Distributional Effects of the Increasing Heat Incidence on Labor Productivity*

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Abstract

This paper examines how temperature affects worker productivity beyond the usual "on average" analysis, with a particular focus on distributional impacts of the increasing heat incidence across high- and low-productivity areas. Using a recentered influence function regression approach, we estimate unconditional reduced-form effects of a location shift in the temperature distribution—consistent with climate change trends—on the labor productivity distribution across counties in the contiguous U.S. We find that labor productivity is largely insensitive to changes in the frequency of cool-to-moderate maximum daily temperatures. However, as temperatures shift above 24°C, the effects on productivity turn increasingly negative, albeit with their magnitudes attenuating as a county's productivity rank rises. While highly productive locations in the top 5% are not adversely impacted even by the hottest temperatures, permanently increasing the incidence of ≥ 36°C temperatures just by a day lowers productivity at the bottom vigintile by a nontrivial 0.22% per year, an equivalent of 10.5 hours of work by a minimum-wage worker. As temperatures continue to rise, not only does worker productivity worsen on average, but the cross-county dispersion therein widens too. Given existing climate forecasts, we predict that future extreme temperatures would further deepen worker productivity inequality.

Keywords: Labor Productivity, Inequality, Climate Change, Unconditional Quantile, Distributional Heterogeneity

JEL Classification: J24, Q54

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1 Introduction

This paper estimates effects of the increasing incidence of heat on labor productivity, with a particular focus on their distributional implications. Extensive literature has already linked climate change to many economic outcomes (e.g., Schlenker and Roberts, 2009; Dell et al., 2012; Burke et al., 2015; Burke and Emerick, 2016; Deryugina and Hsiang, 2017; Zhang et al., 2018a; Adhvaryu et al., 2020; Malikov et al., 2020; Zhang et al., 2023), documenting negative nonlinear effects of higher temperatures. Understanding how rising temperatures affect *worker* productivity is particularly critical as, arguably, it represents a key mechanism through which a warming climate impacts economy and, more so, because it is the ultimate driver of improvements in workers' standards of living. Per ample experimental evidence in physiology, heat stress impairs people both physically and cognitively (Seppänen et al., 2006; Hancock et al., 2007), reducing their performance. Somanathan et al. (2021) and Burke et al. (2023) also corroborate such negative effects of heat on labor using non-experimental data from manufacturing and professional sports.

Our contribution to this line of research is in examining how the rising temperatures affect U.S. worker productivity beyond the usual "on average" analysis, aiming to understand distributional heterogeneity in overheat effects across high- and low-productivity areas and, eventually, implications thereof for spatial wage inequality in the country. While quantifying average impacts—the standard approach—is essential, they provide an incomplete characterization of climate change effects as global warming, naturally, affects workers in different parts of the productivity distribution differentially, resulting in shifts not only in the mean but also in the overall shape of distribution, notably dispersion. Since labor productivity is already distributed highly unevenly, e.g., with workers in urban areas being far more productive,[1] understanding this distributional heterogeneity is first-order for producing more accurate projections of future productivity losses associated with climate change and for effectively targeting mitigation efforts.

Distributional effects of rising temperatures also have significant implications for welfare of workers and for inequality as extreme weather events tend to disproportionately affect vulnerable populations and exacerbate existing inequalities (e.g., see Mendelsohn et al., 2006; Burzyński et al., 2022; Paglialunga et al., 2022). Marginalized groups often bear the heaviest burden of climate change impacts (IPCC, 2022). Inequality is further propagated by the differential capacity to adapt and mitigate climate change impacts, with more productive, wealthier communities generally having more capabilities to invest in climate resilience measures (Hallegatte et al., 2016). This can create a feedback loop whereby the

[1] See Figure A.1 in Appendix A.

impacts of a warming climate further widen economic disparities. As such, understanding distributional effects of rising temperatures is imperative for ensuring that policy interventions are designed if not to mitigate then at least to not exacerbate inequalities and protect the welfare of most vulnerable populations. Our study contributes to this effort and, more generally, to the emerging literature on climate change impacts on welfare and inequality.

To estimate distributional effects of rising temperatures on worker productivity, we employ Firpo et al.'s (2009) recentered influence function (RIF) regression approach which provides distinct advantages over both ordinary mean regressions and Koenker and Bassett (1978)-style conditional quantile regressions. First of all, it enables us to measure the effect of heat incidence on *any* functional of the labor productivity distribution and not just the mean. Second, unlike conditional quantile methods designed to measure treatment effects on quantiles of the outcome conditional on specific values of regressors, the RIF regression can identify "unconditional" quantile effects that are marginalized over the distribution of all explanatory covariates. Heuristically, in a relationship between Y and X the conditional quantile model identifies the impact of a marginal change in a realized value x on a quantile of Y within a subpopulation characterized by the x level of X, producing condition-specific insights. Whereas, the RIF regression estimates how marginally shifting the location of the distribution of X—effectively, a small increase in the mean level[2] of X—affects a quantile of Y across the entire population (unconditional of the level of X). It thus delivers a more generalized description of how X affects Y, not tied to specific conditions and which can be interpreted in a broader context, making it valuable for policy-making. Basically, an unconditional quantile effect is a weighted average (over the distribution of X) of conditional effects.

This is a subtle but practically important distinction. For example, finding that an additional day of excessively high temperatures decreases worker productivity more severely in areas at the 10th than the 90th *conditional* quantile would mean that overheat increases inter-quantile productivity dispersion within narrow subpopulations of locations that have the same ("conditioning") values of regressors. But this does not tell us how much the rising overheat incidence aggravates the *overall* productivity dispersion as measured by the difference between the 90th and 10th quantiles across all locations unconditional of explanatory variables, which is what policy-makers actually would like to know. Besides the increase in a within-subpopulation productivity dispersion, an RIF-based unconditional quantile regression also captures a between-subpopulation effect due to the intensifying overheat also affecting the wedge between *conditional* means of productivity across areas that are already

[2]Besides, because measured is the partial effect of an increase in the *expected value*, i.e., the long-run mean, of X (weather, in our case) we effectively capture the effect of long-run change in weather.

generally hot and those that are not so. Should these between- and within-subpopulation effects of overheat align, then the inequality between areas of unconditionally lower and higher worker productivity would be exacerbated by even more. This intuition is akin to a textbook decomposition of the unconditional dispersion into the mean of within-group variances and the across-group variance of means, albeit such a decomposition for quantiles or other distributional statistics is not as mathematically straightforward.

2 Empirical Approach

Consider a reduced-form relationship between the economic outcome variable of interest Y—the log of labor productivity—and J weather variables $X = (X_1, \ldots, X_J)'$. Let F_Y be a univariate distribution of Y and, correspondingly, F_X be a J-variate joint distribution of weather X. Of interest is the effect that a change in the weather distribution F_X has on functionals of the "unconditional" (i.e., marginal) labor productivity distribution F_Y. Concretely, we seek to identify the partial effect on a distributional statistic of worker productivity Y denoted by $\nu(F_Y)$—such as a quantile, mean or variance—of a small location shift in the distribution of weather F_X, keeping the conditional distribution of $Y|X$ unchanged. By measuring the effect of a marginal rightward shift in the entire weather distribution F_X (as opposed to an increment in its realization $X = x$ capturing short-run variation) we can identify productivity implications of the long-run change in weather due to a warming climate. To accomplish this, we rely on Firpo et al.'s (2009) RIF regression approach.

Per Corollary 1 in Firpo et al. (2009), when shifting the jth continuous covariate in X, the corresponding unconditional partial effect (UPE) of a small change in the joint distribution of covariates F_X on the distributional functional of interest, $\nu \equiv \nu(F_Y)$, is the average derivative of an RIF regression, i.e.,

$$\underbrace{\mathbb{E}_X\left[\frac{d\mathbb{E}\left[\mathrm{RIF}(Y;\nu,F_Y)\middle|X=x\right]}{dx_j}\right]}_{\mathrm{UPE}(\nu)_j} = \int \frac{d\mathbb{E}\left[\mathrm{RIF}(Y;\nu,F_Y)\middle|X=x\right]}{dx_j} dF_X(x), \tag{1}$$

where $\mathbb{E}[\mathrm{RIF}(Y;\nu,F_Y)|X=x]$ is an RIF regression, i.e., a mean regression of $\mathrm{RIF}(Y;\nu,F_Y)$ on X, with the RIF defined as the influence function (IF) of ν plus the distributional statistic itself: $\mathrm{RIF}(Y;\nu,F_Y) = \mathrm{IF}(Y;\nu,F_Y) + \nu(F_Y)$, such that $\mathbb{E}[\mathrm{RIF}(Y;\nu,F_Y)] = \nu$ by construction.[3]

It is evident from (1) that conditional partial effects of local weather X on the produc-

[3]For a practitioner-oriented treatment of the IF theory and RIF regressions, see Borah and Basu (2013) and Alejo et al. (2021).

tivity distributional statistic ν are marginalized over the distribution of weather variables F_X to arrive at an unconditional partial effect. This UPE can be readily identified by running a *linear* RIF regression. Besides, given a strictly exogenous variation in weather X, the use of a linear least-squares projection is convenient because it facilitates controlling for confounding unobservables via fixed effects in a longitudinal setting. Namely, explicitly indexing locations $i = 1, \dots, N$ and time periods $t = 1, \dots, T$, we have the following panel-data RIF regression model for a given distributional statistic ν of labor productivity:

$$\mathbb{E}\left[\text{RIF}(Y_{it};\nu,F_Y)\middle|\mathbb{X}_{it}\right] = X'_{it}\gamma + \alpha_i + \lambda_t, \tag{2}$$

where α_i and λ_t are county and year fixed effects, respectively, and let $\mathbb{X}_{it} = (X'_{it}, \alpha_i, \lambda_t)'$. The exact form of $\text{RIF}(Y_{it};\nu,F_Y)$ in (2) depends on the choice of distributional statistic ν,[4] and it is constructed using $\{Y_{it}\}$ data —a sample analogue of F_Y—before estimating the above RIF regression.

