of the population and the ideal egalitarian state of everyone having the same income".[6] It ranges from 0 to ∞, where 0 represents an equal distribution and

[6] Bureau, U. S. C. (2021, October 8). Theil index. Census.gov. Retrieved December 20, 2021, from https://www.census.gov/topics/income-poverty/income-inequality/about/metrics/theil-index.html

higher values represent greater levels of inequality. In cleaning this dataset, I dropped three columns: Gini Coefficient, Atkinson Index, and the Relative Mean Deviation. Finally, I dropped data for all the years before 1980. The final dataset contains three columns: state, year, and theil, with data from 1980-2018 for all US states and District of Columbia.

The third dataset utilized in this study contains data on annual minimum wage rates for all US states and the District of Columbia. It was obtained from the Federal Reserve Economic Data (FRED) at the Federal Reserve Bank of St. Louis. After dropping columns for minimum wage rate for Puerto Rico and the Virgin Islands, I transformed this wide data into a long data format. The updated data contains three columns: state, year, and minimum wage rates. Five US states: Alabama, Louisiana, Mississippi, South Carolina, and Tennessee have yet to adopt a state minimum wage; for these five states, I used the federal minimum wage rate. The minimum wage law in Arizona was enacted in 2006; for 1980-2006 in Arizona, I use the federal minimum wage rate. For Florida, Iowa, and Missouri, wage rate data was missing for the 1980-90 period due to absence of minimum wage rate laws: I use the federal minimum wage rate for the three states for this period. After transforming this dataset from a wide format to a long format, I was left with three columns: state, year, and minimum wage rate. The historical minimum wage rates are adjusted for inflation using the Consumer Product Index (CPI) by the US Department of Labor Statistics, with the base year as 1983.

All three datasets contain a few limitations that restrict the scope of this study. In terms of the dependent variable, residential carbon emissions are a proxy for consumption-based carbon emissions. More detailed data on consumption-based emissions, in addition to emissions by fossil fuel combustion at the residential level would have allowed for a more robust examination of the relationship between income inequality and consumption-based CO2 emissions. For both the carbon emissions and income inequality datasets, the geographical unit of analysis is a US state; having more detailed information about the within-state distribution, like at the district-level, would have allowed a more extensive investigation into within-state inequality and its effects on emissions. Finally, in the minimum wage dataset, utilizing the federal minimum wage rate for the five states without a minimum wage law might fail to capture the state effects of income and income inequality on carbon emissions in those five states.

The three datasets are merged on state and year to obtain the final dataset. The resulting dataset has 1989 rows over 8 columns: year, state, emissions, minimum wage rate, theil index, CPI, inflation adjusted minimum wage rate, and a categorical variable for region with four classes- Northeast (NE), South (SO), Midwest (MW), and West (WE).

Descriptive Statistics

	emissions	min_wage	adj_wage	theil
count	1989.000000	1989.000000	1989.000000	1989.000000
mean	6.879336	5.073962	2.938089	0.708330
std	8.019149	2.010401	0.548270	0.226273
min	0.000000	1.250000	0.899831	0.291326
25%	1.800000	3.350000	2.697897	0.574881
50%	3.400000	5.150000	2.960075	0.687277
75%	8.000000	7.100000	3.257944	0.815147
max	40.000000	13.250000	5.255529	1.498469

Table 1: Summary Statistics

Table 1 breaks down the summary statistics for emissions, minimum wage (unadjusted and inflation adjusted), and the theil inequality measure.

Looking at the emissions column, the minimum residential carbon emissions in the dataset is 0; the actual CO_2 emissions are not zero, but some of the observations are extremely small due to the unit of analysis being million metric tons of CO_2. The maximum emissions throughout the dataset, for all US states and the District of Columbia within the 1980-2018 period, was 40 million metric tons of CO_2. The average residential emissions for the entire dataset is approximately 7 million metric tons of CO_2. However, from figure 1, we can see that the average million metric tons of CO_2 varies immensely by year. Although the trend line in figure 1 shows that the average US carbon emissions have been decreasing over the years. But it is important to note here that the standard deviation for carbon emissions over the years is quite high: there is a lot of variation in the data. Thus, just by looking at the average carbon emissions over the years would not give us a good estimate for the overall carbon emissions in the US.

