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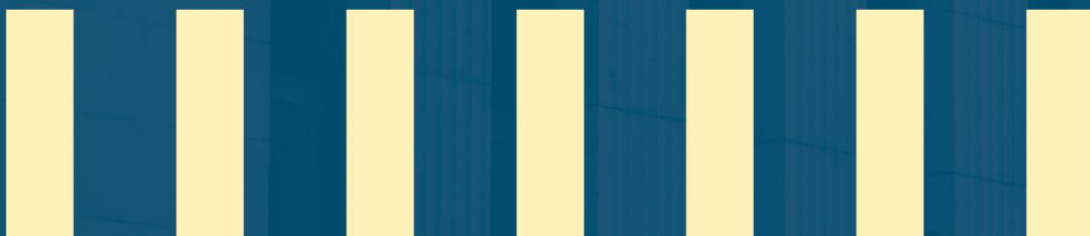

Climate change and socio-economic inequality in the US*

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Abstract

In this paper, we study the effects of climate change on income inequality in the United States. To do so, we characterize climate change in the US and introduce the climate-inequality vector autoregression (VAR). Constructing a data set of daily temperatures for the contiguous US from 1920–2019, we document that climate change is more than a phenomenon that increases mean temperatures since the whole temperature distribution has shifted asymmetrically, with temperatures in lower percentiles increasing at a faster rate than those in higher percentiles for most US states. Using the climate-inequality VAR, we estimate the effects of climate change on income inequality by identifying shocks to temperature distribution characteristics (such as mean and percentiles) via a combination of zero and sign restrictions. We find that the effects of climate change on income inequality not only vary across temperature distribution characteristics, but also vary widely across US states. We find both negative and positive impacts on within-state inequality across the US. There is no strong link between a state's climate or per capita income and the within-state effects on income inequality once we consider effects due to changes across the several temperature percentiles.

JEL Classification: Q54, D63, C32, C11

Keywords: Climate change, Temperature distribution, Inequality, SVAR

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1 Introduction

Climate change is one of the biggest challenges facing societies worldwide. As temperatures rise, droughts, wildfires, storms, and other disasters occur more frequently and increase in severity. Hence, understanding the socio-economic effects of higher temperatures is crucial for societies to be able to adapt to and mitigate effectively.

At the same time, climatologists' definition of climate looks at the full weather distribution and its characteristics. Climate change manifests not only as an increase in mean temperatures but also as changes in other characteristics of the temperature distribution, such as higher moments or percentiles (see IPCC, 2014). Taking into account trends in different characteristics of the temperature distribution and their interaction is fundamental for analysing the socio-economic effects of climate change.

In this paper, we ask the following two questions: What type of climate change exists in the US? What are the effects on income inequality within the US? We address these questions by making two important contributions to the climate-economy literature. First, we characterize climate change in the US and analyze trends in the characteristics of temperature distributions across the contiguous US states. Second, we introduce a unified empirical framework that allows us to assess the effects of changes in temperature distribution characteristics both individually and jointly. Specifically, we introduce the climate-inequality vector autoregression (VAR) to endogenously model inequality and several temperature characteristics for each US state. To estimate the effects on inequality, we identify shocks to the temperature distribution characteristics via a combination of zero and sign restrictions.

While our approach can be used to study the effects of climate change on any (economic) variable of interest, we focus on the effects on income inequality across and within US states. Understanding the distributional impact of climate change on income—vital to assess the burden on the most vulnerable—is in its early phases. The climate-economy literature typically focuses on the effects of climate change on economic growth (see, e.g., Dell et al., 2014; Bansal et al., 2016; Hsiang et al., 2017; Fan et al., 2018; Kahn et al., 2021; Bilal and Känzig, 2024, among many others). Despite being a fundamental determinant of poverty, economic growth is not the only channel through which climate change can affect poverty. One can imagine a scenario where only the poorest are affected by climate change, in which case GDP would barely change but poverty would dramatically. These works, therefore, offer no insight regarding the distributional implications of these gains/losses among the population.

The literature that looks at the distributional effects of climate change has been mainly concerned with the distribution across rich and poor countries. It is largely documented that poorer (and generally hotter) countries are more vulnerable to climate change and experience more negative impacts of climate change, thus exacerbating global inequality (see, e.g., Burke and Tanutama, 2019; Diffenbaugh and Burke, 2019; Acevedo et al., 2020; Tol, 2021; Paglialunga et al., 2022). Further, productivity is often assumed to be lower in countries with a hotter climate, fueling inequality across countries. Letta and Tol (2019) show that higher temperatures affect productivity only in poor countries.[1] Heal and Park (2013) find that hotter-than-average years lead to lower productivity in already hot countries and find the reverse effect in colder countries, in which hot years are associated with increased productivity.

It is unclear how these findings translate to the US context and within-country inequality. That is, a priori, it is not clear whether hotter and poorer regions of the US are more vulnerable to and affected more by climate change and which economic mechanisms matter. To that extent, Burke and Tanutama (2019) show that temperature exposure and income are much less correlated across districts within the same country (including the US). Moreover, the relation between income and temperatures shows non-linearities—that is, after a certain temperature threshold (around 13°Celsius) the relationship between income and temperature turns from positive to negative (see, e.g., Burke et al., 2015; Nath et al., 2024). Further, US economic activity is mostly based in places with air conditioning, thus hotter temperatures potentially do not disrupt productivity as much.[2]

The bulk of the above-mentioned works are based on cross-country analyses and assess the effects of higher annual mean temperatures. We contribute along the following dimensions. First, we advance the existing literature by modeling climate change in a holistic way using all characteristics of the weather distribution, instead of focusing on the change in mean temperatures only. To do so, we start by constructing a data set of daily temperatures over the past century covering the contiguous US. This allows us to obtain annual temperature distributions for each US state from which we extract several characteristics (such as mean, higher moments, and percentiles).[3] We analyze how these characteristics, and thus the temperature distribution, have changed over time.

Second, with these insights in mind, we estimate the effects of changes in these characteristics (e.g.,

[1]Negative impacts of higher temperatures on worker productivity are also documented in Adhvaryu et al. (2020) and Somanathan et al. (2021) for Indian manufacturers.

[2]As of 2020, 88 percent of US homes use some type of air conditioning, and 66 percent have central air conditioning installed.

[3]Similarly, Chang et al. (2020) and Gadea-Rivas and Gonzalo (2020) assess trends in the distributional characteristics of global temperatures. We expand their analysis to US states.

increases in temperatures in the mean, upper, and lower percentiles) on income inequality within the US. Considering changes in different distributional temperature characteristics, we also contribute to the limited but growing literature that argues that seasonal temperatures are a better approximation of climate than annual mean temperatures since temperature can vary greatly within a year (see, e.g., Wilson, 2019; Colacito et al., 2019; Nguyen, 2024). In our case, we can think of, for example, changes in temperatures in the low (high) percentiles—low (high) temperatures—reflecting changes in extreme cold (hot) weather, which can be associated with winters (summers). Colacito et al. (2019) and Nguyen (2024) analyze the economic effects of changes in seasonal temperatures and find opposing seasonal effects. Colacito et al. (2019) find negative effects on output and productivity in response to higher summer (extreme hot weather) temperatures, while the reverse is true for higher fall (chilly weather) temperatures. Similarly, Nguyen (2024) finds that higher winter temperatures increase employment, while higher summer temperatures decrease it. However, these papers consider equal temperature increases across seasons and do not allow for the possibility that warming occurs asymmetrically—that is, winters (extreme cold temperatures) may warm up faster than summers (extreme hot temperatures). We model temperature characteristics both individually and jointly, with the latter capturing the endogenous relationships among the seasonal temperatures. This allows us to take into account asymmetric changes in the temperature distribution.

Finally, we contribute to the scant literature analyzing within-country effects of climate change. The US has several climate zones, and therefore temperatures vary widely across the country. To the best of our knowledge, Nguyen (2024) is the only paper that explores the economic impacts of climate change across US states. They show that employment effects vary widely across states in response to increases in seasonal temperatures. For example, while on aggregate higher summer temperature decrease employment, employment in several states actually increases.[4] By estimating state-specific VARs, we can analyze the effects of climate change on inequality within the contiguous US states.

Our findings are twofold. First, we document that climate change is more than a phenomenon that increases mean temperatures since the whole temperature distribution has shifted asymmetrically in the US. Specifically, while US-wide average temperatures have risen by 0.020°C per year over 1960–2019, we also observe significant increases in all the percentiles of the temperature distribution, with temperatures

[4] In a recent work, Kim (2024) finds heterogeneous temperature effects on real GDP growth and inflation across seasons and states within the US. We note, however, that they rely on a restricted sample not including all contiguous US states in their analysis.

in the lower percentiles increasing at a faster rate than those in the mean and in the upper percentiles. This suggests that US-wide extreme cold temperatures are warming up faster than hot ones.[5] Moreover, trends in the standard deviation and skewness of the temperature distribution are negative and positive, respectively (albeit insignificant). Therefore, climate change in the US is not only a phenomenon of an increase in the average temperature but also of a larger increase in lower temperatures, leading to an asymmetric change in the temperature distribution.

Turning to the spatial distribution of warming across US states, we find that the rate of temperature increases varies not only across temperature distribution characteristics (as for the US aggregate) but also widely across states. For most of the contiguous US states, lower temperatures have been increasing at a faster rate than higher temperatures. However, there are a few states where the opposite is true. For example, in California the temperatures in the mean and upper percentiles seem to have grown at a somewhat faster pace than temperatures in the 5th or 1st percentiles, suggesting that warming has been more pronounced for hot and mild temperatures.

