Article

Climate Change and Economic Outcomes: a State-Level Analysis in the US

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Abstract
Growing economic inequality and increasing climate disruption are two major issues that are not always studied in accordance despite their interconnectedness. A better understanding of their relationship can help policy makers address both of these issues. Combining data from a study on city-level climate risk and readiness with data from the 2020 US Census, I run a series of OLS regressions to estimate the size effect of these two variables on 3 different economic outcomes. Although further research is required to establish causality, my findings suggest climate risk and unemployment rates are associated, in turn suggesting that policy-makers consider tackling both issues simultaneously.

Keywords: Climate Change; Inequality; Unemployment; USA

1. Introduction

This paper explores the intersection of two widely researched topics: the economic impacts of climate change and geographic inequality of incomes. By combining the data of a study on variations in climate change risk and preparation across United States cities (Chen et al., 2015) with socio-economic state-level data from the 2020 Census, the paper aims to estimate the contributions of climate change to economic inequality in the US.

2. Literature review

2.1. Income inequality in the US: national and geographic trends

2.1.1. Rising income inequality in the United States

Using data from income tax returns and national accounts, Piketty and Saez (2014) find that income inequality in the United States has followed a U-shaped pattern over the last century. The share of pre-tax income belonging to the highest 10% fell from 45% in 1910 to 35% in the 1960s, and started rising in the early 1970s to reach a record-level of nearly 50% in 2010. In contrast, the same measure of income inequality in Europe, which started the 20th century at higher levels than the US, neighbours 35% nowadays. Panel A of figure 1 illustrates US and Europe trends in income inequality, in particular, it shows how their paths significantly deviated from one another from the 1970s onward.

2.1.2. Geographic pattern to income inequality

The Brookings Institution, an American research group, studied the evolution of various economic indicators over the last century, as part of a paper on “the geography of prosperity” (Nunn, Parsons and Shambaugh, 2018). With regard to income per capita, there are significant differences across regions of the US, with areas such as New England and the Mideast consistently scoring higher than the Southwest and Southeast. Similarly to the evolution of national income inequality, the authors find that geographic inequality has followed a U-shaped pattern since the start of the 20th century. Differences between regions fell between 1930 and 1980 but have gradually risen since the 1980s. Over this latter period, income per capita in New England rose from 105% to 125% of the national average, while that of the Southwest fell from 98% to 90%. Panel B of figure 1 illustrates these regional trends. The parallel with panel A illustrates how both overall inequality and geographic inequality in the US have followed similar time trends.

2.2 Climate change risk and readiness across cities

2.2.1 Around the world

In an increasingly urbanised world, with two-thirds of the global population expected to live in cities by 2050 (Guilyardi et al., 2018), no city is immune to climate risks. The Carbon Disclosure Project, a non-profit organisation, found the five most common climate risks among a sample of 620 studies to be flooding, heat waves, rainstorms, extreme temperatures, and droughts (2019). For every city, they calculate a “hazard score” (HS) which increases with the amount of climate risks and the severity of the threat. For instance, Santiago, Chile (HS=5) has relatively few climate risks while Sydney, Australia (HS=27) is much more vulnerable. In both the short and long-run, the authors find that these risks threaten to exacerbate pre-existing social and economic challenges such as access to healthcare and social services, prevalence of diseases, and unemployment (CDP, 2019).

2.2.2. Across the United States

The Notre Dame Global Adaptation Initiative (2015) ranked the 270 US cities with a population of 100,000 and above according to climate change vulnerability, and readiness scores. Risk is an index of a city’s adaptive capacity (e.g., water quality, insurance coverage), sensitivity (e.g., access to vehicle, housing quality) and exposure (e.g., percentage of high-risk flood zones). Readiness is an index of a city’s economic (e.g., debt per inhabitant), governance (e.g., percentage of climate change deniers) and social (e.g., civic engagement) readiness against climate change. Cities such as Seattle (WA) which score high on readiness and low on vulnerability will be less impacted by climate change than cities such as Newark (NJ) which score low on readiness and high on vulnerability. In addition to highlighting significant differences in climate vulnerability and

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readiness across US cities, the data also shows a negative correlation between the two indices. In other words, cities with the greatest climate threats are also those that are the least prepared to face them. The composition of the two variables is represented in figure 2.