We further explore carbon emissions through figure 2: average carbon emissions for the period 1980-2018 for all US states. This visualization provides deeper insight into the emissions summary statistics in table 1. We see that New York has the highest average carbon emissions in the 1980-2018 period, whereas Hawaii has the lowest.

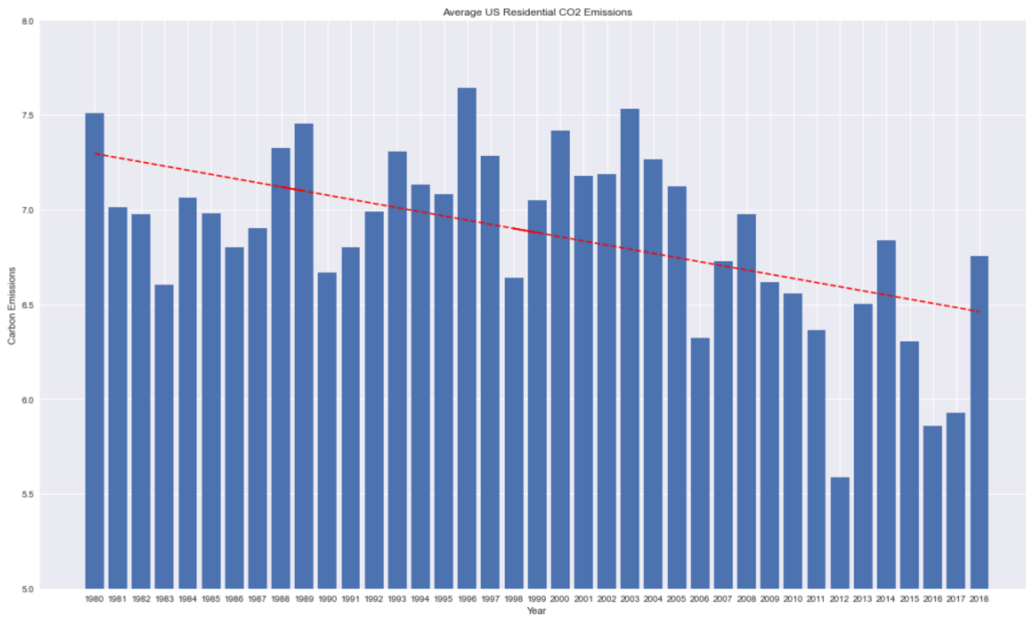

Figure 1: Average US Residential Carbon Emissions (1980-2018)