Second, we show that the effects of climate change on income inequality vary not only across temperature distribution characteristics but also widely across US states. Motivated by the trends in income inequality in the US since the 1970s—where the income going to the wealthiest has been growing consistently faster than that of middle-income groups, which has remained rather stable—we focus our analysis on the top percent income share as indicators of inequality (see, e.g., Piketty et al., 2017; Chu and Wang, 2021, among others). We start by assessing the effects of individual temperature distribution characteristics on US-wide income inequality (i.e., including income inequality and one temperature characteristic in the climate-inequality VAR). While higher mean temperatures do not affect income inequality, temperature increases in certain percentiles do. For example, warmer extreme cold temperatures (1st and 5th percentiles) contribute to a persistent decrease in inequality, while warmer chilly temperatures (temperatures in the 20th percentile) increase it. If we were to focus our analysis on mean temperatures only, we would miss the distinct effects of changes in different percentiles of the temperature distribution. Further, we show that including several distributional characteristics in our climate-inequality VAR captures the asymmetric change in the temperature distribution nicely. US-wide income inequality falls (albeit not significantly) in response to the change in the temperature distribution, likely reflecting the opposing effects of different percentiles.

[5] This is also reported in official climate change reports, e.g., IPCC (2014) and Wuebbles et al. (2017).

Moreover, we observe large heterogeneity across the contiguous US states regarding the impact of warmer temperatures on income inequality—that is, we find both positive and negative effects on income inequality. Generally, the northeastern region (one of the most populated) shows a reduction in inequality due to warmer temperatures, while most of the southwestern region presents the opposite effect. As for the US aggregate, the impacts also vary widely across different temperature distribution characteristics. For example, for some southern states, such as Texas, income inequality falls in response to warmer temperatures in the 95th percentile, while it rises in response to an increase in mean temperatures. Modeling the temperature distribution characteristics jointly, we obtain a very different spatial distribution of inequality impacts across states if compared to mean temperatures only.

Finally, in contrast to the cross-country findings established in the literature (i.e., hotter and poorer countries are affected more), in the US there is no evident link between a state's climate or per capita income and the within-state effects on income inequality. That is, hotter and poorer states across the US are not necessarily affected more. However, states with more land used for pasture are associated with higher effects on income inequality, whereas those with larger urban areas are associated with smaller inequality effects. To shed light on the role of industries in how climate change may affect income inequality in the US, we also assess the relationship between a state's industry share and the inequality effect. A few things stand out: states with higher shares in climate-sensitive industries, such as agriculture, construction, and transportation, have larger inequality impacts in response to temperature increases in the upper percentiles (warmer hot temperatures). States with a higher share in finance, insurance, real estate, and services, such as professional and business services and education and health experience, have more negative effects on inequality (inequality decreases more).

From our analysis it is apparent that climate change affects income differently across states and segments of the population. Those impacts also vary across the annual temperature distribution (i.e., seasons). Understanding the distinct effects across space and seasons helps policy makers design better and more targeted adaptation policies and climate responses.

However, more studies are needed to understand the more nuanced effects of a warming US climate on socio-economic factors (such as income inequality) or the economy and the underlying economic mechanisms. In particular, analyzing the effects of climate change at the firm or industry level and at a sufficient spatial granularity (e.g., state or county level) will help our understanding of how factors such

as productivity, employment, and output are affected in the presence of the diverse US climate.

The remainder of the paper is structured as follows. Section 2 describes the data and how we obtain temperature distributions. We also characterize the nature of climate change in the US by analyzing trends in the temperature distribution characteristics across US states. We assess the effects of climate change on income inequality in Section 3, and Section 4 concludes.

2 Characterizing Climate Change

We start by analyzing the nature of US warming due to climate change. We characterize the type of climate change by assessing the trends in the distributional characteristics of temperatures. We start by creating a data set of daily US temperatures from 1920-2019 for the contiguous US states and obtain temperature distributions across states and time. Finally, we assess the trends in the distributional characteristic to shed light on the type of warming (i.e., how it differs across states and seasons).

2.1 Data

2.1.1 From Station Records to State-Level Data

We use weather data from Global Historical Climatology Network-Daily (GHCN-Daily) from the National Climatic Data Center (NCDC Climate Services Branch, 2011). This consists of an integrated database providing daily climate summaries from land surface weather stations across the globe. GHCN-Daily contains records from over 100,000 stations in 180 countries and territories. This database provides measurements of daily maximum, minimum, and average temperatures; total daily precipitation and snowfall; and snow depth. The earliest records available go back 145 years (i.e., to 1880).

For this paper, we access daily data for stations in each state in the US from January 1, 1920, until December 31, 2019. The weather variables we extract are daily maximum (Tmax) and minimum (Tmin) temperature and daily average (Tavg) in degrees Celsius ($^{\circ}C$). Transforming the daily station records to state-level data of daily temperatures is not trivial, since apart from more general data cleaning there are several other challenges. First, since the GHCN-Daily data report weather at a set of weather stations spaced irregularly across the US, there is no one-to-one correspondence with macroeconomic spatial units, such as US counties or states. Second, since reporting stations may enter and exit over time, using, for example, a simple average across-station daily temperature to obtain aggregates may lead to artificial

biases in the trends and dynamics of the aggregated daily temperature series. To obtain daily temperature time series from 1920–2019 for the contiguous US states we follow several steps:

[6]

Step 1: Cleaning Weather Station Data

We clean the station data by, for example, correcting stations with the same coordinates or with missing county ids. Moreover, GHCN-Daily station data are subject to a set of quality assurance reviews that include checking for duplicated records, weather data that exceed physical or climatological limits, consecutive records that show excessive persistence gaps, and data with inconsistencies across time or neighboring stations. We delete the records that have been flagged as outliers by those reviews.

Step 2: Constructing Daily Temperature Series for Each County

We construct daily temperature series for each county (in each state) as the weighted average of bias-corrected temperature data for weather stations within 50 miles of each county (see Ranson, 2014 and Wilson, 2019). This entails two steps: First, we obtain weather station weights for each county by dividing the surface of the contiguous United States into a 5-mile by 5-mile grid and calculating the inverse of the distance (i.e., 1/distance) from each weather station to each grid point within the county. Then, for each weather station, we calculate the average of the inverse distances (averaging across grid points within the county) to obtain the weights. Second, to avoid bias from the changing composition of reporting stations over time, we generate bias-corrected temperature time series for each station as in Ranson (2014). This bias correction procedure adjusts the intercept of the temperature time series at each station to better reflect the average long-term weather conditions in each county.

Step 3: Calculating Daily State-Level Temperature Time Series

We spatially aggregate the daily county temperature series to the state level by using county population weights. We use fixed weights over time based on the 2010 Census.

2.1.2 From Daily Series to Temperature Distributions

With the data set of daily temperatures across the 48 contiguous US states at hand, we then obtain annual time-varying temperature distributions for each state. We calculate temperature distributions for each year t, where $t = 1920, ..., 2019$. The distribution of temperatures in year t is calculated from N days.

[6]Figure A-1 in the Appendix provides an example of how station entry and exit can affect daily temperature trends. Toward the end of the sample, several stations with lower temperature readings (blue bars) enter, creating artificial negative trends if simple spatial averages across stations were constructed.

with $N = [365, 366]$ depending on whether a certain year was a leap year or not. Let the temperature variable at any given day d, year t, and state s be x_{dts} with $d = 1, ..., N$. The temperature density for each year t for $x = (x_{1ts}, ..., x_{Nts})$ for state s is $f_{ts}(x)$. From these annual empirical distributions for each state, we calculate various distributional characteristics i for each state, C^i_{ts}. We consider the mean, variance, skewness, and lower and upper percentiles in our analysis.

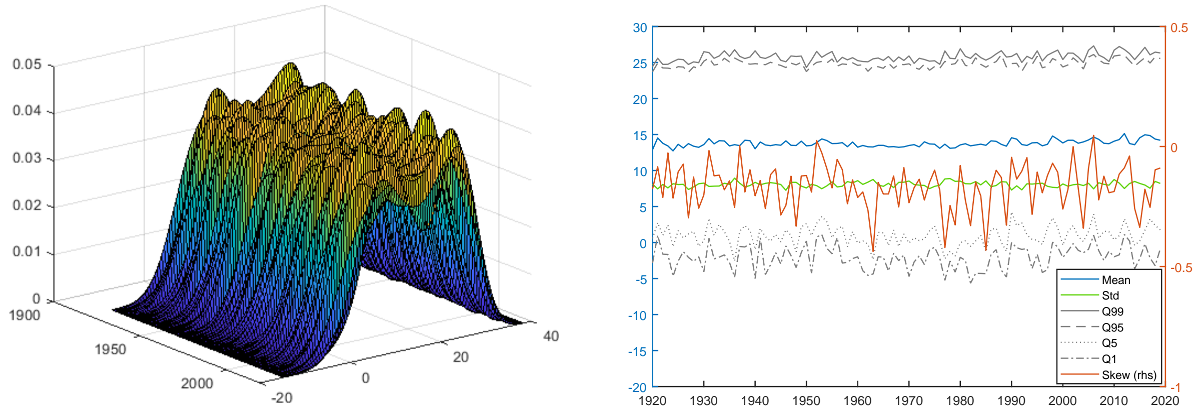
2.2 Temperature Distributions Across States and Time

We start by presenting the temperature distribution for the US aggregate temperature. We obtain the nationwide temperature distribution by taking the population-weighted average of the state temperatures. Then, we shed light on the heterogeneity in the temperature distributions across states reflecting the diverse US climate. While we have data for daily minimum and maximum temperatures, for brevity we focus our discussion on the daily average temperatures (Tavg).