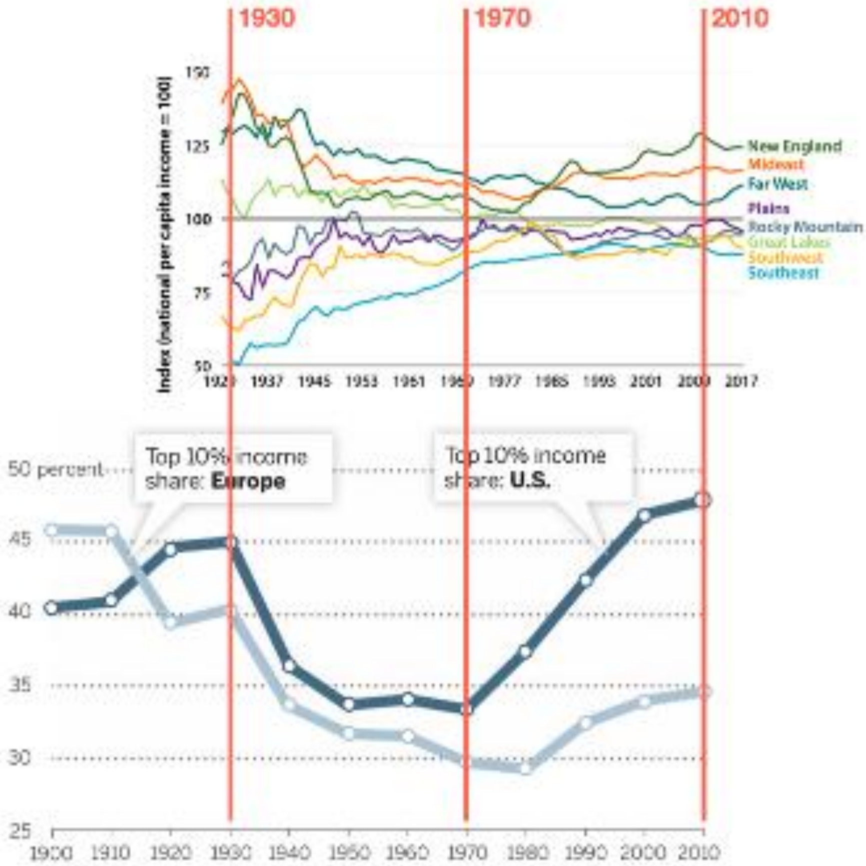

Figure 1(A): US Regional Relative Per Capita Income (Nunn, Parsons and Shambaugh, 2018) (Upper Panel); *Figure 1(B):* Share of Top Income Decile in Total Pretax Income (Piketty and Sae) (Lower Panel)

2.3. Climate change and inequality

2.3.1 Climate change and inequality between countries

Climate change and inequality have traditionally been studied separately, yet they are firmly linked to each other. On the one hand, climate change exacerbates poverty and inequality, both within and between countries. For instance, one channel via which climate change impacts world inequality is through global warming. Diffenbaugh & Burke find that, because growth is highest when temperatures are moderate, global warming boosts the economies of cold and wealthy nations while harming those of tropical, and impoverished ones. They further estimate that around a quarter of between-country inequality today is explained by this dual effect of global warming. On the other hand, inequality and climate change are linked in that countries' historical contributions to climate change are highly unequal, with the US alone having contributed 60% of today's climate change (Evans, 2021).

2.3.2. Climate change and inequality between cities

Through the channels identified by the CDP's study (2019), variations in cities' levels of vulnerability and readiness towards climate change can translate into different economic outcomes at the city level, hence explaining some of the inequality between US cities observed by Nunn, Parsons and Shambaugh (2018). Similarly to Diffenbaugh & Burke's (2019) work on countries, the aim of this paper is to quantify the respective effects of climate change vulnerability and readiness on cities' economic outcomes, and subsequently estimate how much geographic inequality has resulted, and might result, from these factors. One obstacle to this analysis is the possible existence of reverse causality (i.e., economic outcomes might affect cities' levels of vulnerability and readiness).