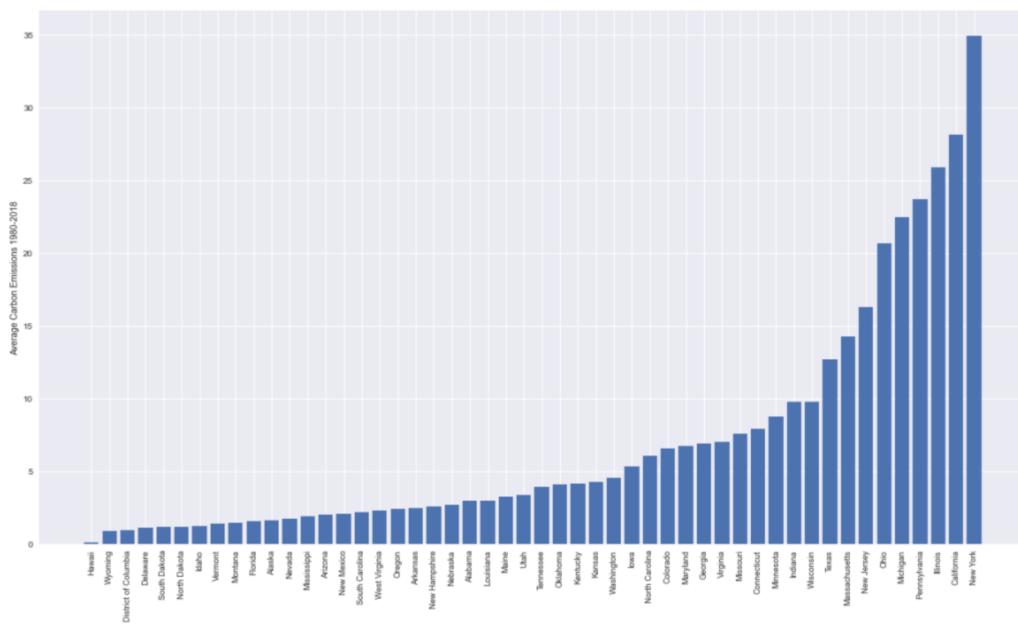

Figure 2: Average Carbon Emissions Between 1980 and 2018 by US states

Next, we compare the unadjusted and inflation adjusted minimum wage rate for all US states. The adj_wage variable is the inflation adjusted minimum wage rate for all US states, adjusted using the Consumer Price Index provided by the US Department of Labor. I used the 1983 CPI as the base CPI, since this is prescribed by the US DOL.

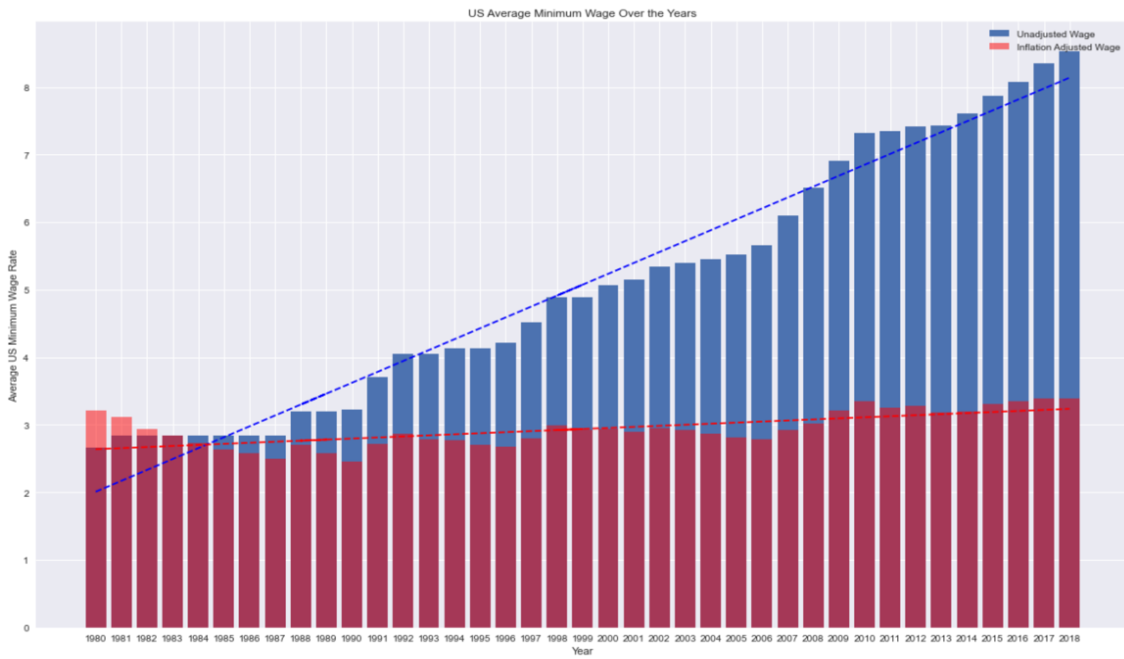

Figure 3: US Minimum Wage Over the Years (Adjusted & Unadjusted)