Figure 1 shows the annual empirical distribution (left panel) from 1920–2019 for the US aggregate temperature.[7] The distributions vary quite a bit over time and are bimodal for the US aggregate temperature. This reflects seasonal weather patterns present in most of the US climate zones. The distributions also show an asymmetric tail extending out toward the left (negative skewness), implying more extreme cold events. The right panel of Figure 1 plots some of the corresponding characteristics over time. The mean temperature for the US aggregate is just under 15 degrees Celsius and the 95th and 99th percentiles are fluctuating above 25 degrees. The lower percentiles lie in the range of -5 to 5 degrees. The lower percentiles exhibit larger annual fluctuations than the upper percentiles and the mean. We observe trends in most of the distributional characteristics. The mean, skewness, and the lower and upper percentiles are all increasing since the 1980s but not at the same rate—an observation that we will assess in more detail in the next section.

[7] We use the ksdensity() function in Matlab to obtain the annual empirical distributions.

Figure 1: Temperature Distributions and Their Characteristics Over Time: US Aggregate



We now turn to state-level temperature distributions over time and shed light on differences in temperature patterns across states. The contiguous United States are divided into nine climatically consistent regions based on climate analysis conducted by the National Centers for Environmental Information (NCEI): Northeast, Upper Midwest, Ohio Valley, Southeast, Northern Rockies and Plains, South, Southwest, Northwest, and West.[8] Figure 2 shows annual empirical temperature distributions for exemplary states belonging to each climate region. We observe that temperature distributions vary across states and time. For example, states like Florida (FL) or Kentucky (KY) exhibit more asymmetry in the tail extending out toward cold temperatures.

[8]The states are classified as follows. Northeast: Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. Upper Midwest: Iowa, Michigan, Minnesota, and Wisconsin. Ohio Valley: Illinois, Indiana, Kentucky, Missouri, Ohio, and Tennessee. Southeast: Alabama, Florida, Georgia, North Carolina, South Carolina, and Virginia. Northern Rockies and Plains: Montana, Nebraska, North Dakota, South Dakota, and Wyoming. South: Arkansas, Kansas, Louisiana, Mississippi, Oklahoma, and Texas. Southwest: Arizona, Colorado, New Mexico, and Utah. Northwest: Idaho, Oregon, and Washington. West: California and Nevada.

Figure 2: Temperature Distributions Over Time: Selected States in US Climate Regions

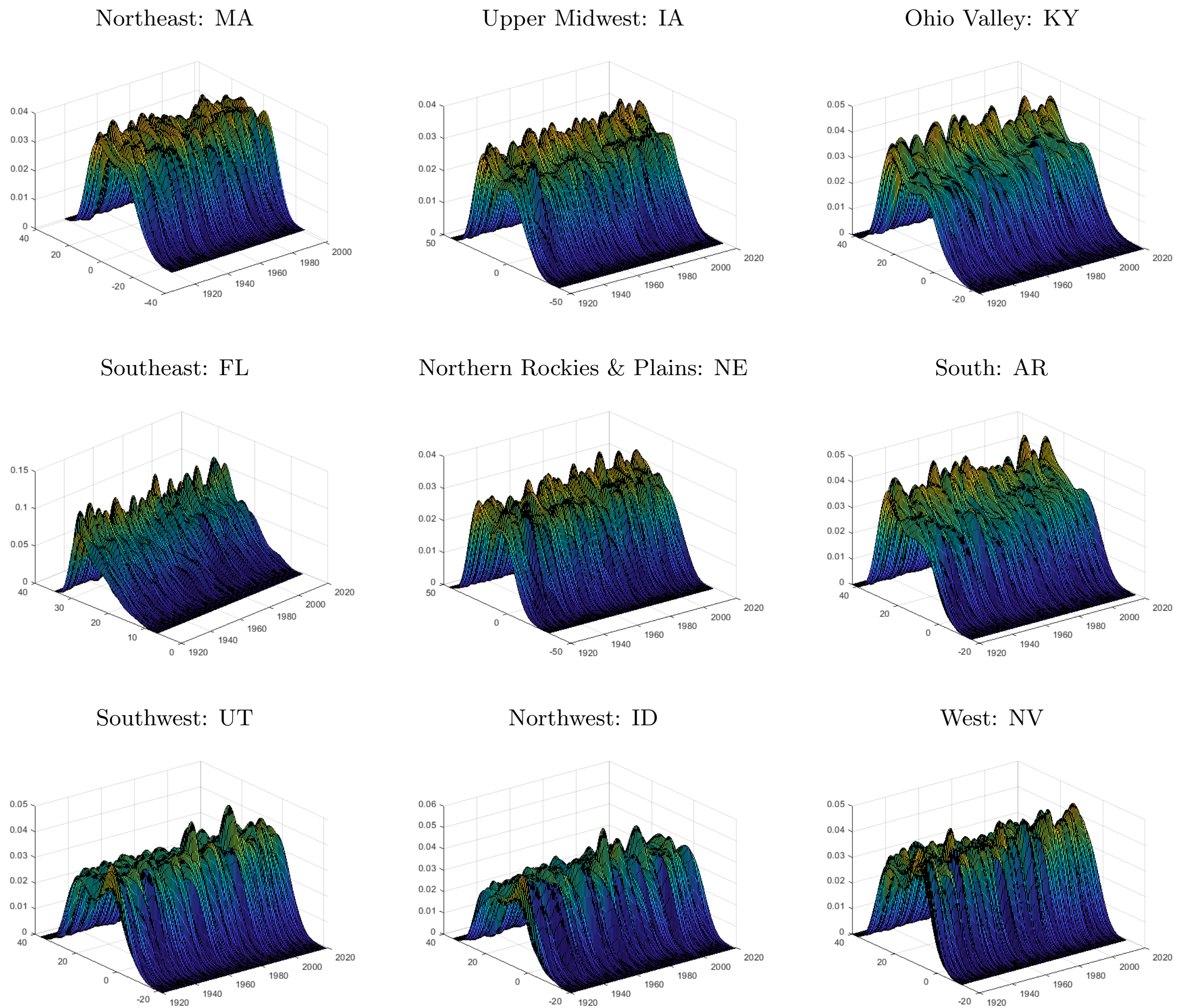
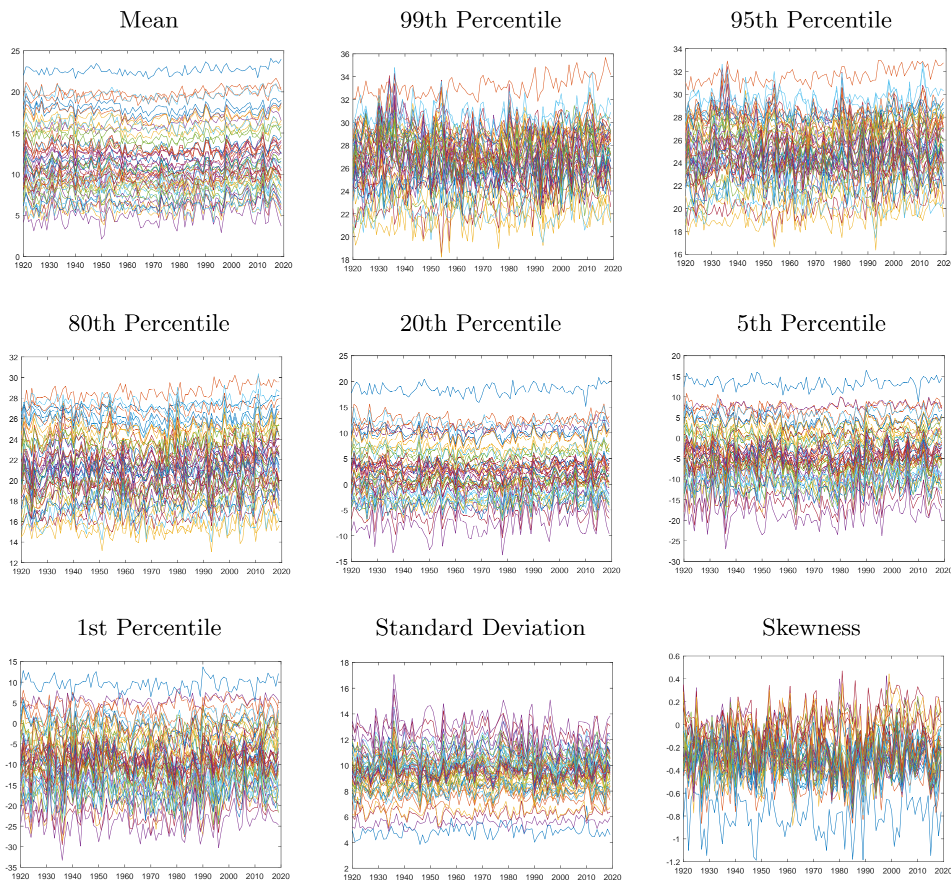


Figure 3 plots the considered temperature distribution characteristics over time. The characteristics of the aggregate US temperature distribution described above mask the great diversity present in the US climate across states. Annual mean temperatures range between 2 and 25 degree Celsius. Temperatures in the higher percentiles also vary widely across states (e.g., 99th percentile temperatures range between 18 to 36 degrees). The highest temperature variations across states can be found in the lower percentiles (e.g., temperatures in the 1st percentile range from -35 degrees to 15 degrees). This implies that temperatures in winters vary the most across US states. In each state, the variance in daily temperature over a given year also varies (e.g., the annual standard deviations across states vary from 4 to 15 degrees). That is, some states have distinct seasons with cold winters and warm summers (e.g., New York) while others

(e.g., Florida) have more consistent temperatures across the year. Moreover, the US aggregate skewness across states is mostly negative, meaning that across the US states temperature are more tilted toward colder temperatures. Again, there is variation in the extent of this tilt, with states like Florida exhibiting a long left tail (reflecting higher negative skewness).

Like for the US aggregate distributional temperature characteristics, we can observe an increase in annual mean temperatures and their upper and lower percentiles starting around the 1980s. There could also be positive trends in the skewness of annual temperatures and a negative one in standard deviation. We test more formally for trends in the distributional characteristics in the next subsection.