Integrating (2) over $F_{\mathbb{X}}$, we get $\mathbb{E}[\text{RIF}(Y_{it};\nu,F_Y)] = \mathbb{E}[X_{it}]'\gamma + \alpha_0 + \lambda_0$, where α_0 and λ_0 are respective means of α_i and λ_t. Thus, under linearity of the RIF regression, the UPE of a location shift in X_j on an unconditional distributional statistic ν for Y conveniently equals the coefficient γ_j, viz.,

$$\frac{\partial \nu}{\partial \mathbb{E}[X_j]} = \frac{\partial \mathbb{E}[\text{RIF}(Y_{it};\nu,F_Y)]}{\partial \mathbb{E}[X_{j,it}]} = \gamma_j, \tag{3}$$

since $\mathbb{E}[\text{RIF}(Y;\nu,F_Y)] = \nu$. Also conveniently, γ_j is a UPE of a marginal increase in the (long-run) population mean of X_j as opposed to in a realization $X_{j,it}$ of X_j in a short run.

Of note, since we have panel data, the observed variation in Y_{it} is both across locations and over time which muddies the interpretation of distributional heterogeneity as just "across locations" because the distribution of Y_{it} likely shifts over time. Including λ_t in (2) does not address this as the $\{\text{RIF}(Y_{it};\nu,F_Y)\}$ series is computed prior to running the regression. Instead, we first residualize Y_{it} by detrending it using year dummies[5] so that the resultant RIF is for a statistic ν that describes (spatial) distribution of Y across locations net of temporal variation. So long as one is not concerned with interpreting levels of productivity—we are not—but focuses on *relative* comparisons and marginal *changes* therein, interpretation is unaffected by this adjustment. To avoid notational clutter, we continue denoting the detrended outcome as Y_{it}.

[4]RIF expressions for distributional statistics that we focus on are provided in Appendix B.
[5]Detrending using time polynomial yields similar results.

3 Data

We perform our analysis for the contiguous United States over 2001–2019 at the county level. We measure temperature using its daily maximums which happen during usual working hours, making it a reasonable proxy for heat exposure in the workplace. Using daily maximum temperatures over daily averages also avoids smoothing out hot and cold weather within a day, which would inhibit the measurement of effects of extreme heat on labor productivity. Daily temperatures (T_d) in a county i are aggregated to the annual level for each year t by calculating the number of days during that year on which daily maximums fell within non-overlapping temperature bins. Such a step-function approach to modeling temperature is popular because it provides an easy—and effectively quasi-nonparametric—means to capture nonlinearities. Constructed bins are in 3°C increments and are $T_d < -6°\text{C}$, $T_d \in [-6°\text{C}, -3°\text{C})$, $\ldots$, $T_d \in [33°\text{C}, 36°\text{C})$, $T_d \geq 36°\text{C}$. We also control for precipitation measured using the annual total and its square. Together with two-way fixed effects, these temperature and precipitation variables are our $\mathbb{X}_{it}$ regressors in the RIF regression (2).

To measure worker productivity Y_{it}, we use the county-level average worker compensation (deflated to 2020 dollars) calculated as the annual compensation of employees (in thousands of dollars) divided by the total wage-and-salary employment in each county in that year. If wage reflects marginal productivity of workers (the two are equal under perfect competition), the idea is that the average worker compensation can proxy for the marginal labor productivity of an average employee in the county. For details on variable construction, data sources, summary statistics and maps, see Appendix A.

4 Empirical Results

We estimate the fixed-effects RIF regression in (2) for the following functionals of the unconditional *log*-productivity[6] distribution: i) the expected value, ii) 5th, 10th, 20th,..., 90th and 95th percentiles, iii) the standard deviation and iv) the inter-decile ratio (IDR). Together, these functionals of F_Y can provide us with a holistic picture of how changes in the temperature distribution affect labor productivity along its entire distribution, including its centrality and dispersion. Further, modeling temperature using its discretized within-year frequency distribution as described earlier, with the key regressors of interest being day counts for overheat temperatures in the top bins, conveniently facilitates the interpretation

[6]Hence, the measured effects are semi-elasticities. With coefficients scaled by a 100 (on default, in all figures and tables summarizing UPEs), the effects are in % of productivity per unit change in a weather variable.

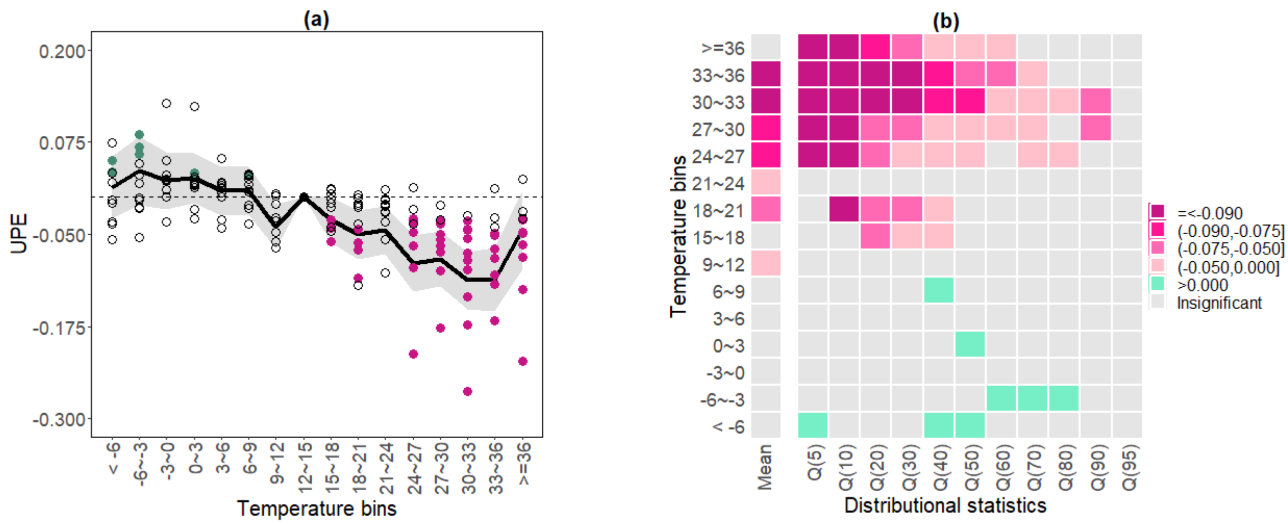

Figure 1. UPEs of Temperature on the Mean and Quantiles of Labor Productivity ($\times 100$)

Notes: Subfigure (a) plots the estimates of UPEs on worker productivity of permanently relocating a day within a year from a $[12°\text{C}, 15°\text{C})$ temperature interval—the omitted reference bin—to each one of the other temperature bins on the horizontal axis. Bubbles show UPEs on the 5th, 10th, 20th, …, 90th, 95th productivity *percentiles* and are filled with solid color if their point estimates are statistically significant at the 5% level. The solid black line, with a 95% gray-shaded confidence band around it, corresponds to UPEs on the *mean* productivity. Subfigure (b) summarizes these UPE estimates across models in the form of a matrix, color-coded based on their sign, size and statistical significance at the 5% level. Regardless of their sign and magnitude, all statistically *in*significant estimates are shown using the same shade of gray.

of their UPEs as in response to a marginal increase in the long-run mean of within-year overheat incidence due to a rightward shift in the entire temperature distribution away from non-overheat towards overheat (since the number of days within a year is fixed).

In what follows, we present the results estimated using the entire 2001–2019 sample period, which implicitly assumes time homogeneity of slopes in the productivity-temperature relationship. We investigate if there is evidence of significant temporal changes in the relationship due to increasing/diminishing resiliency to rising temperatures in Appendix F. Whereas, Appendix G reports the results from population-weighted RIF regressions: the conclusions are quantitatively unchanged.