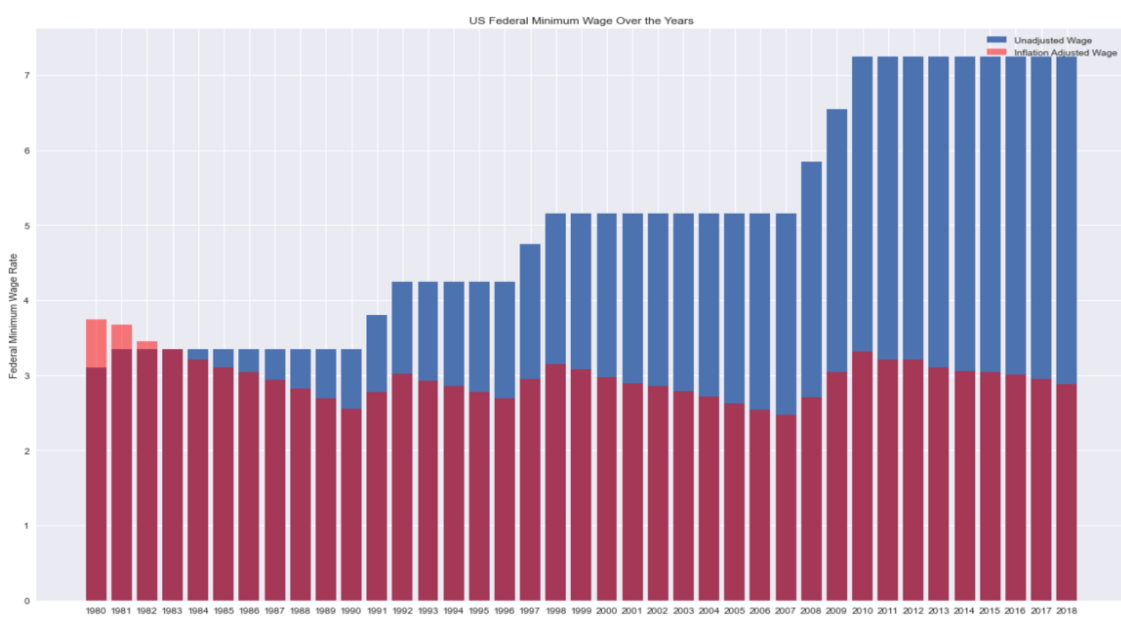

Figure 4: Federal Minimum Wage Rate (1980 - 2018)

Figure 3 compares the unadjusted and inflation adjusted average US minimum wage rate for the 1980-2018 period. The average minimum wage rate is the average for all US states, including the District of Columbia, and is different from the Federal minimum wage rate, which is depicted in figure 4. In figure 3, the unadjusted wage rate seems to be increasing over the years. But when we control it for inflation, we get a completely different picture: there is minimal increase in the US average minimum wage rate throughout the years. This difference in the unadjusted and adjusted minimum wage is visible through the trend lines: the blue trend line shows the changes in the unadjusted average US minimum wage rate, whereas the red trend line shows the changes in the inflation adjusted average US minimum wage rate. There is a stark difference between the two trend lines; the blue line is very steep and upward sloping, whereas the red trend line is almost flat. Similarly in figure 4, the unadjusted Federal minimum wage rate has progressively increased over the period of analysis but controlling it for inflation shows that the Federal minimum wage rate has just varied slightly around \$2.979 in the 1980-2018 period.

The Theil is a measure of income inequality; it ranges between 0 and ∞, where 0 represents a completely egalitarian society where everyone has the same income and higher values represent greater levels of inequality. In the dataset, the theil measure ranges from 0.29 to 1.50 units. This is an aggregated value for all the US states between 1980 to 2018. To get a more nuanced insight into this measure, we compare the theil measure between 1980 and 2018 in figure 5.