Figure 3: Temperature Distribution Characteristics Over Time: US States



2.3 Evaluating Trends 1960–2019

To evaluate how US climate has evolved over time, we rely on trend regressions. We allow for heterogeneity across US states with respect to changes in the temperature distribution over time and estimate the

following state-specific regressions for each temperature distribution characteristic C^i:

$$C^i_{ts} = \alpha^i_s + \beta^i_s t + \varepsilon^i_{ts}, \quad t = 1960, ..., 2019, \; s = 1, ..., 48, \tag{1}$$

$$i = [mean, \; Q99, \; Q95, \; Q80, \; Q20, \; Q5, \; Q1, \; std, \; skew] \tag{2}$$

We also estimate the trend regression for the US aggregate temperature distribution, which we obtain by population-weighting the state data.[9] Table 1 shows the estimated β coefficients for the US aggregate temperature distributional characteristics for the daily minimum, maximum, and average temperatures. Average temperatures (based on Tavg) for the US aggregate have risen by 0.020°C per year over 1960–2019.[10] We also observe significant increases in all percentiles of the temperature distribution. For example, Q99 temperatures have increased by 0.019°C and Q5 temperatures by 0.034°C . It appears that temperatures in the lower percentiles increase at a faster rate than those in the mean and in the upper percentiles of the temperature distribution. Very low temperatures (Q1) increase twice as fast as very high temperatures (Q99)—that is, winters warm way faster than summers. This is also reported in official climate change reports (e.g., IPCC (2014) and Wuebbles et al. (2017)). Moreover, trends in the standard deviation and skewness of the temperature distribution are negative and positive (albeit not always significant), respectively. Therefore, climate change in the US is not only a phenomenon of an increase in the average temperature but also of a larger increase in lower temperatures, leading to an asymmetric change in the temperature distribution.

Table 1: Estimates of the Changes in Annual Temperature Distribution Characteristics: US Aggregate

	Mean	Q99	Q95	Q80	Q20	Q5	Q1	Std	Skew
Tmin	0.027*	0.027*	0.029*	0.031*	0.024*	0.043*	0.044*	-0.001	0.002*
Tmax	0.014*	0.010*	0.009*	0.011*	0.017*	0.026*	0.033*	-0.005	0.001
Tavg	0.020*	0.019*	0.019*	0.020*	0.022*	0.034*	0.041*	-0.003	0.001*

Notes: The coefficients β and corresponding p-values are the Newey-West estimates of the trend test regression for the US annual temperature distribution characteristic i, such that $C^i_{t,US} = \alpha^i_{US} + \beta^i_{US} t + \varepsilon^i_{t,US}$ for $t = 1, ..., T$. The period under consideration is from 1960 to 2019. * denotes significance at the 5% level.

Since the US climate is diverse, we assess how US warming differs across states. Table 2 summarizes the results of the trend tests for the temperature distribution characteristics for each state. Focusing

[9]While we have data starting in 1920, for the trend evaluation we start our sample in 1960 since this is often considered the starting point of the reference period for temperature anomalies. Starting our sample in 1920 gives similar results, albeit less strong and less significant.

[10]This is consistent with the US Climate Science Special Report; see Wuebbles et al., 2017, which documents trends in the average temperature in the range of 0.0160–0.0284 per annum for the period 1979–2016 depending on underlying weather data sources (e.g., satellite and surface thermometer records).

on the distribution of daily average temperature, we find that all states have experienced temperature increases in the mean, the lower percentiles (Q1, Q5, Q20), and the 80th percentile (albeit coefficients are not significant at the 5% level for every state). The temperatures in the 99th and 95th percentiles also increased in most states. Moreover, we detect negative trends in the standard deviation of temperatures and positive trends for the skewness for most states (although these turn out to not be significant for most states). The state-level trend results align with the changes in the temperature distribution observed at the national level. Generally speaking, we observe increases in temperatures across the US states and across the percentiles of the distribution. The evidence is stronger in the case of temperatures in the lower percentiles (with more states showing highly significant trend estimates), suggesting that winters are warming up more across most of the US states as well.

Table 2: Trends in Annual Temperature Distribution Characteristics: US States

		Positive Trend			Negative Trend		
		Tmin	Tmax	Tavg	Tmin	Tmax	Tavg
Mean	% of states	100%	98%	100%	0%	2%	0%
	% of significant states	98%	70%	96%	NA	0%	NA
Q99	% of states	96%	75%	88%	4%	25%	12%
	% of significant states	85%	36%	76%	0%	0%	0%
Q95	% of states	98%	71%	94%	2%	29%	6%
	% of significant states	94%	47%	76%	0%	0%	0%
Q80	% of states	100%	85%	100%	0%	15%	0%
	% of significant states	98%	65%	73%	NA	0	NA%
Q20	% of states	98%	100%	100%	2%	0%	0%
	% of significant states	85%	65%	73%	NA	0%	NA
Q5	% of states	100%	98%	100%	0%	2%	0%
	% of significant states	96%	77%	96%	NA	0%	NA
Q1	% of states	100%	100%	100%	0%	0%	0%
	% of significant states	92%	77%	90%	NA	NA	NA
Std	% of states	17%	6%	8%	83%	94%	92%
	% of significant states	0%	0%	0%	0%	0%	0%
Skew	% of states	98%	81%	96%	2%	19%	4%
	% of significant states	70%	26%	37%	0%	0%	0%

Notes: The reported percentages are obtained from $\beta_{s,i}$ estimates and corresponding p-values (5% significance level) of the trend test regression for temperature distribution characteristic i of state s: $C_{ts}^i = \alpha_s^i + \beta_s^i t + \varepsilon_{ts}^i$ for $t = 1960, ..., 2019$.

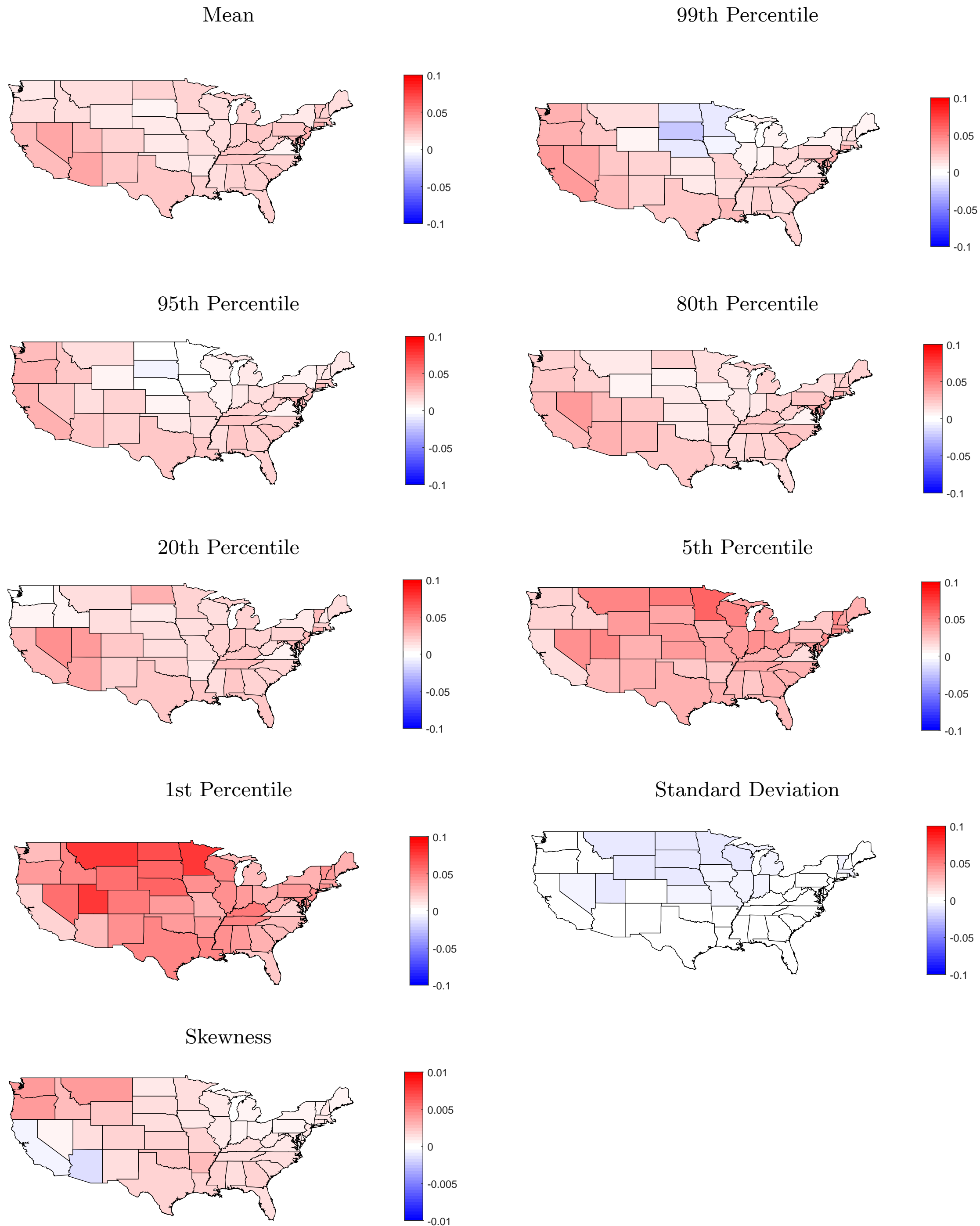
Figure 4 sheds light on how these trends in the temperature distribution characteristics vary across space. We obtain heatmaps by plotting the estimated β coefficient for each temperature distribution characteristic and state. We use the same temperature scale (°C) across characteristics to render the rates of temperature changes comparable (except for skewness). We observe the following. First, the

pace of warming not only varies across temperature distribution characteristics but also across states, and not proportionally so. For example, while in Arizona temperatures in the mean have increased at the highest rate among the US states, those in the 1st percentile have increased at lower rates than most other states. Second, for most of the contiguous US states, lower temperatures have been increasing at a faster rate than higher temperatures. However, there are exceptions: in California the temperatures in the mean and upper percentiles seem to have grown at a somewhat faster pace than temperatures in the 5th or 1st percentiles, suggesting that warming has been more pronounced for summer temperatures (in line with Milanes et al., 2022). Third, temperature increases in the lower percentiles (e.g., 5th and 1st) are widespread and have been most intense in the Rocky Mountains and parts of the Midwest. Moreover, changes in temperatures in the 99th percentile (warm extremes) are more nuanced than changes in the cold extremes. In particular, while the warming of summer temperatures (Q99 or Q95) has been most extensive along the East Coast and in the western third of the United States, we can observe negative trends (albeit not significant) in parts of the Great Plains and the Midwest. These spatial differences are also documented in Wuebbles et al. (2017).[11] Finally, trends in the standard deviations of daily average temperatures are generally negative or small but non-significant, and trends in the skewness are mostly positive except in California or Arizona, for example.