Circle bubbles in Figure 1(a) correspond to the estimates of UPEs on worker productivity *percentiles* of permanently relocating a day within a year from a $[12°\text{C}, 15°\text{C})$ temperature interval—the excluded reference bin—to each one of the other temperature bins on the horizontal axis. Bubbles are filled using solid color if the corresponding estimates are statistically significant at the 5% level. The solid black line, with a 95% gray-shaded confidence band, corresponds to temperature UPEs on the *mean* productivity, which is included for comparison and helps underscore distributional heterogeneity in the effects. Point esti-

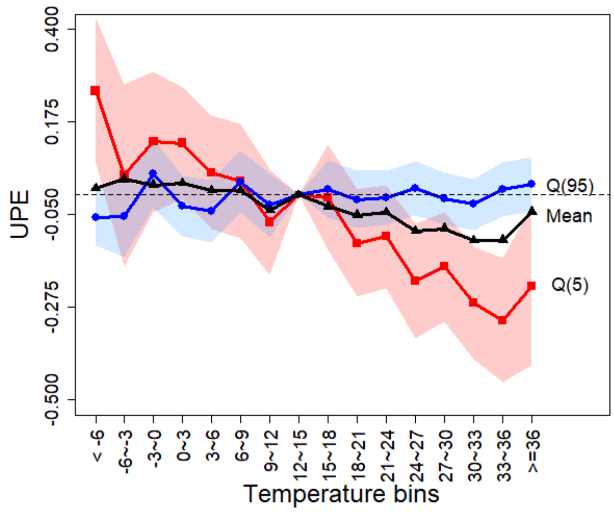

Figure 2. UPEs of Temperature on Centrality and Tails of the Labor Productivity Distribution ($\times 100$)

Notes: The red (blue) line with a 95% shaded confidence band around it shows the estimates of UPEs on the 5th (95th) productivity percentile of permanently relocating a day within a year from a $[12°C, 15°C)$ temperature interval—the omitted reference bin—to each one of the other temperature bins on the horizontal axis. The black line shows the corresponding effects on mean productivity.

mates are also reported in Table C.1 in Appendix C.

We find that unconditional quantile partial effects of temperature on worker productivity are largely statistically insignificant in a cool-to-moderate range, but turn increasingly negative as temperatures rise above 24°C across most percentiles. This is consistent with prior evidence that heat can reduce productivity by causing discomfort, fatigue and cognitive impairment in workers (e.g., Seppänen et al., 2006; Hancock et al., 2007; Somanathan et al., 2021; Zhang et al., 2024; Burke et al., 2023). Notably, cross-percentile dispersion in adverse effects of the rising overheat incidence on productivity increases as temperatures rise, indicating that the distributional heterogeneity is especially salient when temperatures are hot. This is even more apparent from Figure 1(b) which summarizes how labor productivity is influenced by temperature across its unconditional distribution. Plotted is a matrix of estimated UPEs of temperature on the mean and percentiles of worker productivity, color-coded based on their sign, size and statistical significance. It shows that heat is increasingly detrimental for productivity of workers, with the most adverse effects thereof concentrated at the bottom of productivity distribution. The negative effects of hot temperatures generally decrease as productivity rises towards the right tail of the distribution.

To zoom in on these differential effects at different points of the worker productivity distribution, in Figure 2 we plot UPEs on the expected value (central tendency) and the bottom and top vigintiles (the left and right tails) of productivity. We observe that temperature uniformly has *no* significant impact on worker productivity at the 95th percentile but, when above 24°C, its effects are statistically negative in locations in the bottom 5%. That is, highly productive locations in the top 5% experience no significant adverse effects even from the hottest temperatures. Such locations likely rely more on non-agricultural sectors, which are generally less vulnerable to climate change. On the other hand, permanently increasing the average incidence of extreme 36°C-and-above maximum temperatures just by a day, relative to $[12°C, 15°C)$, lowers annual labor productivity by a nontrivial 0.22% at the bottom 5th percentile. With a sample bottom vigintile of worker productivity being about $34,770 per year, this implies an annual cost of one such hot day of $76.5 per worker (2020 USD), an equivalent of 10.5 hours of work by a federal-minimum-wage worker.[7] This distributional heterogeneity buttresses arguments that highly productive locations are likely to be more resilient to a warming climate, reinforcing concerns about inequality-fueled disproportionate effects of climate change on poorer, less productive communities.

Figure 2 also shows that, with temperatures exceeding 18°C, their effects on the bottom vigintile of labor productivity begin to significantly diverge from those on the top vigintile, with adverse impacts on the former increasing with heat intensity. Consequently, as temperatures continue to rise with a changing climate, not only would worker productivity worsen on average as evidenced by negative UPEs of overheat on the mean, but the productivity gap between the most and least productive U.S. counties would widen as well. We test this dispersion inflation effect more directly by estimating RIF regressions for the standard deviation and the IDR of productivity distribution. Figure 3 plots the corresponding UPEs across temperature intervals.[8] Clearly, the increasing incidence of hot temperatures significantly raises the dispersion of worker productivity across locations, magnifying spatial inequality therein. For example, shifting the temperature distribution by relocating a single day from a $[12°C, 15°C)$ temperature interval to a $[33°C, 36°C)$ interval is estimated to increase the ratio of top and bottom deciles of annual productivity by 0.96% and the standard deviation by about 0.20%.

Distributional heat effects on worker productivity could occur via both within-industry and between-industry channels. We reproduce Figure 1(b) based on estimates obtained using county-industry-level data, controlling for two-digit industry fixed effects in addition to county and year effects, so the identifying variation relied on is within industry and county. (Details are available in Appendix D.) The new Figure D.1 in the Appendix is largely consistent with our main findings in Figure 1(b), with both diagrams showing a similar distri-

[7] The federal minimum wage in 2020 was $7.25 an hour.

[8] Point estimates are available in Table C.1 in Appendix C.

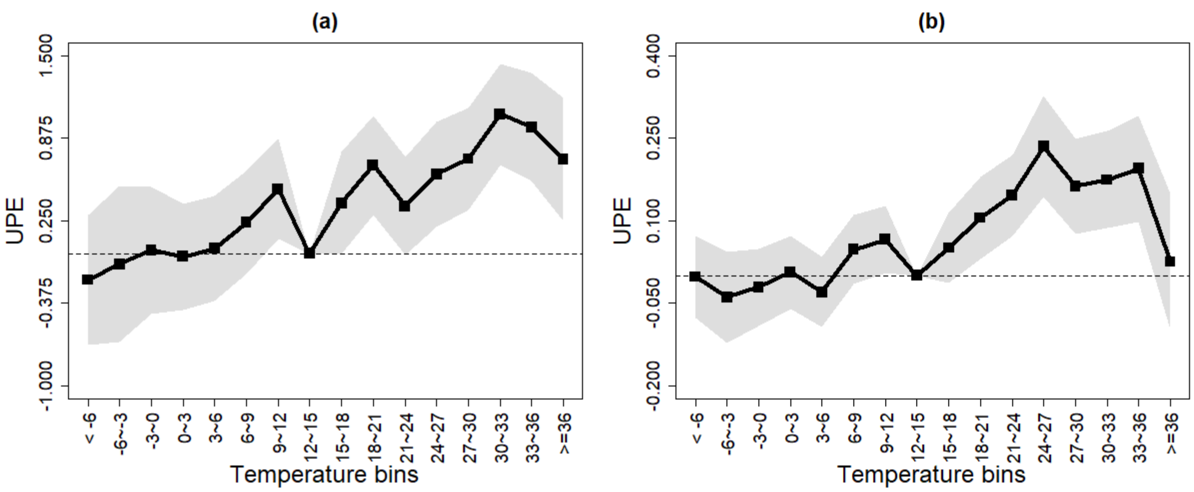

Figure 3. UPEs of Temperature on Dispersion of the Labor Productivity Distribution ($\times 100$)

Notes: Plotted are the estimates, along with 95% confidence bands, of UPEs on the inter-decile ratio (a) and the standard deviation (b) of productivity resulting from permanently relocating a day within a year from a $[12°C, 15°C)$ temperature interval—the omitted reference bin—to each one of the other temperature bins on the horizontal axis.

butional pattern of heat impacts on productivity: hot temperatures are increasingly detrimental to worker productivity, with the most adverse effects concentrated on the left side of the county-industry-level distribution. Thus, it is reasonable to conclude that our main county-level results are at least partially due to distributional heterogeneity in heat effects on productivity *within* industries. Next, we heuristically explore if cross-region heterogeneity in local composition of industries also plays a role for our county-level results. Table D.1 in Appendix D reports correlation coefficients between each two-digit industry's share of total county employment and county-level average productivity (over all industries). Predictably, employment shares of industries such as agriculture or mining are negatively correlated with aggregate productivity, whereas industries such as finance and management are correlated with it positively. This is well illustrated in Figure D.2 in Appendix D which maps the employment share of agriculture, arguably the most climate-sensitive industry. Correlating this figure with Figure A.1 in Appendix A, we discern that counties with higher agricultural employment shares tend to be less productive (e.g., the Great Plains). In light of this correspondence between local industrial composition and the average productivity of counties and since low-productivity industries (such as agriculture) are the ones that tend to be more vulnerable to heat, we cannot reasonably rule out that our finding of distributional heat effects across counties is also partially driven by cross-region heterogeneity in industrial composition.