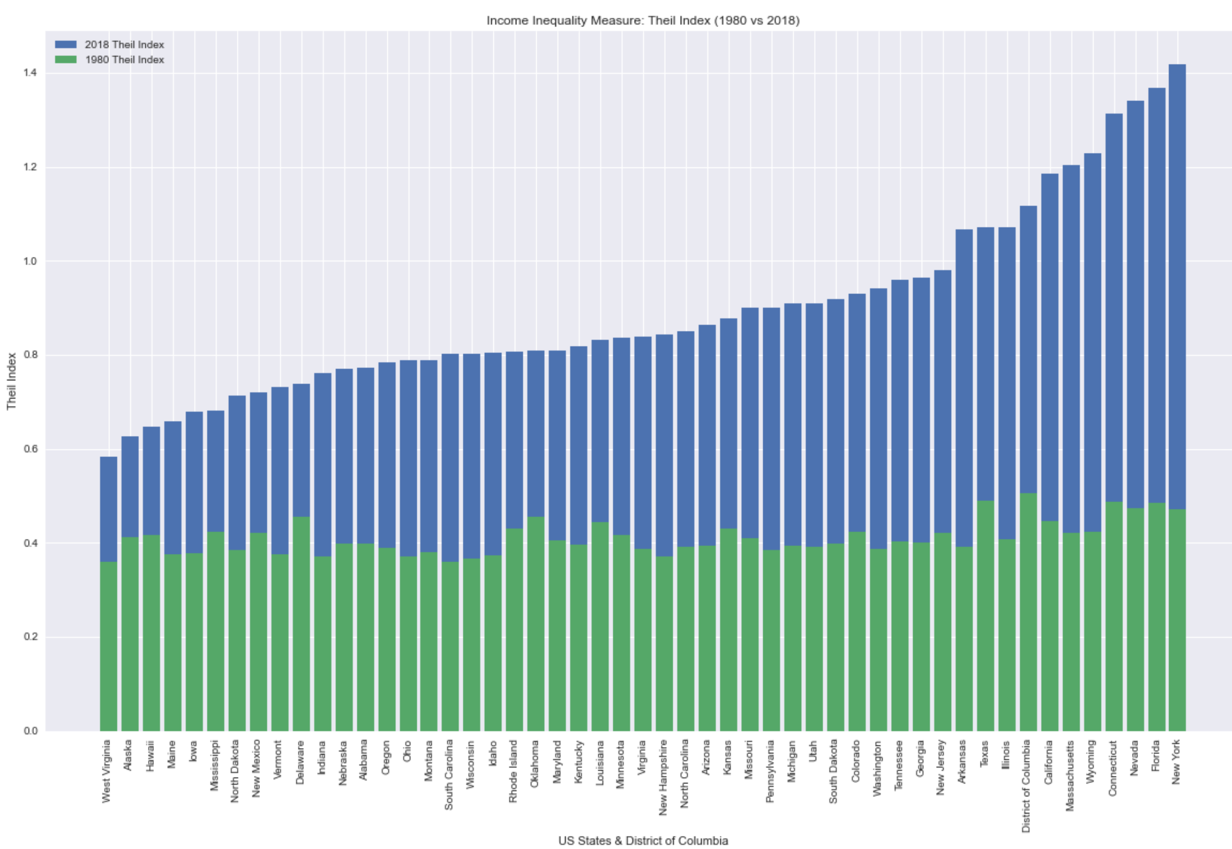

Figure 5: US Income Inequality by State (1980 vs. 2018)

In 1980, there was little variation in income inequality, as measured by the theil index, for all US states and the District of Columbia. In 2018, there is a massive variation in the within-state income inequality for all US states. In 2018, West Virginia had the least within-state income inequality (lowest Theil measure) in the US, whereas New York had the highest within-state income inequality in the US.

Initial Models

OLS Regression Results

Dep. Variable:	emissions	**R-squared:**	0.051
Model:	OLS	**Adj. R-squared:**	0.051
Method:	Least Squares	**F-statistic:**	107.3
Date:	Sun, 19 Dec 2021	**Prob (F-statistic):**	1.59e-24
Time:	22:40:43	**Log-Likelihood:**	-6910.2
No. Observations:	1989	**AIC:**	1.382e+04
Df Residuals:	1987	**BIC:**	1.384e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.1971	0.576	2.079	0.038	0.068	2.326
theil	8.0221	0.774	10.359	0.000	6.503	9.541

Omnibus:	615.641	**Durbin-Watson:**	0.083
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1483.297
Skew:	1.718	**Prob(JB):**	0.00
Kurtosis:	5.468	**Cond. No.**	6.72

Table 2: Initial Regression Model

Table 2 illustrates the regression of carbon emissions on income inequality as measured by the theil index. This model explains about 5% of the variation in the carbon emissions. This is a pooled OLS model that ignores the fact that this dataset contains information for the same observations over time, and considers all observations separately, regardless of year or state. In this model the intercept represents complete equality, where all individuals earn the same amount of income. The intercept can be interpreted as: on average, the million metric tons of CO_2 emitted - 1.97 million metric tons - if income inequality did not exist, that is, if the theil index was zero. The coefficient of theil can be interpreted as the change in million metric tons of carbon emissions with every additional unit increase in inequality, as measured by the theil index. This would be: with every additional unit increase in inequality as measured by the theil index, carbon emissions would increase by 8.02 million metric tons. Both the intercept and the variable seem to be statistically significant at the 5% level of significance.