Summing up, we document that climate change is more than a phenomenon that increases mean temperatures, since the whole temperature distribution has shifted asymmetrically in the US. Moreover, these shifts differ across states. For most states, the lower and upper percentiles have both increased, but the lower ones have increased at a faster rate. This suggest that winter temperatures have warmed up faster than summer ones. However, there are a few states, such as California, where the opposite is true. In the next section we model these phenomena through the lens of the VAR model to assess their effects on income inequality.

[11] Moreover, they document that the frequency of intense heat waves has generally increased since the 1960s in most regions except the Midwest and the Great Plains.

Figure 4: Estimated Changes in Annual Temperature Distribution Characteristics: US States



Notes: The colors represent the size of the estimated β coefficients corresponding to the Newey-West estimates of the trend test regressions for each temperature distribution characteristic i and state s, such that $C^i_{ts} = \alpha^i_s + \beta^i_s t + \varepsilon^i_{ts}$ for $t = 1, ..., T$. Darker (lighter) red and blue colors represent larger (smaller) positive and negative coefficients (trends), respectively. The period under consideration is from 1960 to 2019.

3 Climate Change and Income Inequality

We now analyze the effects of climate change on income inequality across the US. As documented above, climate affects the whole distribution of daily temperatures over time and distinctly across states. We start by introducing the Climate-Inequality SVAR, which we use to obtain the effects of shifts in the temperature distribution. Moreover, we discuss the effects on income inequality across the US and within states. Finally, we provide some economic intuition and narratives for our findings.

3.1 The Climate-Inequality SVAR

To assess the effects of climate change on the economy, we introduce a climate-inequality structural VAR. This SVAR includes both a measure of income inequality and our time-series characteristics of the temperature distribution described above. As before, let C^i_{ts} be the sufficient statistics of the empirical temperature distribution, $f_{ts}(x)$, in year t for state s and statistic i where i=[$mean$, $Q99$, $Q95$, $Q80$, $Q20$, $Q5$, $Q1$], s=1, ..., 48, and t=1920-2019. Socio-economic inequality is denoted by y_{ts} and given by the Top 1% income share in state s in year t. We use data on socio-economic inequality at the state level for the US provided by Frank (2009). The data offer a panel of annual income inequality measures for the 48 states with a sufficiently long history, from 1917–2018.[12] The inequality measures are derived from tax data published by the Internal Revenue Service (IRS). The IRS reports the pretax adjusted gross income, which constitutes a broad measure of income. Specifically, it consists of wages, salaries, capital income (dividends, interest, rents, royalties), and entrepreneurial income (self-employment and small businesses). Top income shares have been adjusted by Frank (2009) based on the methodology of Piketty and Saez (2003, 2006) and present evidence of the consistency of its aggregate US data with that of the authors.

We estimate the climate inequality VAR for the US aggregate and each US state separately. The climate-inequality SVAR is given by

$$z_{ts} = B(L)_s u_{ts} \tag{3}$$

$$B(L)_s = C(L)_s B_{0s} \tag{4}$$

$$u_{ts} = B_{0s}^{-1} \epsilon_{ts}, \tag{5}$$

[12] Ideally, to assess the distributional effects of climate change one would like to use the full income distribution. However, for our purposes we require sufficiently long time series to estimate effects at the state level, and distributions of income are not readily available over our sample starting in 1920.

where $C(L)_s$ and ϵ_{ts} are reduced form parameters and residuals. We consider two cases. First, we introduce a bivariate model in which we include income inequality and one temperature distribution characteristic at a time. This allows us to assess whether effects vary across characteristics (e.g., are different for warmer winter temperatures or summer ones). To model the temperature distribution characteristics jointly, we introduce a multivariate VAR that includes several weather statistics and income inequality at the same time. In both approaches, we define climate change as a shock that shifts the characteristic(s) of the empirical temperature distribution. Estimating separate VARs for each state allows for state-specific climate shocks. This captures the heterogeneity in trends of the temperature distributions across states discussed above. That is, climate change affects temperature distributions differently across US states. Hence, we can model that, for example, in California climate change is associated with summer temperatures warming up somewhat faster than winter ones, while for most other states the opposite is true.

Bivariate Model: In the bivariate model we include our measure of inequality y_{ts} and one characteristic of the temporal weather distribution (e.g., mean):

$$z_{ts} = [\Delta C^i_{ts} \; \Delta y_{ts}] \tag{6}$$

In the bivariate setting, we think about climate change as a shock that changes a particular temperature distribution characteristic. Since the distributional characteristics exhibit trends over time (and so does the Top 1% income share), we include them in first differences. This implies that we can think about climate as a shock that shifts the temperature distribution permanently (in the long run). For example, climate change shifts mean temperatures permanently.

We identify the climate change shock by a combination of zero and sign restrictions, as in Arias et al. (2018). In particular, our identification scheme makes two assumptions. First, we rely on our trend analysis from the former section, which provides us with the sign restrictions for each characteristic. For example, annual mean temperatures increase, which translates into a positive sign restriction for mean temperatures. Second, we impose an impact zero restriction from income inequality on the distribution characteristic. This means that shocks related to income inequality do not have contemporaneous effects on the distribution of temperatures. Any unexpected changes in the Top 1% income share from one year to the next are, therefore, assumed to have no influence on the occurrence of changes in temperatures in

the next year. This seems reasonable, given that income inequality and economic activity (to the extent that it is related to inequality) are unlikely to immediately affect the climate. However, note that this assumption does not exclude the possibility that long-run trends of income can influence the climate and temperature distributions.[13]

While the literature has mostly focused on the effects of changes in mean temperatures, our framework allows us to extend the analysis to other characteristics of the temperature distribution. By looking at how shocks to certain characteristics affect income inequality, we can learn, for example, whether the effects due to increases in the percentiles differ from those due to increases in mean temperatures. This allows us to shed light, for example, on whether the effects of warmer winters differ from those of hotter summers.

Multivariate Model: As documented in the former section, climate change is ultimately a phenomenon that involves asymmetric changes of the whole temperature distribution affecting, for example, the mean and percentiles differently. This can be easily captured in our framework by expanding the bivariate VAR and including additional distribution characteristics. The vector of endogeneous variables in the multivariate case for state s is given by

$$z_{ts} = [\Delta C_{ts}^{1}, \Delta C_{ts}^{2}, ..., \ \Delta y_{ts}] \tag{7}$$

As we have documented, not only the mean but also other characteristics of the weather distributions exhibit time trends, and these trends vary across characteristics. For example, the lower percentiles show stronger trends than the upper percentiles in most US states—that is, extreme cold temperatures are warming up faster than hot ones. The multivariate VAR models endogenous relationships between the different characteristics of the temperature distribution time series and can, thus, capture these asymmetric shifts in the temperature distributions that characterize climate change across US states. In particular, since we have identified strong and significant trends (for most states) in the mean and upper and lower percentiles, we will focus our analysis on those characteristics and include them jointly in our climate-inequality VAR. By considering a shock that shifts various characteristics simultaneously, we can analyze the joint effect of climate change. As we will see later in our bivariate analysis, we find that in some states warmer temperatures in certain percentiles can have opposing effects on income inequality.

[13]The zero impact assumption is similar to Kim et al. (2021).

The multivariate VAR will allow us to assess the aggregate effects on inequality since we model the percentiles jointly.

We estimate the VAR for each state and the US aggregate using standard Bayesian methods.[14] We use the toolbox by Canova and Ferroni (2021) to do so and to obtain the impulse response functions to climate shocks.