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3. Data

3.1. Variables

This paper seeks to evaluate the overall effect of climate change on economic outcomes. Climate change is a complex phenomenon whose effects, both direct and indirect, happen at various levels. For this reason, it is difficult to quantify such a concept. As mentioned in section 2.2, the Urban Adaptation Assessment, led by the Notre Dame Global Adaptation Initiative by Chen et al. (2015) ranks the 270 largest US cities according to climate change risk (*Risk*) and readiness (*Readiness*).

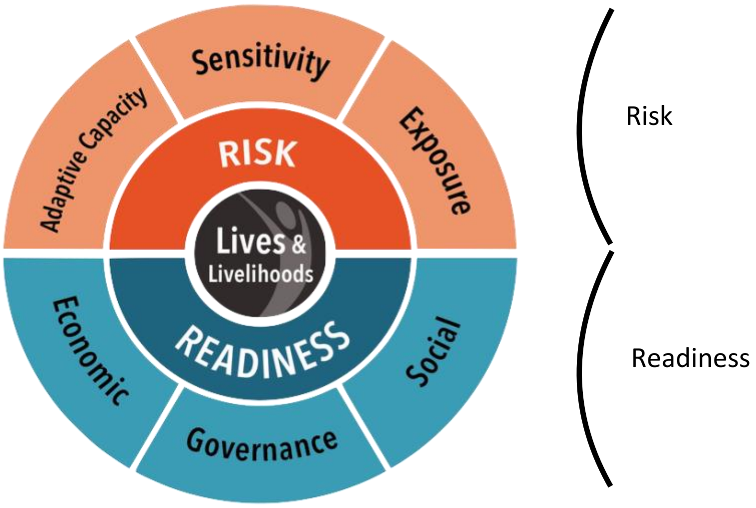

Figure 2: The components of Risk and Readiness (Nunn, Parsons and Shambaugh, 2018)

The rest of the data comes from the 2020 United States Census [census.gov] which was collected during the Covid-19 pandemic and marked the 24th census in US history. The census provides state-level data (including Washington DC) on a range of economic, social, housing and demographic factors, from which I was able to construct new variables better suited for my analysis. I will be looking at state median household incomes, unemployment rates and poverty rates. Other variables from the Census serve as controls. Table 1 lists the variables included in my study, alongside their label and source. Additionally, the variable *State_Code* denotes individual observations.

Variable	Label	Source
Climate Change		
Risk	Average climate change risk score for cities belonging to state	Nunn, Parsons and Shambaugh, 2018
Readiness	Average climate change readiness score for cities belonging to state	Nunn, Parsons and Shambaugh, 2018
Economic		
Median_Fam_Inc	Median family income in the past 12 months (in 2020 inflation-adjusted dollars)	US Census 2020
Unemployment	Ratio of unemployed civilian labour force to civilian labour force in state	Constructed from US Census 2020
Poverty_rate	Share of population with income below poverty line in state	Constructed from US Census 2020
Private_HU	Share of the population with private health insurance in state	Constructed from US Census 2020

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Variable	Label	Source
Social		
High_School	Share of the population over 25 that has at least graduated from high school in state	Constructed from US Census 2020
College	Share of the population over 25 that has graduated from college in state	Constructed from US Census 2020
Spanish_HH	Share of Spanish speaking HH, with or without limited English speaking in state	Constructed from US Census 2020
Limited_English_HH	Share of HH with limited English speaking in state	Constructed from US Census 2020
Computer_access	Share of households with access to a computer in state	Constructed from US Census 2020
Demographic		
Population	Population in state	US Census 2020
Sex_ratio	Male to female ratio in state	Constructed from US Census 2020
Married_Couple_Fam	Share of own children under 18 living in married-couple families	Constructed from US Census 2020
Share_pop_under_18	Ratio of population under 18 years of age to total population in state	Constructed from US Census 2020
Race_1 to Race_7	7 variables corresponding to the share of population identifying as (1) White alone, (2) Black or African American alone, (3) American Indian and Alaska native alone, (4) Asian, (5) native Hawaiian and other Pacific Islander alone, (6) some other race alone and (7) two or more races, in state	Constructed from US Census 2020
Occupation_1 to Occupation_5	5 variables corresponding to the share of civilian employed population 16 years and over working in (1) management, business, science, and arts occupations, (2) service occupations, (3) sales and office occupations, (4) natural resources, construction, and maintenance occupations and (5) production, transportation, and material moving occupations, in state	Constructed from US Census 2020