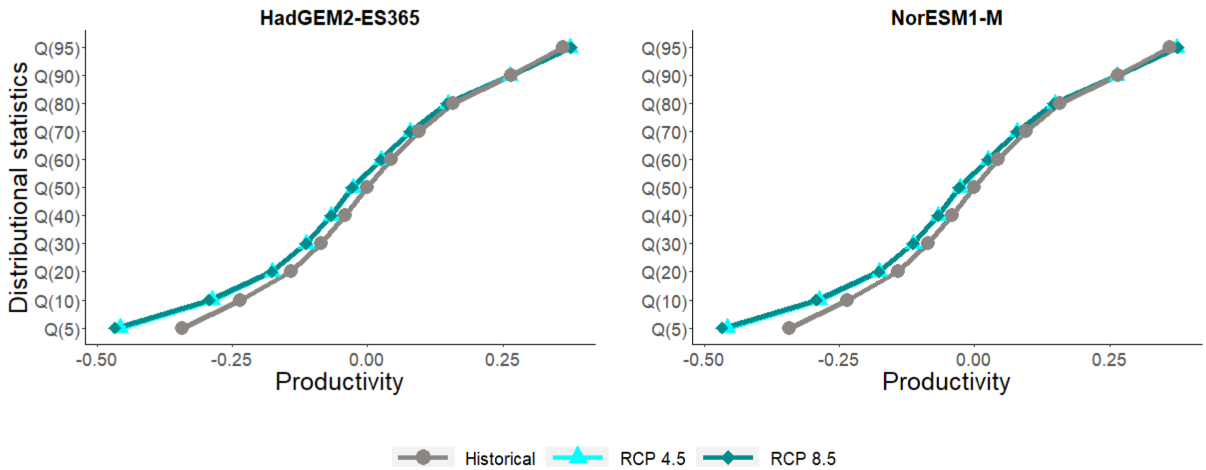

Figure 4. Historical and Projected Labor Log-Productivity Distributions

Notes: Reported are historical quantiles of the 2001–2019 labor productivity and their 2040–2059 analogues predicted using two global climate models—HadGEM2-ES365 and NorESM1-M—and two scenarios: medium (RCP4.5) and the warmest (RCP8.5).

Given this significant variability in historical effects of heat on workers across low- and high-productivity areas, it is of interest to examine how this distributional heterogeneity influences projections of expected future climate change damages. Using the estimated historical productivity-temperature relationship and climate forecasts for the mid-century (2040–2059) we predict future unconditional labor productivity distribution at different percentiles.[9] The difference between these out-of-sample projections and historical estimates using the 2001–2019 data measures the expected impact of a warming climate. Appendix E provides details on the construction of such projections.

Figure 4 plots ogives using historical estimates of worker log-productivity at different points of its distribution in 2001–2019 along with their corresponding future projections for 2040–2059 under two global climate models—HadGEM2-ES365 and NorESM1-M—each of which predicts climate under medium (RCP4.5) and the warmest (RCP8.5) scenarios. As a result of adverse effects of rising temperatures, our analysis predicts that most of the mass of productivity distribution will shift leftwards in the future. Consistent with lower-

[9]One caveat is that temperature effects on productivity may change over time due to adaptation. Adaptation can affect both location and scale of the productivity distribution. On the one hand, adaptation will enhance overall productivity and thus shift the entire distribution. On the other hand, because adaptation often requires financial resources (Sussman et al., 2014), it is reasonable to expect that more productive areas are better equipped for adaptation than are less productive areas. As a result, future climate change may aggravate productivity dispersion between areas. However, predicting the magnitude of adaptation between 2001–2019 and 2040–2059 is challenging and beyond the scope of our study. To avoid arbitrary speculations about future adaptation and remain focused on examining distributional effects of the increasing heat incidence, our projections assume that the productivity-temperature relationship does not change over time. As such, they are worst-case-scenario projections that produce an upper bound of the future heat impact on worker productivity, but perhaps are best-case-scenario projections that generate a lower bound of productivity inequality across areas.

Table 1. Projected Labor Productivity Damages due to Climate Change by the Mid-Century

Distributional Statistic	*Future Climate Scenarios* HadGEM2-ES365 RCP 4.5	HadGEM2-ES365 RCP 8.5	NorESM1–M RCP 4.5	NorESM1–M RCP 8.5
Q(5)	**–0.114**	**–0.125**	**–0.090**	**–0.112**
	(0.032)	(0.042)	(0.021)	(0.027)
Q(10)	**–0.053**	**–0.057**	**–0.044**	–0.054
	(0.014)	(0.018)	(0.009)	(0.012)
Q(20)	**–0.034**	**–0.035**	**–0.029**	**–0.036**
	(0.008)	(0.011)	(0.006)	(0.007)
Q(30)	**–0.027**	**–0.028**	**–0.024**	**–0.029**
	(0.006)	(0.008)	(0.004)	(0.006)
Q(40)	**–0.025**	**–0.026**	**–0.022**	**–0.027**
	(0.005)	(0.007)	(0.004)	(0.005)
Q(50)	**–0.027**	–0.029	**–0.022**	**–0.028**
	(0.005)	(0.006)	(0.003)	(0.004)
Q(60)	**–0.018**	**–0.020**	**–0.015**	**–0.019**
	(0.004)	(0.005)	(0.003)	(0.004)
Q(70)	**–0.015**	**–0.016**	**–0.013**	**–0.016**
	(0.005)	(0.006)	(0.003)	(0.004)
Q(80)	–0.010	–0.010	**–0.007**	**–0.010**
	(0.005)	(0.006)	(0.004)	(0.005)
Q(90)	–0.001	0.000	–0.002	–0.002
	(0.007)	(0.008)	(0.005)	(0.006)
Q(95)	0.014	0.016	0.007	0.011
	(0.010)	(0.012)	(0.007)	(0.009)
Mean	**–0.020**	–0.017	**–0.019**	**–0.024**
	(0.009)	(0.012)	(0.006)	(0.008)

Notes: Reported are logarithmic differences between historical 2001–2019 labor productivity mean/quantile estimates and their 2040–2059 analogues predicted using two global climate models—HadGEM2-ES365 and NorESM1-M—and two warming scenarios: medium (RCP4.5) and the warmest (RCP8.5). A negative (positive) difference indicates that the future worker productivity is smaller (larger) than the historical value. Robust standard errors are clustered at the climate division and year level. Statistically significant (at the 5% level) predictions are boldface.

productivity counties suffering from more severe climate change impacts, the wedge between historical and forecast ogives of worker productivity is widening as a county's productivity rank falls. On the other hand, our projections suggest that, in the most productive counties at the top, worker productivity will largely stay unaffected. As such, the cross-county inequality in productivity levels is to rise as climate continues to warm up.

The (horizontal) distances between the historical labor productivity distribution and its future forecasts in Figure 4 are summarized in Table 1, where we also provide evidence speaking to their statistical significance. Compared to 2001–2019 levels, worker productivity for the bottom 70-80% is estimated to decline by 1 to 12% by the mid-century, depending on global climate projections and the rank in productivity distribution. Least productive areas are to see the largest declines. All in all, while these mid-range productivity loss projections might appear modest, they are in fact sizable, given how sluggish labor productivity growth has been in the U.S. over the last decade. Although locations in the far right tail of the distribution may see their productivity stay roughly the same, absent adaptation, the *mean* worker productivity in the U.S. is projected to decrease by 2040–2059 by roughly 2% solely due to climate change. With the current sample mean productivity of about \$51,230, this amounts to cumulative economic damages of \$1,025 per worker annually on average. Then again, over the 2001–2019 historical period, the average labor productivity growth rate in our sample was about 0.8% per year. If this growth rate persists without climate change then, by 2050, worker productivity will be $(1.008^{2050-2019}-1)\times 100$ =28% higher than its 2019 level. Thus, a 2% reduction in the level of mean productivity due to climate change will have curtailed cumulative growth on average by $2/28\times 100 = 7.1\%$ by the mid-century.

5 Concluding Remarks

This study finds that the sensitivity of U.S. labor productivity to shifts in the temperature distribution exhibits significant distributional heterogeneity. The nonlinear negative effects of an increasing incidence of overheat attenuate as a county's productivity rank rises and become insignificant at the top percentiles. Weakening in resiliency of workers to extreme weather is not uniform either, with it occurring mostly in the bottom two thirds of the labor productivity distribution. Considering all of this, were there no technical improvement, by the mid-century worker productivity in the bottom of distribution would decline by up to 12% (depending on the rank) relative to current historical levels due to climate change, with the least productive counties to see the largest losses. This suggests that future climate change would exacerbate worker productivity inequality and thus, ultimately, income inequality in the United States.

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Online Appendix

A Data Details

To study worker productivity effects of heat stress, we measure temperature using its daily maximums which happen during working hours, making it a reasonable proxy for heat exposure in the workplace. Using daily maximum temperatures over daily averages also avoids smoothing out hot and cold weather within a day, which would inhibit the measurement of effects of extreme heat on labor productivity. Although our focus is on the reduced-form effects of temperature, we also control for precipitation in our analysis because, when coupled with heat, changes in precipitation patterns can also adversely affect human thermoregulatory capacity (see Mora et al., 2017) and, hence, worker performance. Additionally, heavy precipitation events associated with climate change can disrupt workers' commute, also resulting in productivity losses.

Historical temperature and precipitation data are obtained from the PRISM Climate Group.[10] Daily temperatures (T_d) in a county i are aggregated to the annual level for each year t by calculating the number of days during that year on which daily maximums fell within non-overlapping temperature bins. Such a step-function approach to modeling temperature is popular (e.g., Schlenker and Roberts, 2009; Deryugina and Hsiang, 2017; Zhang et al., 2018a; Somanathan et al., 2021) because it provides an easy—and effectively quasi-nonparametric—means to capture nonlinearities in its effects. Constructed bins are $T_d < -6°\text{C}$, $T_d \in [-6°\text{C}, -3°\text{C})$, …, $T_d \in [33°\text{C}, 36°\text{C})$, $T_d \geq 36°\text{C}$. Precipitation is measured using the annual total and its square.