3.2 National Effects

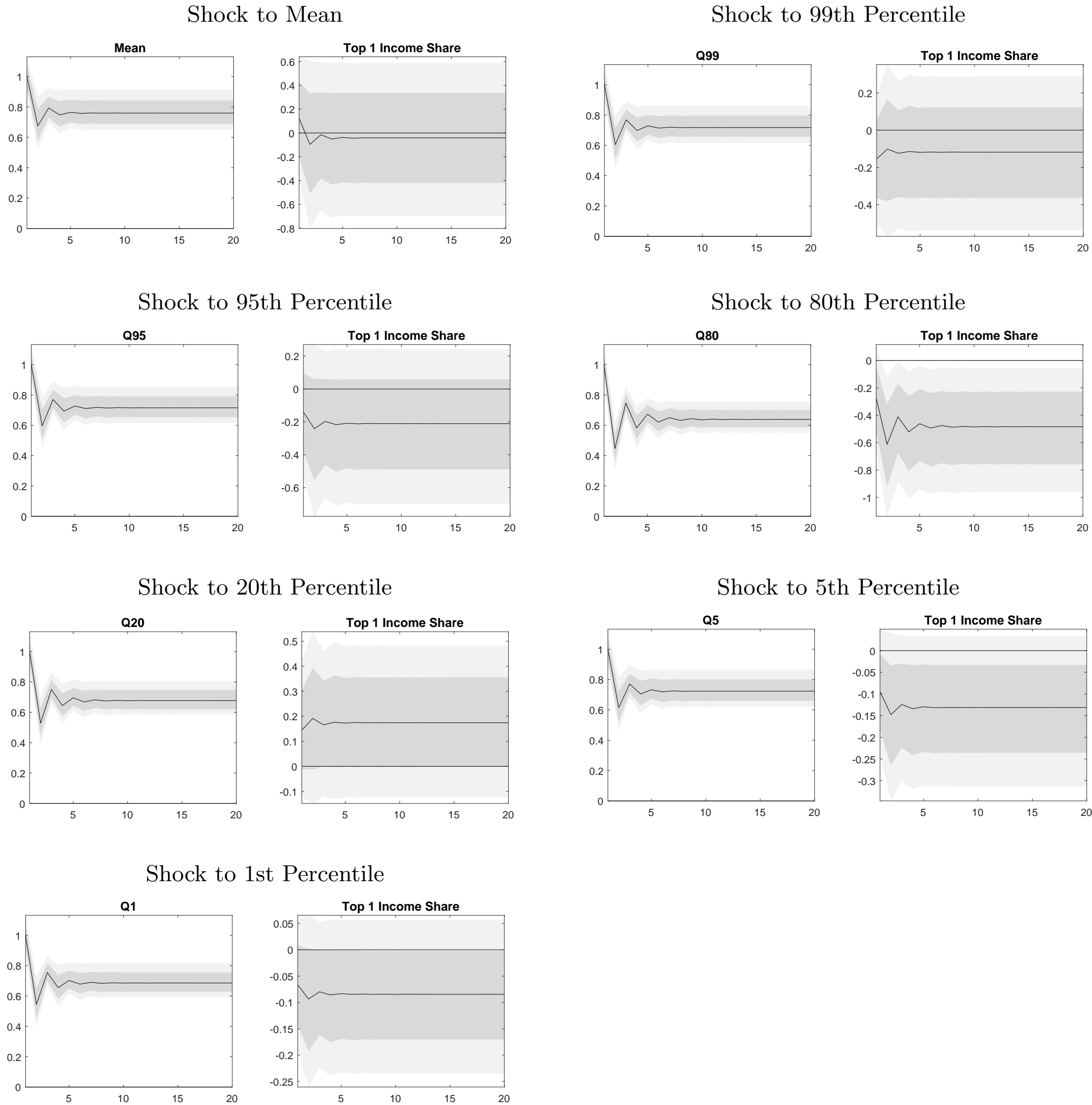
We start by assessing the effects of climate change on nationwide income inequality. Using aggregate US data, we first estimate several bivariate VARs for each temperature distribution characteristic and our measure of income inequality. Figure 5 shows the response of the Top 1% income share to a 1 degree (°C) shock to each of the temperature distribution characteristics. We normalize the size of the shock to one °C across distribution characteristics to render them comparable to each other. We do not observe any effect on the national Top 1% income share in response to an increase in mean temperatures. However, when looking at the impact of shocks to the other characteristics of the temperature distribution we observe a different story. When we look at positive shocks to temperatures in the upper percentiles (i.e., Q99 and Q95), we see the Top 1% income share falling (although not significantly). A 1 degree increase in temperatures in the 80th percentile leads to a significant decrease in the Top 1% income share (by about 0.3 percentage points on impact), while a 1 degree increase in temperatures in the 20th percentile causes income inequality to increase significantly (by about 0.15 percentage points). Following positive shocks to low-temperature extremes (i.e., Q5 and Q1), the Top 1% income share also falls on impact by 0.1 and 0.05 percentage points, respectively.

Intuitively, this means that while average temperatures show no effect on income inequality, warmer extreme cold weather, for example, contributes to a persistent decrease in inequality. If we were to focus our analysis on mean temperatures only, as is often done in the climate-economy literature, we would therefore miss the distinct effects of trends in different percentiles of the temperature distribution. Similarly, distinct effects of temperature increases across different percentiles of the temperatures distribution—to the extent that they can be interpreted as different seasons—have been documented in the context of US economic activity. Colacito et al. (2019) find that summer and fall temperatures have

[14] For parsimony, we set the lag length to 1 for national and state-specific models. Results are robust to including more lags.

opposite effects on economic growth—that is, an increase in the average summer temperature negatively affects the growth rate of GDP, while an increase in the fall temperature affects the growth rate positively. Moreover, Nguyen (2024) discovered opposing effects on employment of higher temperatures in the winter and summer—higher summer temperatures reduce private sector employment growth, while higher winter temperatures increase it.[15]

Figure 5: Effect of Temperature Distribution Characteristic Shock on Income Inequality: US Aggregate



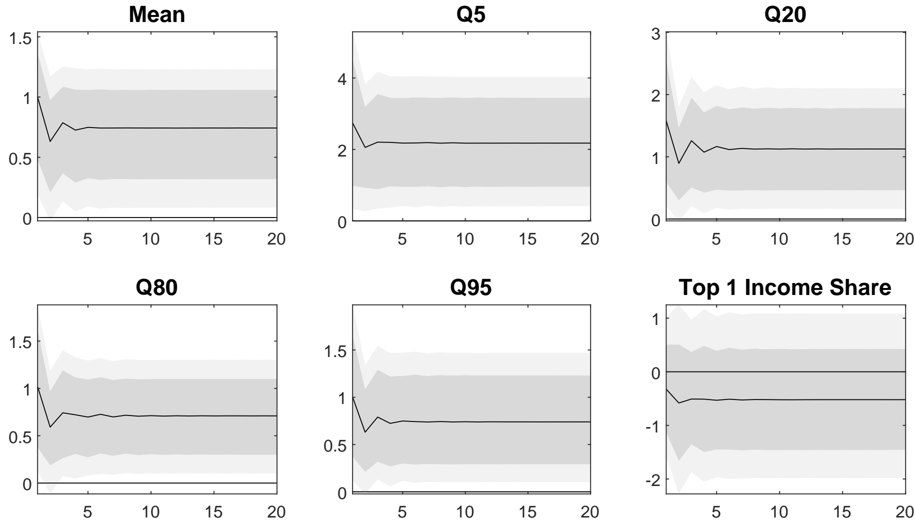
Notes: Impulse responses of a positive 1 degree (°C) shock to a temperature distribution characteristic (mean, 99th, 95th, 80th, 20th, 5th, and 1st percentile) in bivariate VARs. Light- and dark-grey areas correspond to the 90% and 68% confidence sets, respectively.

In the above analysis, we have treated the percentiles of the temperature distribution independently

[15]Both papers define winter as January through March, the spring as April through June, the summer as July through September, and the fall as October through December.

and assumed they all increase at the same rate (by one degree). However, as discussed, climate change shifts the whole distribution in an asymmetric way. For US aggregate temperatures, the lower percentiles are increasing at a much faster pace than the higher percentiles or the mean. Figure 6 shows the impulse responses of the multivariate VAR, including the mean, 5th, 20th, 80th, and 95th percentiles. The climate change shock is identified as a shock that increases the percentiles and mean simultaneously.[16] We have normalized the response to a 1 degree increase in mean temperatures. It becomes apparent that this shock captures the asymmetric changes in the temperature distribution nicely. In particular, the identified climate change shock normalized to a 1 degree increase in mean temperatures increases temperatures in the 5th and 20th percentile by just above 2 and 1.5 degrees, respectively. Aggregate US temperatures in the 80th and 95th percentiles increase by about one degree, which is similar to the increase in mean temperatures. This is consistent with the trend analysis in which we established that climate change shifts the US aggregate temperature distribution in such a way that lower temperatures increase at a faster rate than warmer temperatures. Turning to the effects on income inequality, the climate change shock shifting the whole temperature distribution leads to a fall in the Top 1% income share but not significantly. This likely reflects the opposing effects from warmer temperatures in different percentiles that we documented above.