Table 1: List of variables with label and source

3.2. Discussion on Data

My original idea for socio-economic outcomes was to look at city-level data by Nunn, Parsons and Shambaugh (2018) who constructed a "prosperity index" for a large sample of cities based off 6 socio-economic factors (median household income, poverty rate, unemployment rate, adult employment rate, house vacancy rate and life expectancy). However, the study by Nunn, Parsons and Shambaugh (2018) is at the county level, while the work of Chen et al. (2015) defined cities as a metropolitan area which could correspond to a part of a county or encompass multiple counties. This caused two problems: firstly, it made it impossible to have STATA append the data, secondly it made comparisons inaccurate. After an attempt to manually append the two datasets, I decided to use state-level data from the 2020 Census. In turn, this meant transforming

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the data on climate change from the city-level to the state-level as an average of cities included in the dataset belonging to each state. Transposing data from the city level to the state level requires strong assumptions (developed in a section 5.3). A future project could directly include state-level data, so far I was not able to find a study assessing both risk and readiness for each state.

Furthermore, I have dropped data from Puerto Rico as it is not a part of the 2020 Census, as well as DC because it is an outlier with regard to many factors (e.g., GDP per capita much higher than any state). Using the software STATA, I used ordinary least squares (OLS) regression to analyse the potential climate predictors of three economic outcomes (median household incomes, unemployment rates, and poverty rates).

4. Model

Using the software STATA, I ran 3 sets of ordinary least squares (OLS) regressions to analyse the potential climate predictors of the 3 economic outcomes I considered. OLS minimises the sum of squared residuals between the true data and their linear estimation.

For each of the three explanatory variables, I ran a first regression without any controls, and a second with controls, as follows:

$$y = \beta_1 \cdot \mathit{Risk} + \beta_2 \cdot \mathit{Readiness} \qquad (1)$$

$$y = \beta_1 \cdot \mathit{Risk} + \beta_2 \cdot \mathit{Readiness} + X \cdot \beta_X + \epsilon \qquad (2)$$

Where:

- y consecutively corresponds to *Median_Fam_Inc*, *Unemployment* and *Poverty_rate*, the explained variables
- *Risk* and *Readiness* are the explanatory variables
- X is a matrix containing all the remaining variables from Table 1
- β_1, β_2 and β_X are the respective estimated coefficients for *Risk*, *Readiness* and the X matrix
- ϵ is the error term

The basic assumptions of OLS are correct specification, strict exogeneity, no linear dependence and spherical error.

5. Results

5.1. Scatterplots

For US states, a higher climate change risk score is correlated with higher median family income, higher unemployment, and lower poverty rates. Specifically, one extra point is associated with an extra $93514 (SE: 18442) median family income, a 0.05 (SE: 0.017) increase in the unemployment rate, and a 0.09 (SE: 0.036) decrease in the poverty rate.

Apart from unemployment, higher climate risk therefore correlates with better economic outcomes - a surprising finding given one might expect poorer people to live in more exposed areas due to self-selection of wealthier people into safer areas. Perhaps this correlation captures the effect of other covariates. Figure 3 plots fitted values of these variables for different levels of Risk. Higher climate readiness has little correlation with median family incomes. This is surprising as one would expect wealthier areas to invest more in protection against climate risks, however this might be counterweighted if wealthier individuals self-selected in safer areas. Higher readiness is associated with lower unemployment rates and slightly associated with lower poverty rates. Specifically, one extra point is associated with a $947 (SE: 29555) decrease in median household income, a 0.06 (SE: 0.0235) decrease in the unemployment rate and a 0.029 (SE: 0.49) decrease in poverty rate. Figure 4 plots fitted values of these variables for different levels of Readiness.