To measure worker productivity, we use the Regional Economic Information System data published by the U.S. Bureau of Economic Analysis (BEA).[11] The data are reported at the county-year level. We use the average employee compensation as a labor productivity measure for our analysis. It is calculated as the annual compensation of employees (in thousands of dollars) divided by the total wage-and-salary employment in each county in that year. If wage reflects marginal productivity of workers (the two are equal under perfect competition), the idea is that the average worker compensation can proxy for the marginal labor productivity of an average employee in the county. Worker compensation used in our calculations is the total remuneration payable by employers to employees in return for their work during the period; it consists of wages and salaries and supplements thereto. Wage-and-salary employment, also referred to as wage-and-salary jobs, measures the average

[10] Source: https://prism.oregonstate.edu/.

[11] Source: https://apps.bea.gov/regional/downloadzip.cfm.

annual number of full- and part-time jobs in each county by place of work. All jobs for which wages and salaries are paid are counted.[12] We deflate our labor productivity measure to 2020 dollars using implicit county-level gross domestic product (GDP) price deflators.[13]

To quantify potential impacts on labor productivity associated with a continued warming of climate in the near to medium future, we obtain projected future climate data (2040–2059) from the Multivariate Adaptive Constructed Analogs dataset.[14] We use data generated by two global climate models: HadGEM2-ES365 and NorESM1-M. The former (latter) model tends to predict the largest (lowest) temperature increases among a host of global climate models (Warszawski et al., 2014). Moreover, each model contains predicted climate data under two greenhouse gas representative concentration pathways (RCP4.5 and RCP8.5) that represent medium and the warmest scenarios, respectively. Summary statistics for historical and projected data are provided in Tables A.1–A.2. Included are also maps of historical distributions of labor productivity (Figure A.1) and the incidence of overheat (Figure A.2).

[12] Per the BEA, although compensation paid to jurors, expert legal witnesses, prisoners, and justices of the peace (for marriage fees), is counted in wages and salaries, these activities are not counted as jobs in wage-and-salary employment. Corporate directorships are counted as self-employment. Since such categories constitute a trivial share in total compensation and total jobs, their distortionary effects on our worker productivity measure are plausibly negligible.

[13] Implicit price deflators are constructed by dividing the county-level GDP in Current Dollars by the corresponding Real GDP in Chained Dollars, with both series published by the BEA.

[14] Source: https://climate.northwestknowledge.net/MACA/index.php.

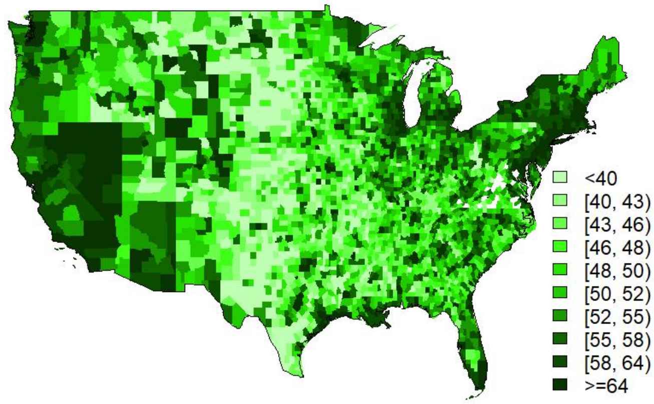

Figure A.1. Spatial Distribution of U.S. Labor Productivity

Notes: Shown are county-level 2001–2019 averages of labor productivity, measured as the average employee compensation (in 1,000s of 2020 USD) and color-coded based on a decile interval of the cross-county distribution they fall in.

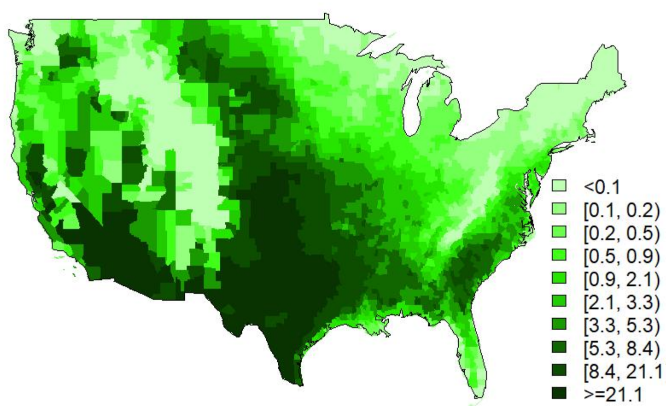

Figure A.2. Spatial Distribution of Overheat Incidence in the Contiguous U.S.

Notes: Shown are county-level 2001–2019 average day counts (per year) when maximum temperatures exceeded 36°C, color-coded based on a decile interval of the cross-county distribution they fall in.

Table A.1. Summary Statistics of Historical Data (2001–2019)

Variable	Mean	10th Pctl.	Median	90th Pctl.	SD
Labor Productivity	51.23	39.03	49.99	64.84	12.04
$T_d \geq 36°C$	6.60	0.00	0.00	21.00	14.22
$T_d \in [33°C, 36°C)$	20.13	0.00	14.00	50.00	20.12
$T_d \in [30°C, 33°C)$	37.60	8.00	36.00	67.00	23.05
$T_d \in [27°C, 30°C)$	43.25	25.00	43.00	62.00	14.83
$T_d \in [24°C, 27°C)$	39.06	26.00	38.00	53.00	10.52
$T_d \in [21°C, 24°C)$	33.87	23.00	33.00	45.00	8.64
$T_d \in [18°C, 21°C)$	29.75	20.00	30.00	39.00	7.70
$T_d \in [15°C, 18°C)$	27.66	19.00	27.00	37.00	7.88
$T_d \in [12°C, 15°C)$	25.59	16.00	25.00	35.00	8.29
$T_d \in [9°C, 12°C)$	22.92	12.00	23.00	33.00	9.34
$T_d \in [6°C, 9°C)$	20.66	7.00	21.00	33.00	10.51
$T_d \in [3°C, 6°C)$	17.98	3.00	18.00	32.00	11.22
$T_d \in [0°C, 3°C)$	15.68	0.00	15.00	32.00	12.14
$T_d \in [-3°C, 0°C)$	10.52	0.00	8.00	25.00	9.92
$T_d \in [-6°C, -3°C)$	6.23	0.00	3.00	17.00	7.19
$T_d < -6°C$	7.73	0.00	2.00	25.00	12.80
Annual Precipitation	1040.36	460.93	1052.79	1578.84	420.72

Notes: County-level labor productivity is measured using the annual average employee compensation (in thousands of deflated dollars) obtained from the BEA. Temperature variables measure the count of days within a year on which daily maximums in a county (T_d) fell within each on of non-overlapping temperature bins. Annual precipitation in the county is measured in cm. Historical weather data come from the PRISM Climate Group.

Table A.2. Summary Statistics of Future Climate Variables (2040–2059)