Figure 6: Effect of Climate Change Shock on Income Inequality: US Aggregate



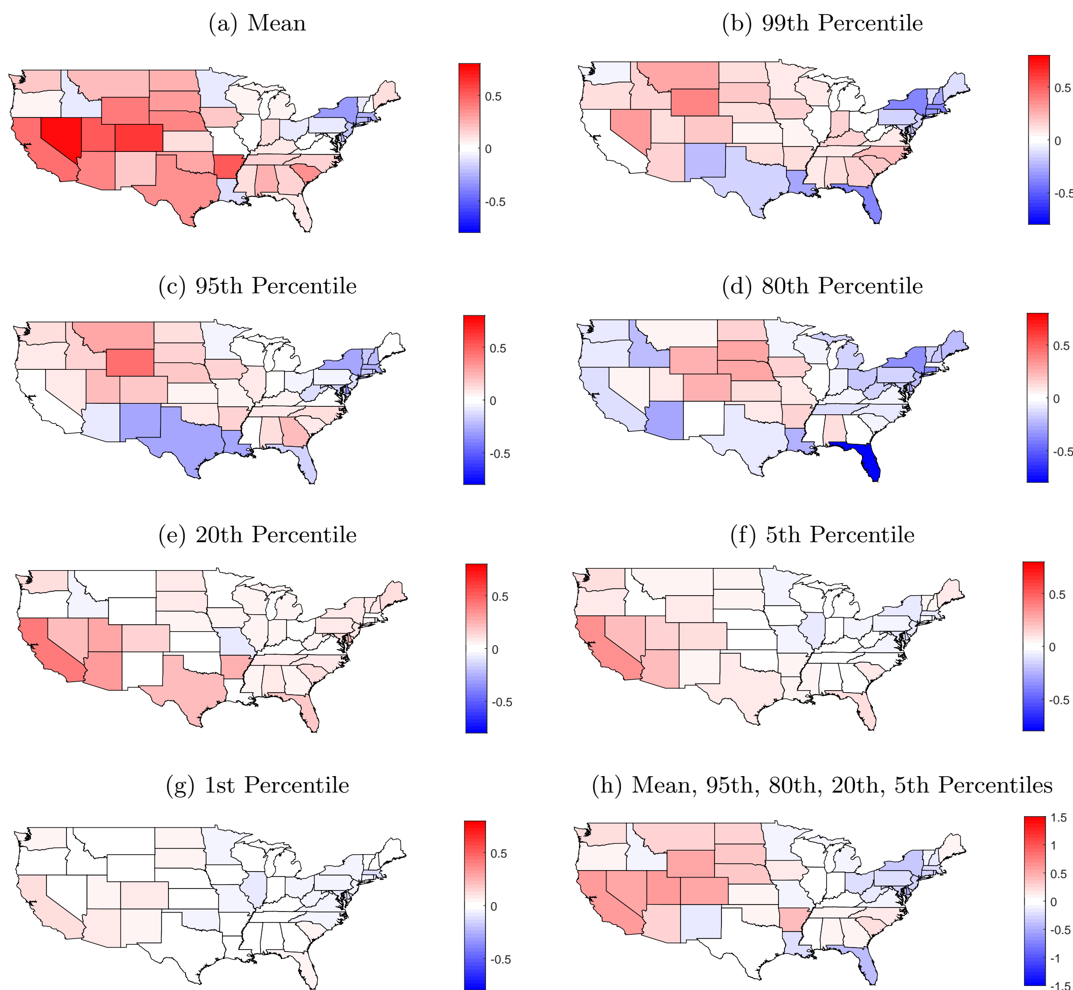
Notes: Impulse responses of a climate change shock normalized to a 1 degree (°C) increase in mean temperatures. The climate change shock is identified via sign restrictions on mean, 95th, 80th, 20th, and 5th percentiles jointly. Light- and dark-grey areas correspond to the 90% and 68% confidence sets, respectively.

[16]As in the bivariate case, there are also zero restrictions on the impact response of the percentiles and mean to the innovation related to the Top 1% income share.

3.2.1 State-Specific Effects

We now estimate separate climate-inequality VARs for each state. This allows us to assess differences in effects on inequality across states and temperature distribution characteristics. Therefore, we can assess how the impact on income inequality varies across the wide US climate. The existing literature has claimed that poorer and hotter countries are more affected by an increase in temperatures, consequently amplifying inequality at the global level. Here we can assess how higher temperatures in the percentiles and mean affect income inequality within each state differently and whether this depends on the state's climate.

Figure 7: Impact Effect of Temperature Distribution Characteristic Shock on Income Equality: US States



Notes: Panels (a)–(g): Impact effects ($h = 0$) of a 1 degree shock to a temperature distribution characteristic (mean, 99th percentile, 95th percentile, 80th percentile, 20th percentile, 5th percentile, 1st percentile) in the bivariate climate-inequality VAR for each US state. Panel (h): Impulse responses of a climate change shock normalized to a 1 degree increase in mean temperatures. The climate change shock is identified via sign restrictions on mean, 95th, 80th, 20th, and 5th percentiles jointly in the multivariate climate-inequality VAR.

Figure 7 plots the spatial distribution of the impacts (response at $h = 0$) of higher temperatures in

the mean and percentiles. We start by assessing the effects on income inequality for each temperature distribution characteristic. Panels (a)–(g) show the impact effect of a 1 degree shock to a temperature distribution characteristic (mean, 99th percentile, 95th percentile, 80th percentile, 20th percentile, 5th percentile, 1st percentile) in the bivariate climate-inequality VAR estimated for each US state over 1920–2019. The red color shows states with a more positive impact effect (higher income inequality), while the blue color shows states with a more negative impact effect (lower income inequality). A few things stand out. First, the effects on income inequality vary widely across states. For each of the temperature distribution shocks, we observe both positive and negative effects on income inequality. For example, looking at panel (a), a positive 1 degree shock in mean temperatures decreases income inequality in most states of the Northeast, while it increases inequality in most southern and western states.

Second, the spatial distribution of impacts is not the same across temperature distribution characteristics. Looking at the impacts of higher summer temperatures (such as panel (b) for Q95 temperatures), we can see that the spatial distribution differs from the one in panel (a) for mean temperatures, as not only the size of the effects varies but also their signs. For some southern states, such as Texas, income inequality falls in response to warmer temperatures in the 95th percentile. Moreover, higher temperatures in the 80th percentile decrease income inequality in more than two-thirds of US states with only states in parts of the Northern Rockies and Plains and the Midwest experiencing an increase in inequality. The spatial distribution of inequality impacts changes again in response to 20th percentile temperature shocks, with income inequality increasing the most in Southwest states such as California, Arizona, and Nevada. Finally, effects of positive 1 degree shocks to the low percentiles (Q1 and Q5) reflecting warmer extreme cold temperatures are generally smaller in size, with most western states experiencing an increase in income inequality and eastern states (in particular the Northeast and parts of the Midwest) experiencing a decrease in inequality.

As mentioned earlier, there is very little analysis concerning the spatial distribution of climate change impacts on the US economy, which makes comparing our results difficult. To our knowledge, there is only one other paper that analyzes the effects of temperature increases in different seasons—which we can, to a certain degree, relate to temperature increases in percentiles—on economic activity (i.e., employment) across US states (see Nguyen (2024)). The paper also finds distinct spatial distributions of impacts across different percentiles of the weather distributions. In particular, higher summer temperatures can both

benefit and harm economic activity across states, with Northeast states experiencing positive employment effects. While income inequality and economic activity effects are clearly not one-to-one related, this, however, broadly aligns with our findings that higher temperatures in the 80th, 95th, and 99th percentiles decrease inequality in Northeast states. Moreover, Nguyen (2024) documents that the impact of warmer winter temperatures is generally smaller in size and varies widely across states, as states in the Midwest and on the east coast are mostly positively affected (employment increases), and some states in the West (e.g., Arizona and Utah) and Northern Rockies and Plains are negatively affected (employment decreases). This is also somewhat in line with our findings.

We have shown that increases in temperature in the mean and percentiles affect income inequality within each state differently. To assess the relationship between a state's climate and the impacts on income inequality, we perform cross-sectional regressions across US states. In particular, we regress the impact effects plotted in panels (a)–(g) of Figure 7 for each distribution characteristic on the average temperature over 1920–2019 of that distributional characteristic. Table 3 shows that there is no apparent (significant) relation between a state's climate and its effects on income inequality for most of the percentiles and the mean. However, we observe that states with higher average chilly/cold temperatures (Q20 and Q5) have more positive inequality impacts. That is, states with already warmer chilly/cold temperatures are more prone to experience an increase in income inequality in response to an increase in these temperatures.

Table 3: Relationship Between Inequality Impact and a State's Climate

	Mean	Q99	Q95	Q80	Q20	Q5	Q1
Estimated coefficient	0.010	0.002	-0.010	-0.009	0.006	0.005	0.001
P-value	0.223	0.827	0.282	0.359	0.014	0.013	0.185

Notes: Results of cross-sectional regressions across states of the impact effects in response to temperature distribution characteristic i on the average over 1920–2019 of temperature characteristic i, where $i = [mean, Q99, Q95, Q80, Q20, Q5, Q1]$.

The existing literature and the above analysis treat the temperature changes across percentiles independently and consider same-sized shocks for each characteristic (i.e., 1 degree Celsius). However, as discussed, this ignores the fact that climate change does affect the characteristics differently. Moreover, the distribution of temperatures changes differently across states. Ignoring these asymmetric changes when looking at the effects of climate change likely yields incorrect estimates of the aggregate effects of climate change—for example, averaging the effects along the percentiles to obtain the joint (or

average) effect of warmer temperatures ignores the fact that for most US states extreme cold temperatures warm up way faster than hot ones.

To get a sense of the effects of these asymmetric shifts in the temperature distribution, we model the temperatures in the mean and percentiles jointly. Panel (h) of Figure 7 plots the impulse responses of the climate change shock (which is identified via a combination of zero and sign restrictions on the mean and percentiles) in the mulivariate VAR. The shock is normalized to a 1 degree increase in mean temperatures. We see that in most of the western states, income inequality increases in response to the asymmetric shift of the temperature distribution, while it decreases mostly in states along the east coast and in the Midwest. This is a very different spatial distribution of impacts if compared to the one of mean temperatures only (see panel (a)). Regressing these joint impact effects across states on each of the average temperatures (1920–2019) in the mean and percentiles, there is no apparent relationship between the joint effects on income inequality and a state's climate.

3.2.2 On the Potential Economic Mechanisms

We have shown that in response to rising temperatures there are states in which inequality increases and states in which it decreases. These positive and negative impacts not only vary across states but also across the temperature distribution.