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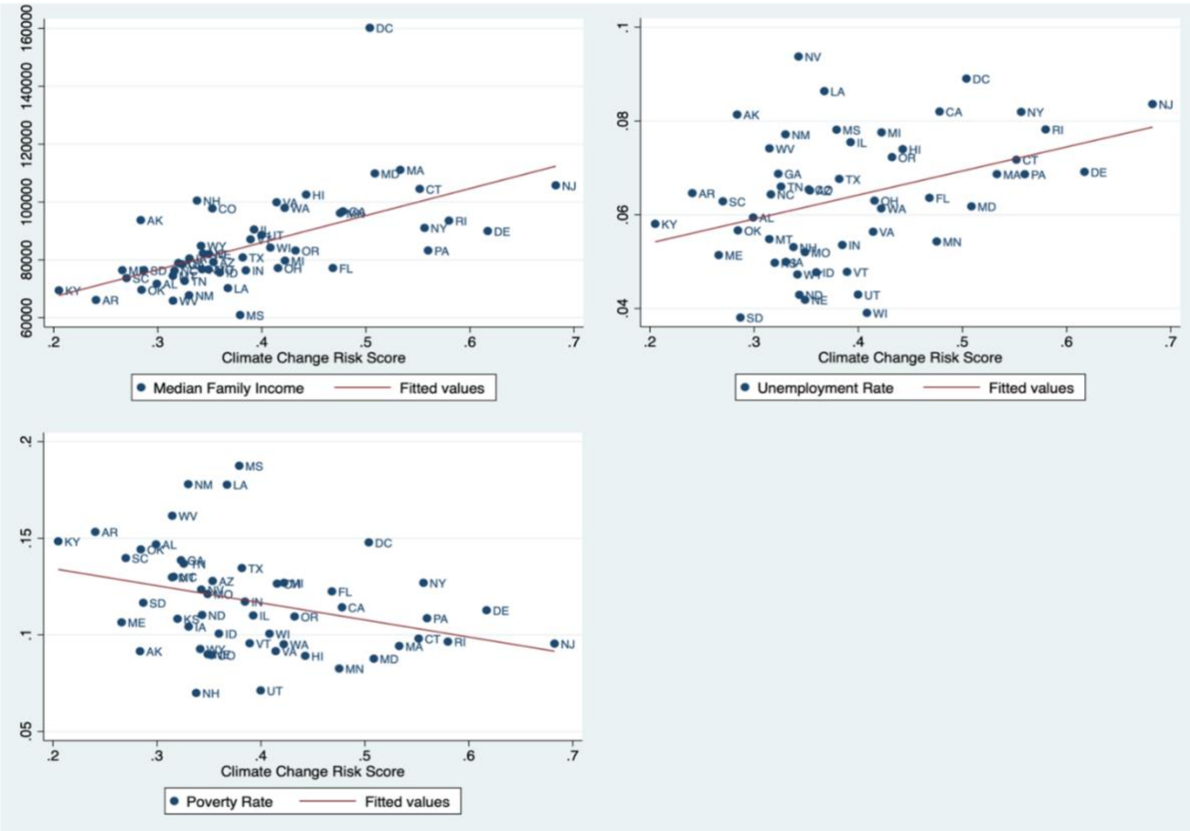