Variable	Mean	10th Pctl.	Median	90th Pctl.	SD	Mean	10th Pctl.	Median	90th Pctl.	SD
	HadGEM2-ES365 RCP 4.5					**HadGEM2-ES365 RCP 8.5**				
$T_d \geq 36°C$	40.27	3.00	34.00	87.00	32.91	54.85	6.00	51.00	108.00	37.76
$T_d \in [33°C, 36°C)$	32.98	13.00	31.00	53.00	17.84	31.14	15.00	30.00	48.00	15.44
$T_d \in [30°C, 33°C)$	36.57	21.00	35.00	54.00	14.12	34.51	21.00	33.00	51.00	13.12
$T_d \in [27°C, 30°C)$	36.06	22.00	35.00	51.00	11.97	34.09	21.00	33.00	49.00	11.47
$T_d \in [24°C, 27°C)$	33.94	22.00	33.00	47.00	10.02	32.15	20.00	31.00	46.00	10.01
$T_d \in [21°C, 24°C)$	31.48	21.00	31.00	43.00	9.03	29.02	19.00	28.00	40.00	8.47
$T_d \in [18°C, 21°C)$	28.76	19.00	28.00	39.00	8.50	26.72	17.00	26.00	36.00	8.14
$T_d \in [15°C, 18°C)$	25.98	16.00	25.00	36.00	9.03	24.85	15.00	24.00	35.00	8.89
$T_d \in [12°C, 15°C)$	23.31	11.00	23.00	35.00	9.80	22.59	12.00	22.00	34.00	9.70
$T_d \in [9°C, 12°C)$	20.81	6.00	21.00	34.00	10.62	20.41	7.00	20.00	33.00	10.19
$T_d \in [6°C, 9°C)$	18.62	2.00	19.00	35.00	12.18	18.70	2.00	19.00	34.00	11.87
$T_d \in [3°C, 6°C)$	15.96	0.00	14.00	35.00	13.38	15.92	0.00	14.00	34.00	12.91
$T_d \in [0°C, 3°C)$	9.98	0.00	6.00	26.00	10.70	9.92	0.00	7.00	25.00	10.46
$T_d \in [-3°C, 0°C)$	5.16	0.00	2.00	15.00	6.99	5.19	0.00	2.00	15.00	6.86
$T_d \in [-6°C, -3°C)$	2.63	0.00	0.00	9.00	4.48	2.62	0.00	0.00	9.00	4.53
$T_d < -6°C$	2.76	0.00	0.00	9.00	6.54	2.58	0.00	0.00	8.00	6.30
Annual Precipitation	1006.83	427.82	1033.83	1495.45	416.90	947.74	411.03	956.67	1435.70	394.34
	NorESM1-M RCP 4.5					**NorESM1-M RCP 8.5**				
$T_d \geq 36°C$	26.18	1.00	18.00	65.00	27.01	32.39	2.00	24.00	78.00	30.15
$T_d \in [33°C, 36°C)$	34.61	10.00	32.00	63.00	20.94	35.88	12.00	33.00	62.00	20.11
$T_d \in [30°C, 33°C)$	41.66	23.00	41.00	62.00	15.75	41.85	24.00	40.00	62.00	16.02
$T_d \in [27°C, 30°C)$	38.57	26.00	38.00	52.00	10.98	38.07	25.00	37.00	53.00	11.76
$T_d \in [24°C, 27°C)$	33.59	23.00	33.00	45.00	9.07	33.49	22.00	33.00	46.00	9.41
$T_d \in [21°C, 24°C)$	29.44	20.00	29.00	40.00	8.49	29.65	20.00	29.00	40.00	8.30
$T_d \in [18°C, 21°C)$	27.12	18.00	26.00	37.00	8.30	27.06	17.00	27.00	37.00	8.13
$T_d \in [15°C, 18°C)$	25.19	15.00	24.00	36.00	8.78	24.61	15.00	24.00	35.00	8.38
$T_d \in [12°C, 15°C)$	23.42	12.00	23.00	34.00	9.97	22.10	11.00	22.00	32.00	9.29
$T_d \in [9°C, 12°C)$	21.33	8.00	21.00	33.00	10.46	20.24	6.00	20.00	32.00	10.58
$T_d \in [6°C, 9°C)$	18.91	3.00	19.00	33.00	10.95	18.14	2.00	19.00	32.00	11.15
$T_d \in [3°C, 6°C)$	16.28	1.00	16.00	32.00	11.84	15.69	0.00	15.00	32.00	12.05
$T_d \in [0°C, 3°C)$	13.18	0.00	11.00	31.00	12.08	11.87	0.00	9.00	29.00	11.42
$T_d \in [-3°C, 0°C)$	8.11	0.00	4.00	23.00	9.37	7.05	0.00	4.00	20.00	8.56
$T_d \in [-6°C, -3°C)$	4.18	0.00	1.00	13.00	5.92	3.60	0.00	1.00	11.00	5.25
$T_d < -6°C$	3.49	0.00	0.00	11.00	6.86	3.57	0.00	0.00	12.00	7.18
Annual Precipitation	982.30	433.02	993.82	1468.28	402.15	1033.55	424.77	1062.47	1561.23	440.66

Notes: Predicted future weather data come from two global climate models (HadGEM2-ES365 and NorESM1-M) under two warming scenarios (RCP4.5 and RCP8.5). The definitions of variables are the same as of their historical analogues summarized in Table A.1.

B RIFs

In our analysis, we consider four functionals ν of the (unconditional) labor productivity distribution F_Y: i) mean $\mu \equiv \mathbb{E}[Y_{it}]$; ii) τth quantile $q_\tau \equiv \inf_q\{q : F_Y(q) \geq \tau\}$ for selected $\tau \in (0,1)$; (iii) variance $\sigma^2 \equiv \mathbb{E}[(Y_{it}-\mu)^2]$; and (iv) selected inter-quantile ratios q_{τ_1}/q_{τ_2}. Their RIFs are respectively given by

$$
\begin{aligned}
\text{i)} \quad & \mathrm{RIF}(Y_{it};\mu^s,F_Y) = Y_{it}, \\
\text{ii)} \quad & \mathrm{RIF}(Y_{it};q_\tau,F_Y) = q_\tau + \frac{\tau - \mathbb{1}\{Y_{it} < q_\tau\}}{f_Y(q_\tau)}, \\
\text{iii)} \quad & \mathrm{RIF}(Y_{it};\sigma^2,F_Y) = \left(Y_{it}-\mu\right)^2, \\
\text{iv)} \quad & \mathrm{RIF}(Y_{it};q_{\tau_1},q_{\tau_2},F_Y) = \left(q_{\tau_1} + \frac{\tau_1 - \mathbb{1}\left\{Y_{it} < q_{\tau_1}\right\}}{f_Y\left(q_{\tau_1}\right)}\right) \Big/ \left(q_{\tau_2} + \frac{\tau_2 - \mathbb{1}\left\{Y_{it} < q_{\tau_2}\right\}}{f_Y\left(q_{\tau_2}\right)}\right),
\end{aligned}
$$

where $f_Y = \mathrm{d}F_Y(y)/\mathrm{d}y$ is the marginal density function, and $\mathbb{1}\{\cdot\}$ is an indicator function.

Notice that, when $\nu = \mu$, the RIF regression in (2) simplifies to a usual conditional-mean regression since $\mathbb{E}\left[\mathrm{RIF}(Y_{it};\mu)\middle|X_{it}\right] = \mathbb{E}\left[Y_{it}\middle|X_{it}\right]$, and the γ_j parameter then measures a familiar "unconditional average partial effect" of X_j on mean of Y:

$$
\frac{\partial\mu}{\partial\mathbb{E}[X_{j,it}]} = \frac{\partial\mathbb{E}\left[\mathrm{RIF}(Y_{it};\mu)\right]}{\partial\mathbb{E}[X_{j,it}]} = \mathbb{E}\left[\frac{\partial\mathbb{E}[Y_{it}|X_{it}]}{\partial X_{j,it}}\right] = \gamma_j(\mu). \tag{B.1}
$$

For a τth quantile, whereby $\nu = q_\tau$, the γ_j coefficient in the linear RIF regression (2) identifies an "unconditional quantile partial effect" of X_j at τ, viz.,

$$
\frac{\partial q_\tau}{\partial\mathbb{E}[X_{j,it}]} = \frac{\partial\mathbb{E}[\mathrm{RIF}(Y_{it};q_\tau)]}{\partial\mathbb{E}[X_{j,it}]} = \mathbb{E}\left[\frac{\partial\mathbb{E}[\mathrm{RIF}(Y_{it};q_\tau)|X_{it}]}{\partial X_{j,it}}\right] = \gamma_j(\tau). \tag{B.2}
$$

Along the same lines, we can identify UPEs on variance and inter-quantile ratios of Y via γ_j in (2) using RIFs that correspond to these statistics.

C UPEs of Temperature on Labor Productivity

See Table C.1 on the next page.

Table C.1. UPEs of Temperature on Distributional Statistics of Labor Productivity (×100)

Variable	Mean	Q(5)	Q(10)	Q(20)	Q(30)	Q(40)	Q(50)	Q(60)	Q(70)	Q(80)	Q(90)	Q(95)	SD	IDR
$T_d \geq 36°C$	–0.043	–0.222*	–0.124**	–0.081**	–0.064**	–0.048**	–0.047**	–0.031*	–0.029	–0.020	–0.030	0.025	0.025	0.714**
$T_d \in [33°C, 36°C)$	–0.112**	–0.307**	–0.167**	–0.118**	–0.105**	–0.082**	–0.070**	–0.052**	–0.048**	–0.027	–0.040	0.012	0.195**	0.959**
$T_d \in [30°C, 33°C)$	–0.113**	–0.264**	–0.173**	–0.135**	–0.098**	–0.086**	–0.076**	–0.043**	–0.045**	–0.031*	–0.056*	–0.025	0.174**	1.058**
$T_d \in [27°C, 30°C)$	–0.083**	–0.176**	–0.100**	–0.074**	–0.065**	–0.050**	–0.036**	–0.032*	–0.033*	–0.031	–0.058**	–0.011	0.162**	0.717**
$T_d \in [24°C, 27°C)$	–0.090**	–0.212**	–0.095**	–0.066**	–0.047**	–0.035*	–0.029*	–0.016	–0.029*	–0.032*	–0.036	0.013	0.235**	0.602**
$T_d \in [21°C, 24°C)$	–0.045**	–0.103	–0.058	–0.033	–0.019	–0.012	–0.011	–0.003	–0.003	0.010	–0.020	–0.010	0.146**	0.359
$T_d \in [18°C, 21°C)$	–0.051**	–0.119	–0.109**	–0.072**	–0.062**	–0.044**	–0.000	–0.008	0.003	–0.011	–0.037	–0.013	0.105**	0.671**
$T_d \in [15°C, 18°C)$	–0.030	–0.008	–0.040	–0.060**	–0.041*	–0.031*	–0.013	0.010	–0.002	0.004	–0.046	0.012	0.050	0.381
$T_d \in [9°C, 12°C)$	–0.040*	–0.068	–0.061	–0.032	–0.032	–0.009	0.005	0.005	0.002	–0.032	–0.048	–0.027	0.065*	0.489*
$T_d \in [6°C, 9°C)$	0.009	0.032	–0.036	0.029	0.017	0.030*	0.025	0.011	0.008	–0.010	–0.015	0.030	0.048	0.235
$T_d \in [3°C, 6°C)$	0.009	0.053	0.020	0.006	0.016	0.012	0.020	0.019	0.001	0.013	–0.031	–0.042	–0.030	0.037
$T_d \in [0°C, 3°C)$	0.026	0.124	0.020	0.028	0.017	0.024	0.033*	0.015	0.013	0.019	–0.017	–0.028	0.006	–0.023
$T_d \in [-3°C, 0°C)$	0.023	0.127	0.024	0.010	0.001	0.024	0.030	0.022	0.022	0.024	–0.033	0.050	–0.021	0.027
$T_d \in [-6°C, -3°C)$	0.036	0.046	0.020	–0.014	–0.015	–0.001	0.030	0.069**	0.058*	0.086**	–0.003	–0.054	–0.040	–0.080
$T_d < -6°C$	0.014	0.250**	0.075	0.033	0.020	0.049**	0.035*	–0.004	–0.008	–0.033	–0.036	–0.057	–0.002	–0.199
Precipitation	0.012**	0.038**	0.021**	0.012**	0.008**	0.006**	0.004**	0.003*	0.003**	0.004**	0.003	0.004	–0.019**	–0.110**
Precipitation Square/1000	–0.005**	–0.016**	–0.008**	–0.005**	–0.004**	–0.003**	–0.002**	–0.002**	–0.002**	–0.001**	–0.001	–0.000	0.007**	0.043**