The paper seeks to explore how changes to economic opportunities for people on the lower end of the income distribution affect carbon emissions. In order to do that, it is important to include minimum wage rates in the regression model. Additionally, just conducting a pooled OLS regression would fail to capture various fixed effects.

Final Model

To test whether a pooled OLS model is the most appropriate, I ran a test for heteroskedasticity in the model's errors using the Breusch-Pagan test (BP test). The BP test uses the simple size, the R-sq., and the number of independent variables to calculate a test-statistic, which tests for the presence of heteroskedasticity. It tests the null hypothesis (homoscedasticity of errors) against the alternative hypothesis (error variances are not equal) using this test-statistic. If the p-value for the test-statistic is smaller than 0.05, the null hypothesis is failed to reject, that is, the model is homoscedastic. I ran the BP test to get a p-value of 4.930731304978504e-20. The p-value is extremely small, and thus, we can conclude that this model is homoscedastic.

Next, I ran the Hausman test to test for endogeneity. The Hausman test tests the null hypothesis that there is no endogeneity against the alternative hypothesis, that endogeneity exists.[7] I stored the residuals from my initial model 1 and regressed the emissions again on the residuals (table 3). The p-value for the residuals is extremely small; the coefficient of the residual variable is statistically significant.

Dep. Variable:	emissions	**R-squared:**	0.949
Model:	OLS	**Adj. R-squared:**	0.949
Method:	Least Squares	**F-statistic:**	3.679e+04
Date:	Mon, 20 Dec 2021	**Prob (F-statistic):**	0.00
Time:	00:35:55	**Log-Likelihood:**	-4007.6
No. Observations:	1989	**AIC:**	8019.
Df Residuals:	1987	**BIC:**	8030.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	3.4397	0.020	168.980	0.000	3.400	3.480
con	3.4397	0.020	168.980	0.000	3.400	3.480
residual	1.0000	0.005	191.817	0.000	0.990	1.010

Omnibus:	158.040	**Durbin-Watson:**	0.208
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	204.932
Skew:	0.689	**Prob(JB):**	3.16e-45
Kurtosis:	3.758	**Cond. No.**	2.14e+17

Table 3: Running Hausman Test for Endogeneity

[7] https://www.kaggle.com/saraach/exercise1-hausman-test-to-investigate-endogeneity

Thus, we reject the null hypothesis and accept the alternative hypothesis that there is endogeneity in the dataset. Since the null hypothesis is rejected, a Fixed Effects model might be a better fit for this data. Thus, we include a categorical variable in our dataset -region. The region variable has four classes: Northeast (NE), South (SO), Midwest (MW), and West (WE). The next regression model includes the region variable to control for region fixed effects.

In the final model in table 4, we also include adj_wage, the inflation adjusted minimum wage rate in our model since we hope to examine how changes in the economic opportunities for people on the lower end of the income distribution would affect carbon emissions. We regress emissions on theil, adj_wage, and region.

Dep. Variable:	emissions	**R-squared:**	0.215
Model:	OLS	**Adj. R-squared:**	0.214
Method:	Least Squares	**F-statistic:**	108.9
Date:	Mon, 20 Dec 2021	**Prob (F-statistic):**	7.32e-102
Time:	01:12:02	**Log-Likelihood:**	-6721.2
No. Observations:	1989	**AIC:**	1.345e+04
Df Residuals:	1983	**BIC:**	1.349e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	6.8654	0.956	7.178	0.000	4.990	8.741
region[T.NE]	1.0234	0.525	1.950	0.051	-0.006	2.053
region[T.SO]	-6.1941	0.432	-14.350	0.000	-7.041	-5.348
region[T.WE]	-6.0683	0.460	-13.182	0.000	-6.971	-5.165
theil	8.1680	0.730	11.182	0.000	6.735	9.601
adj_wage	-0.7967	0.307	-2.596	0.009	-1.399	-0.195