Figure 3: Climate change risk and economic outcomes

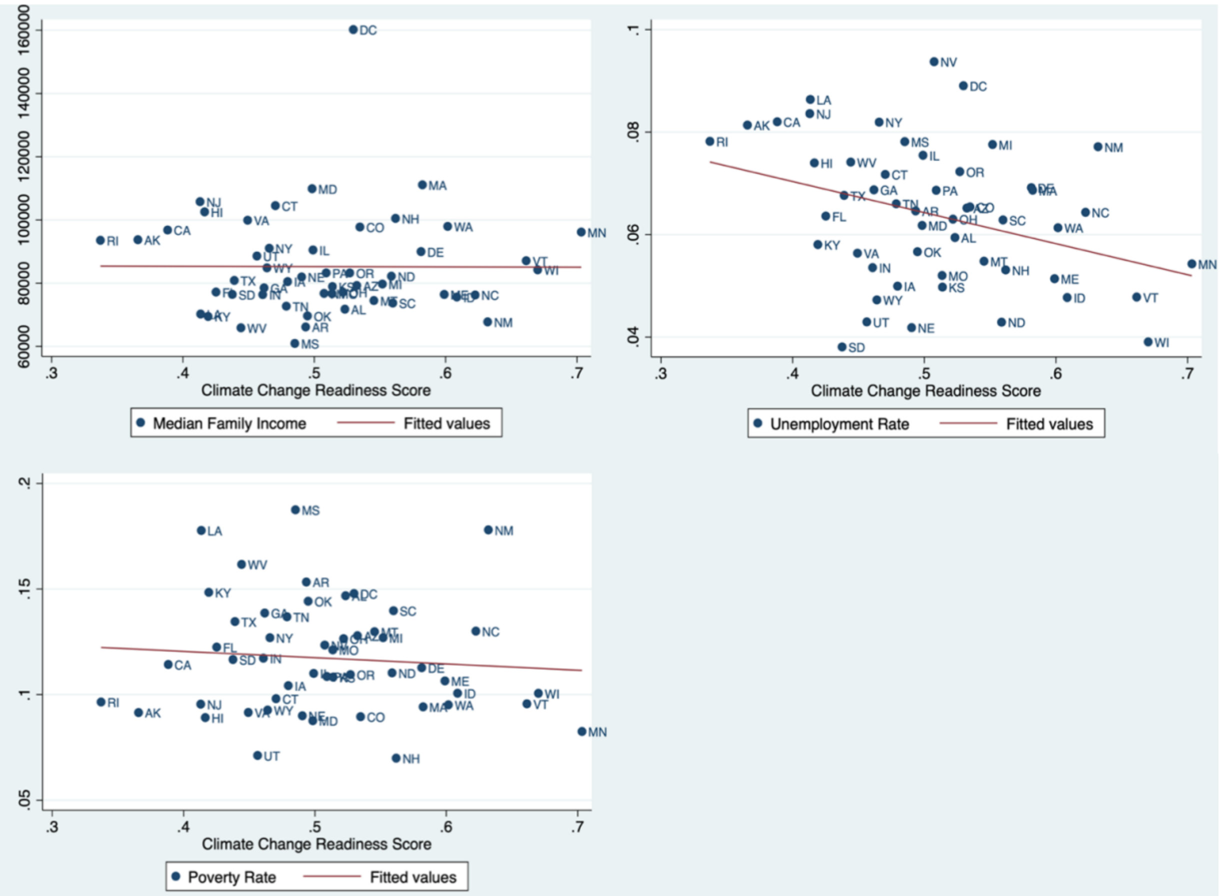

Figure 4: Climate change readiness and economic outcomes

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5.2. Linear regressions

The goal of this section is to estimate how state-level climate scores (i.e., *risk* and *readiness*) impact economic outcomes such as median family incomes, unemployment rates and poverty rates. Tables 2, 3 and 4 repetitively show the results of 2 multiple linear regressions for median family income, unemployment rate and poverty rates as dependent variables. In the 3 tables, the independent variables are (1) risk and readiness and (2) all the variables.

Independent variable	**(1)**	**(2)**
Constant	43894.94*** (14928.18)	7974.365 (256051.6)
Risk	94054.6*** (18668.1)	1878.729 (9762.391)
Readiness	8789.484 (24228.32)	-10462.24 (9426.649)
Only the variables from the Census that are significant at 10% are reported		
Private_HU	-	59454.58** (27254.35)
College	-	-71383* (40726)
Computer_access	-	223066.6*** (73805.55)
Race_1 (white alone)	-	-444433.2** (215153)
Race_2 (black alone)	-	-409798.7* (212761.8)
Race_3 (native alone)	-	-402281.3* (205097.3)
Race_6 (other alone)	-	-410149.7* (209564.3)
Race_7 (mixed race)	-	-544276.2** (243958.3)
Occupation_1 (management, business, science, and arts occupations)	-	288799.4*** (73692.98)
Share_pop_under_18	-	-180925.3** (76748.71)

Table 2: OLS results with *Median Family Income* as dependent variable (standard errors in brackets)
* significant at 10%, ** significant at 5%, *** significant at 1%

Independent variable	**(1)**	**(2)**
Constant	.0733474*** (.0136459)	-.7178007 (.5074005)
Risk	.0478172*** (.0170646)	.0332551* (.0190021)
Readiness	-.0556861** (.0221472)	-.0155255 (.0196043)
Only the variables from the Census that are significant at 10% are reported		
Sex_ratio	-	1.276013*** (.4473252)