Notes: Reported are the coefficient estimates from RIF fixed-effects regressions in (2) estimated for the following distributional statistics v of labor productivity: i) mean, ii) 5th, 10th, 20th, …, 90th and 95th percentiles, iii) standard deviation and iv) the 90th-to-10th inter-decile ratio (IDR). County and year effects are included throughout. The omitted reference category is $T_d \in (12°C, 15°C]$. Statistical significance is determined using robust standard errors clustered at the climate division and year level. $^{**}p < 0.01$, $^{*}p < 0.05$.

D Within- and Between-Industry Effects

Our findings of differential heat effects across the productivity distribution at the county level are reduced-form in a sense that they capture the net of within- and between-industry (i.e., compositional) effects in a county. It would be of interest to further examine whether our findings are primarily driven by the variation in local industrial mixes or heterogeneous heat responsiveness of workers within industries. Unfortunately, reliable county-industry-level data to perform such an analysis is not easily available. For instance, although the BEA publishes employment and compensation data at the county-industry level, in order to avoid disclosure of confidential information, a significant portion (on average, 28.5% in 2001–2019) of these is concealed and, thus, missing not at random. The county-industry-level County Business Patterns dataset from the U.S. Census Bureau suffers from a similarly serious data suppression issue. This is a well-known problem with county-industry data in the U.S. Moreover, since data are missing mainly because of confidentiality protections, it is not unreasonable to conjecture that this issue is likely more acute for county-industries in the far left and right tails of the productivity distribution: those with the lowest/highest productivity have a higher chance of having few establishments and, thus, are more likely to be endogenously left unreported by the agency to preclude individual establishments from being identified. As such, this severe missing-data problem with both industry-level datasets is particularly detrimental to a distributional analysis like ours, rendering a credible implementation thereof at the industry-level infeasible. Nonetheless, ignoring this endogenously missing data issue for a moment, we reproduce our analysis using the available BEA county-industry-level data pooled across two-digit NAICS (North American Industry Classification System) industries. This time, besides county and year effects we also include industry fixed effects so that the variation used in the estimation is within industry-county. The new results in Figure D.1 remain largely consistent with our main findings in the paper.

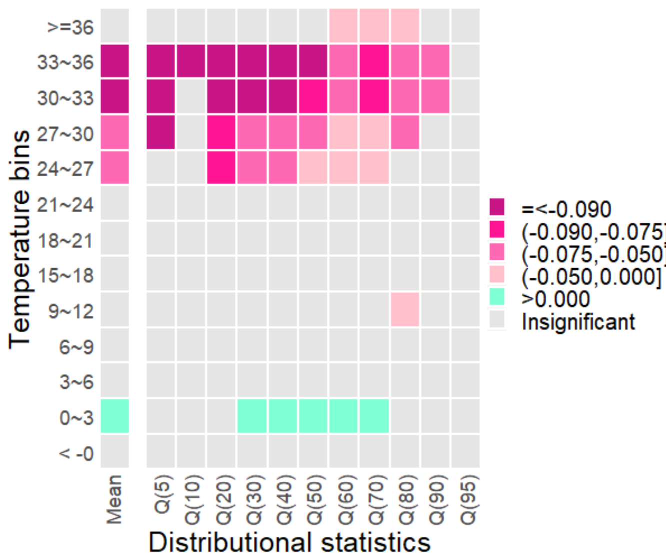

Figure D.1. UPEs of Temperature on the Mean and Quantiles of Labor Productivity ($\times 100$)
Notes: This figure summarizes estimates of UPEs on worker productivity of permanently relocating a day within a year from a $[12°C, 15°C)$ temperature interval-the omitted reference bin-to each one of the other temperature bins on the horizontal axis. The estimates are based on available BEA county-industry-level data pooled across two-digit NAICS industries, controlling for industry, county, and year fixed effects. Effects on the mean and the 5th, 10th, 20th, ..., 90th, 95th percentiles of productivity are presented in the form of a matrix, color-coded based on their sign, size and statistical significance at the 5% level. Regardless of their sign and magnitude, all statistically insignificant estimates are shown using the same shade of gray.

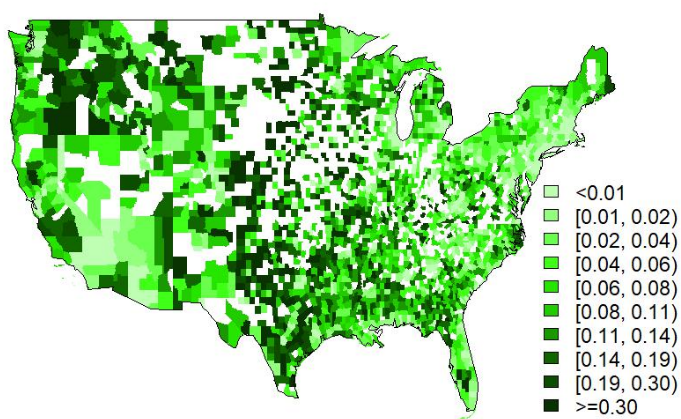

Figure D.2. Spatial Distribution of the Agricultural Share of Employment
Notes: Shown are county-level 2001-2019 averages of the share of total county employment employed in agriculture. Counties without any reported agricultural employment in the BEA data over 2001-2019 are left as blanks.

Table D.1. Correlation Between the Industry's Employment Share and the County's Labor Productivity

2-digit NAISC Industry	Corr. Coeff.
Agriculture	–0.4216
Mining	–0.2179
Utilities	–0.1270
Construction	–0.2583
Manufacture	–0.1811
Wholesale	0.2262
Retail	–0.4914
Transport	–0.0315
Information	0.4896
Finance	0.3833
Management	0.6263
Education	0.3539
Health	–0.0842
Art	0.1300
Accommodation	–0.1685

E Projecting Future Productivity Losses

Integrating the RIF regression over $F_{\mathbb{X}}$ for any given functional of the labor productivity distribution $\nu \equiv \nu(F_Y)$ in eq. (2), we arrive at an "unconditional" relationship:

$$\mathbb{E}[\mathrm{RIF}(Y_{it};\nu,F_Y)] = \mathbb{E}[X_{it}]'\gamma + \alpha_0 + \lambda_0, \tag{E.3}$$

where $\alpha_0 \equiv \mathbb{E}[\alpha_i]$ and $\lambda_0 \equiv \mathbb{E}[\lambda_i]$. Because $\mathbb{E}[\mathrm{RIF}(Y;\nu,F_Y)] = \nu$ by construction, we then have that—net of fixed effects—a distributional statistic ν for the unconditional distribution of labor productivity F_Y can be expressed as being equal to

$$\underbrace{\nu - \alpha_0 - \lambda_0}_{\equiv \nu^\star} = \mathbb{E}[X_{it}]'\gamma. \tag{E.4}$$

With γ estimated via an RIF regression, we can then make use of the relationship in (E.4) to construct functionals of a counterfactual unconditional productivity distribution that corresponds to any values of the long-run weather means $\mathbb{E}[X_{it}]$ of interest, including their future projections.

Specifically, using historical and future data on weather we can estimate average climate $\mathbb{E}[X_{it}]$ in 2001–2019 and 2040–2059 periods via their respective sample analogues:

$$\overline{X}_{\text{hist}} = \frac{1}{19N}\sum_{i=1}^{N}\sum_{t=2001}^{2019} X_{it}, \qquad \overline{X}_{\text{future}} = \frac{1}{20N}\sum_{i=1}^{N}\sum_{t=2040}^{2059} X_{it}, \tag{E.5}$$

where N is the number of analyzed counties. Then, for any statistic of interest—mean and quantiles, in our case—$\nu^\star$ of future and historical labor productivity is trivially given by $\widehat{\nu}^\star_{\text{future}} = \overline{X}'_{\text{future}}\widehat{\gamma}$ and $\widehat{\nu}^\star_{\text{hist}} = \overline{X}'_{\text{hist}}\widehat{\gamma}$. The difference between these two is the projected effect on productivity distribution of a future climate change between the two periods:

$$\Delta\widehat{\nu} = \Delta\widehat{\nu}^\star = \left[\overline{X}_{\text{future}} - \overline{X}_{\text{hist}}\right]'\widehat{\gamma}. \tag{E.6}$$

Since the outcome Y_{it} is actually the log of productivity, as with the estimates of UPEs, projections are in log points and the projected impacts $\Delta\widehat{\nu}$ are logarithmic differences between distributional statistics of the historical and predicted future labor productivity distributions.