The literature studying the effects of climate change globally has shown that poorer and hotter countries are affected more by climate change and, as a consequence, cross-country income inequality rises. In this context, agriculture, industrialization, and technological development are often brought forward as the key channels through which climate change affects poverty and income inequality (see, e.g., Paglialunga et al., 2022). We assess the relevance of these channels for within-state inequality in the US by estimating cross-sectional regressions of the impact inequality effects across states. We consider the following drivers of inequality: income per capita (average over 2010–2019), rural population as a share of total state population (average over 2010–2020), land in urban areas as a share of total state land surface (average over 2002–2012), percentage of household with an internet subscription (average over 2013–2019), agricultural employment as a share of total state employment (average over 2010–2019), cropland as a share of total state land surface (average 2002–2012), grazed grassland as a share of total state land surface (average 2002–2012), and grazed forest-use land as a share of total state land surface

Table 4: Relationship Between Inequality Impact and Economic Drivers

Standard Inequality Drivers	Mean	Q99	Q95	Q80	Q20	Q5	Q1	Joint
Income/capita	-0.006	-0.010*	-0.006	-0.006	-0.000	0.001	-0.000	-0.005
Rural population	-0.001	0.004*	0.002	0.004*	-0.002*	-0.002*	-0.001	-0.000
Agricultural employment	0.010	0.051*	0.036*	0.038	-0.011	-0.007	-0.000	0.028
Cropland	-0.000	0.003	0.002	0.004*	-0.001	-0.002*	-0.000	0.000
Grazed grassland	0.008*	0.004*	0.003*	0.004*	0.001	0.002*	0.001*	0.007*
Grazed forest-use land	0.022*	0.011*	0.009*	0.004	0.005	0.010*	0.005*	0.025*
Land in urban areas	-0.014*	-0.011*	-0.008*	-0.009*	-0.001	-0.004*	-0.003*	-0.014*
Households w/internet subscription	-0.666	-0.759	-0.247	-0.811	0.452	0.223	-0.054	0.244

Notes: Estimated coefficients of cross-sectional regression across states of inequality impacts on economic drivers of inequality. * denotes significance at 10% level.

(average 2002–2012).[17]

Table 4 summarizes the results of the cross-sectional regressions on these drivers. In contrast to the cross-country findings established in the literature (i.e., poorer countries are affected more), there is no evident link between per capita income and the within-state effects on income inequality. That is, poorer states across the US are not necessarily affected more. Concerning indicators that relate to the agricultural channel, such as the shares of rural population, agricultural employment, or cropland, there seems to be a positive relationship with the higher percentiles and a negative one with the lower percentiles. This suggests that states with a higher relevance of agriculture have smaller inequality effects in response to warmer chilly/extreme cold temperatures. At the same time, they show larger inequality effects in response to warmer hot temperatures. Further, states with more land used for pasture (grazed grassland and forest-use land) have larger inequality impacts in response to increases in temperatures in the mean and most percentiles. Finally, states with more urban areas are associated with smaller effects on income inequality. While these findings align generally with cross-country analyses, there could be important non-linearities to consider. For example, the role of agriculture as a driver of income inequality may depend on the percentile under consideration.

While the above channels are key to understanding income disparities between developing and developed countries, in the US other channels could be more relevant to explain the differences in effects on income inequality. One key driver of income inequality in the United States are productivity gaps within and across firms and industries (see, e.g., Song et al., 2019). To shed light on the role of industries through which climate change may affect income inequality in the US, we assess the relationship between a state's industry share and the inequality effect. As before, we rely on cross-sectional regressions across states. We use industry shares in 2019 as regressors. Table 5

[17] The period over which averages are computed depends mostly on data availability across US states.

summarizes the findings and presents the estimated coefficients. States with higher shares in climate-sensitive industries, such as agriculture, construction, and transportation, have larger inequality impacts in response to temperature increases in the upper percentiles (warmer hot temperatures).[18] This aligns with findings in Nguyen (2024), who finds that employment in the construction and transportation sectors falls, or Colacito et al. (2019), who show that gross state output (GSP) in agriculture and construction decreases in response to hotter summer temperatures. Arguably, the increase in the warm extreme temperatures could yield less employment income as well as decreased productivity in these sectors, ultimately exacerbating income inequality.

Moreover, states with a higher share in finance, insurance, and real estate and services, such as professional and business services and education and health, have more negative effects on inequality (inequality decreases more). We also observe a large negative relationship between the inequality impact following an increase in Q80 temperature and a state's industry share in arts, entertainment, and recreation.[19] Interestingly, the relationship is the opposite for inequality effects in response to Q5 temperature increases.

This simple regression analysis shows the important role of industries through which a warmer US climate may affect income disparities within states. From our analysis it becomes clear that climate change affects income differently for each state and industry, and those impacts also vary across the annual temperature distribution. How each state benefits or loses from warming temperatures in different percentiles is a topic for future research.

4 Conclusions

We study the effects of climate change on income inequality in the United States. To do so, we characterize climate change in the US and introduce the climate-inequality vector autoregression (VAR). Constructing a data set of daily temperatures over 1920–2019 covering the contiguous US, we document that climate change is more than a phenomenon that increases mean temperatures, since the whole temperature distribution has shifted asymmetrically with temperatures in lower percentiles increasing at a faster rate

[18] In comparison to the results in Table 4, we also find a negative relationship between the inequality impact and the share of agriculture in response to warmer Q20 temperatures, but the relationship is not significant.

[19] Understanding through which channels these industries are affected differently across states and seasons and are associated with a decrease in income inequality is an important avenue for future research. Climate adaption, such as air conditioning, may also play a role—e.g., more air conditioning in response to warmer temperatures in summer may increase productivity. Finally, while we are not aware of any analysis on the effects of productivity at the sectoral and state level across seasons, Colacito et al. (2019) document that aggregate US productivity increases in response to warmer fall temperatures.

Table 5: Relationship Between Inequality Impact and Industry Shares

Industry Shares in 2019	Mean	Q99	Q95	Q80	Q20	Q5	Q1	Joint
Agriculture, forestry, fishing, and hunting	3.92	5.33*	5.53*	6.56*	-1.12	0.678	1.04*	6.55*
Mining, quarrying, and oil & gas extraction	1.59*	0.830	0.678	1.40*	-0.188	0.238	0.148	1.42
Utilities	7.98	9.84	6.76	9.56	-1.57	0.116	1.19	5.44
Construction	13.194*	7.89*	5.69*	3.18	2.47	4.19*	2.06*	12.6*
Manufacturing	-0.252	0.897	0.485	0.565	-0.321	-0.229	-0.014	-0.028
Wholesale	1.23	2.08	2.87	0.885	-0.527	-0.457	0.536	1.24
Retail trade	5.42	2.74	3.57	-1.70	0.671	3.25*	1.90*	5.52
Transportation and warehousing	9.60*	8.53*	8.55*	7.67*	-0.507	0.912	0.635	10.1*
Information	0.148	-1.71	-0.236	-1.13	1.27*	0.984*	0.478	1.30
Finance, insurance, real estate, rental, & leasing	-1.78*	-1.38*	-1.28*	-1.44*	0.410	-0.450	-0.352*	-1.89*
Professional and business services	-2.59*	-2.64*	-2.17*	-2.25*	0.208	-0.635	-0.510*	-2.97*
Education, health care, & social assistance	-7.05*	-4.35*	-3.50*	-3.58*	-1.46*	-1.46*	-0.884*	-6.43*
Government and government enterprises	1.01	0.896	0.515	1.62	-0.753	-0.006	0.169	0.409
Arts, entertainment, and recreation	6.24	-4.87	-5.13	-12.2*	4.74	5.35*	0.475	3.26
Accommodation and food services	5.36*	1.88	0.232	-0.577	1.10	2.30*	0.541	4.07*

Notes: Estimated coefficients of cross-sectional regression across states of inequality impacts on industry shares. * denotes significance at 10% level.

than those in higher percentiles for most US states.

Using the climate-inequality VAR, we estimate the effects of climate change on income inequality by identifying shocks to temperature distribution characteristics (such as the mean and percentiles) via a combination of zero and sign restrictions. We find that the effects of climate change on income inequality not only vary across temperature distribution characteristics but also widely across US states. We find both negative and positive impacts on within-state inequality across the US. There is no evident link between a state's climate or per capita income and the within-state effects on income inequality.

We also show the important role of industries through which a warmer US climate may affect income disparities within states. From our analysis it becomes clear that climate change affects income differently for each state and industry, and those impacts also vary across the annual temperature distributions. How each state benefits or loses from warming temperatures in different percentiles is a topic for future research. More studies are needed to understand the nuanced effects of a warming US climate on socio-economic factors (such as income inequality) or the economy. In particular, analyzing the effects of climate change at the firm or industry level and at a sufficient spatial granularity (e.g., state or county level) will help our understanding of how productivity, employment, and output are affected in the presence of the diverse US climate. Understanding the distinct and nuanced effects across space, industries, and seasons will help policymakers design better and more targeted adaptation policies and climate responses.

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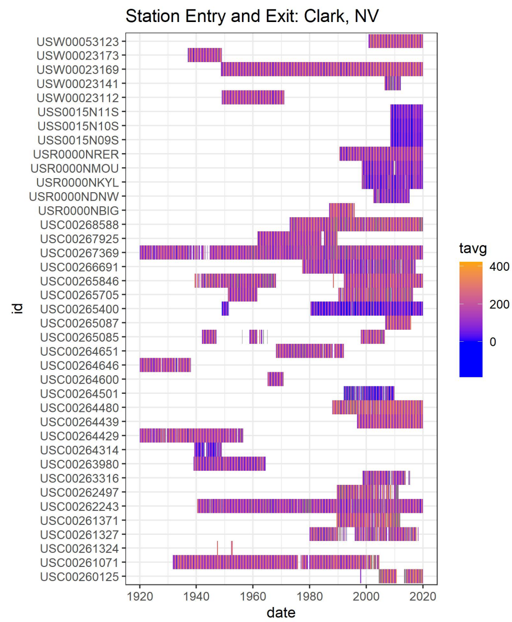
Appendix. Additional Figures

Figure A-1: Example of Station Entry and Exit



Notes: Figure shows recorded daily average temperature readings (Tavg) from 1920-2019 for all weather stations in Clark County in Nevada (NV).