Omnibus:	524.166	**Durbin-Watson:**	0.087
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1218.162
Skew:	1.458	**Prob(JB):**	3.02e-265
Kurtosis:	5.488	**Cond. No.**	21.2

Table 4: Final Regression Model: FE Model

The Adj. R-sq. jumped from 0.051 in the initial model to 0.215 in the final model; more of the variation in the dependent variable is being explained by the model. Additionally, all variables are statistically significant at the 1% significance level except for one of the classes of region - NE. The coefficient for region[T.NE] is statistically significant at the 10% significance level; the p-value is very slightly higher than 0.05. To compare the initial model and the final model, I ran a partial F-test.

Interpretation of final model coefficients:

Coefficients	**Interpretations**
Intercept (6.8654)	On average, holding all other variables constant, states in the Midwest with complete income equality as measured by the Theil Index and no minimum wage emit about 6.9 million metric tons of CO2.
region[T.NE] (1.0234)	On average, holding all other variables constant, with complete income equality as measured by the Theil Index and no minimum wage, states in the Northeast emit 1.0234 more million metric tons of CO2 than states in the Midwest do.
region[T.SO] (-6.1941)	On average, holding all other variables constant, with complete income equality as measured by the Theil Index and no minimum wage, states in the South emit about 6.2 less million metric tons of CO2 than states in the Midwest do.
region[T.WE] (-6.0683)	On average, holding all other variables constant, with complete income equality as measured by the Theil Index and no minimum wage, states in the West emit about 6.1 less million metric tons of CO2 than states in the Midwest do.
theil (8.1680)	On average, holding all other variables constant, every additional unit increase in income inequality as measured by the theil index is associated with an increase of 8.2 million metric tons of CO2 emissions.
adj_wage (-0.7967)	On average, holding all other variables constant, every additional unit increase in inflation adjusted minimum wage is associated with a reduction of about 0.8 million metric tons of CO2 emissions.

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
0	1987.0	121291.620185	0.0	NaN	NaN	NaN
1	1983.0	100292.204120	4.0	20999.416065	103.801293	2.373347e-80

Table 5: Partial F-test

The F statistic (103.801) is statistically significant as the associated p-value is less than 0.05. Thus, we can safely conclude that the final model is a better fit for our dataset than the original model. The partial F test supports the idea of including region and inflation adjusted minimum wage in the regression model.

This regression model supports my initial hypothesis; there is a positive relationship between income inequality and carbon emissions, and a negative relationship between minimum wage and carbon emissions. An increase in income inequality is associated with an increase in carbon emissions at the US state level, and an increase in the inflation adjusted minimum wage rate is associated with a decrease in CO_2 emissions.

Conclusion

This study aims to explore the relationship between minimum wage and income inequality, and consumption-based carbon emissions in the US. The final regression model was a fixed effects model with a dummy variable for the US region. A partial F-test was used to validate the results from the final model against the initial model.

According to the final regression model, there exists a positive relationship between income inequality as measured by the Theil Index and consumption-based carbon emissions; an increase in income inequality is associated with an increase in carbon emissions. Additionally, there exists a negative relationship between inflation adjusted minimum wage and carbon emissions; an increase in inflation adjusted minimum wage is associated with a decrease in carbon emissions. Both these results validate my initial hypothesis that an improvement in the economic opportunities for people on the lower end of the income distribution would lead to a reduction in consumption-based carbon emissions.

These positive results demand an in depth analysis of this relationship. Rapidly growing carbon emissions coupled with worsening income inequality prove to be a policy challenge for the decision makers, but even more so for people directly affected by these phenomena: those on the lower end of the income distribution. Strong policies that tackle both climate change and income inequality simultaneously are imperative. Consequently, these variables and this relationship requires much more research and analysis.

From this project, I learnt to transform a simple idea into a fully formed research project. There were multiple steps involved in this process that were not quite evident at the beginning of the project. The breadth of topics covered in lectures and through various labs prepared me well to tackle this project efficiently. Moving forward, I will reevaluate the scope of the project and also consider how I can expand my research further into a degree thesis.