Table 3: OLS results with *Unemployment* as dependent variable (standard errors in brackets)
* significant at 10%, ** significant at 5%, *** significant at 1%

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Independent variable	(1)	(2)
Constant	0.1728606*** (0.0286775)	2.149898*** (0.6415435)
Risk	-.0910554** (0.035862)	-0.0167751 (0.0291044)
Readiness	-0.0391109 (0.0465433)	0.0071954 (0.0288896)
Only the variables from the Census that are significant at 10% are reported		
Private_HU	-	-0.1517957* (0.0837421)

Table 4: OLS results with *Poverty Rate* as dependent variable (standard errors in brackets)
* significant at 10%, ** significant at 5%, *** significant at 1%

Firstly, we can note that the results between columns (1) and (2) change considerably, reflecting the fact that the economic outcomes considered here are explained by many variables other than climate risk and readiness. Secondly, we can also note that it is not the same variables that significantly explain the 3 economic outcomes.

In the first regression (1), *Risk* is found to be a significant (at 10% or less) predictor of the economic outcomes I consider while *Readiness* is only significant for unemployment. Such significance disappears, however, when controlling for more Census data in the second regression (2). However, there is one exception: although its size effect diminished, *Risk* is still found to significantly affect unemployment rates in a state. Specifically, a 1 unit increase in the score (higher risk) is associated with a 0.0332551 increase in the unemployment rate. Surprisingly enough, out of the 26 independent variables considered, *risk* is the variable with the highest significance in predicting unemployment (with only one other variable - the share of people on private healthcare - found to be significant).

If regression (2) were to control for all covariates likely to influence estimations of the size effect of *Risk* on *Unemployment*, we could conclude that living in a state whose main cities are more exposed to climate risk leads to higher unemployment rates. However, the *Risk* variable is comprised of many factors (e.g., water quality, access to vehicle) which could each indirectly correlate with unemployment. In a future project, I would have to look at these elements individually.

6. Discussion

6.1. Implications for Policy Making

Under the assumptions laid out throughout the paper, higher exposure to climate risk in its main cities is associated with a higher state unemployment rate. Although it is impossible to establish a causal relation, this finding does provide descriptive evidence towards a possible causal chain, highlighting how interconnected environmental and economic issues are, and suggests both issues can be tackled simultaneously. If we could establish a clear causality using more elaborate econometric analysis, this would suggest that some of the economic cost of increased spending against climate change can be mitigated by savings on unemployment benefits, for instance. Furthermore, tackling these two issues together can create positive feedback. In fact, Benegal (2018) finds that lower local unemployment rates lead to a reduced likelihood of being a climate change denier, among Americans identifying as either Republicans and Democrats.

6.2. Study Limits and Further Research

6.2.1. Cities and States

An important assumption was made in section 3 when I created state-level variables from city-level data. This assumed cities within a state shared some correlation for climate risk and readiness, which is not necessarily the case:

- In the case of *Risk*, cities from the same state are geographically closer to each other, and thus share certain characteristics that could affect Risk (e.g., latitude). However, many geographic characteristics depend on other factors (e.g., proximity to the coast affects the likelihood of flooding).
- In the case of *Readiness*, many policies are decided at a state level (for instance, education policy which in turn impacts beliefs about climate change). However, there can be sharp differences between cities. In fact, drawing the parallel with political opinions, the county-level results of the 2016 Trump vs Clinton presidential election show a much sharper contrast between coastal and rural areas than between states. In fact, most states contain counties who

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voted for both parties (Carpenter, Brauer and Niedenthal, 2020).

There are therefore some elements to support my choice to transpose data from the city level to the state level. However, further research that only focuses on the city level would yield more accurate results.

6.2.2. Impact on Inequality

The extent to which the impact of climate risk on unemployment affects inequality levels deserves further investigation. This is something similar to the work done by Diffenbaugh & Burke (2019). By using the relationship between temperature and growth identified by Burke, Hsiang & Miguel (2015) and creating counterfactual levels of growth, the authors estimated how much this effect contributed to between-country income inequality. A similar method could use the relationship between climate risk and state unemployment rates to estimate how much "unemployment inequality" is linked to between-state variations in climate risk.

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