F Diminishing Resilience to Temperatures

In our main analysis, we have abstracted away from temporal changes in temperature effects, but the measurable adverse impacts of heat stress on worker productivity may get smaller (larger) with time as a result of increased (decreased) resiliency to shifts in the temperature distribution due to adaptation (maladaptation) to climate change. Here we investigate if there is any evidence of these temporal changes, which we do by splitting our sample period in two (2001–2010 and 2011–2019), re-estimating the model twice and then testing for significantly non-zero differences in UPEs across these sub-samples. Figures F.1 and F.2 report these results: the first figure visualizes how temperature UPEs shifted over time, and the other figure summarizes these temporal shifts in UPEs between the later and earlier periods, color-coded based on their sign, size and statistical significance.

Taking statistical significance into consideration, in Figure F.2 we see that, over time, workers have become less resilient to incidence of very hot ($\geq 36°C$) and very cold ($< -6°C$) temperatures in the bottom 90% of the productivity distribution (and on average). Counties near the center of the distribution (20th to 60th percentiles) also exhibited a significantly diminished resilience—with growing negative impacts—to hot but less extreme temperatures in a 27-to-36°C range. At the same time, there is also some evidence that, at least in locations from the bottom 20%, labor productivity has become less sensitive to mid-range temperatures. Given the already documented finding that temperature does not significantly effect worker productivity in most productive counties from the far right tail of distribution, it is rather unsurprising that we also do not find evidence of significant temporal changes in extreme temperature effects for the top 5% of highly productive counties. Overall, our findings on the lack of adaptation or the deteriorating resilience to extreme temperatures over time are in line with existing studies (e.g., Burke and Emerick, 2016; Zhang et al., 2018b; Lobell et al., 2020; Burke et al., 2023) of temperature effects on productivity in various sectors.

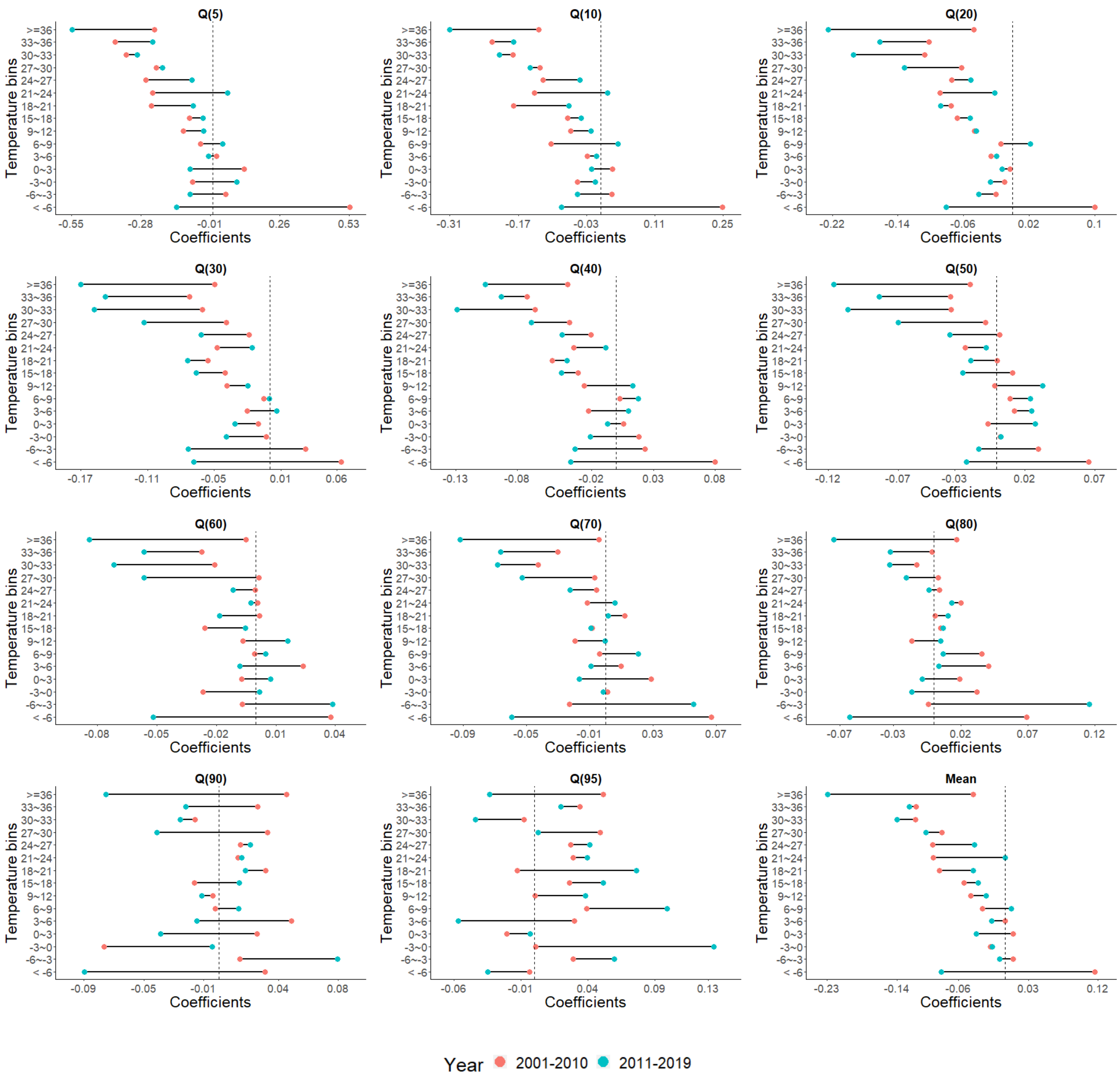

Figure F.1. Temporal Shifts in UPEs of Temperature on the Mean and Deciles of Labor Productivity from 2001–2010 to 2011–2019 ($\times 100$)

Notes: Orange (teal) solid dots show estimated UPEs of temperature on the mean and the 5th, 10th, 20th, ..., 90th, 95th percentiles of productivity estimated using 2001–2010 (2011–2019) sub-samples. The omitted reference temperature bin is [12°C, 15°C).

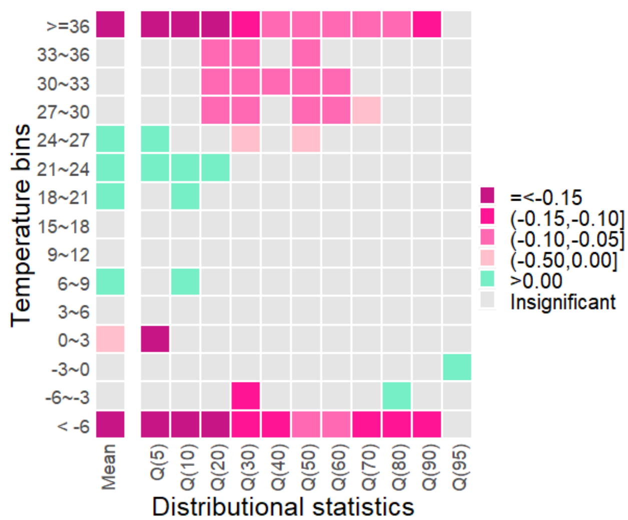

Figure F.2. Temporal Differences in UPEs of Temperature on the Mean and Deciles of Labor Productivity between Two Subperiods, 2011–2019 vs. 2001–2010 (×100)

Notes: The matrix summarizes difference in UPEs across models for the mean and the 5th, 10th, 20th, …, 90th, 95th percentiles of productivity, estimated using two sub-samples: 2011–2019 and 2001–2010. Estimated differences are color-coded based on their sign, size and statistical significance at the 5% level. Red (green) colors indicate diminished (increased) resilience over time. Regardless of their sign and magnitude, all statistically *in*significant differences are shown using the same shade of gray. The omitted reference temperature bin is [12°C, 15°C).

G Population-Weighted Results

We replicate the main results reported in the paper using weighted estimation accounting for the size of counties. Albeit the theory for weighted RIF regressions is yet to be developed and with it hardly being a clear-cut issue even in the context of standard linear regressions (see Solon et al., 2015), one may still wonder if our results are driven by a few small counties with unusual climates, particularly given the spatially uneven distribution of population in the U.S. We therefore re-estimate RIF regressions using the log-population of counties in 2001 to weight observations[15] and redo our entire analysis.

Results in Figures G.1–G.3 and Tables G.1 and G.2 below are direct counterparts of unweighted estimates reported in Figures 1–3 and Tables C.1 and 1, respectively. By and large, our findings remain unchanged, with all the key results being qualitatively similar.

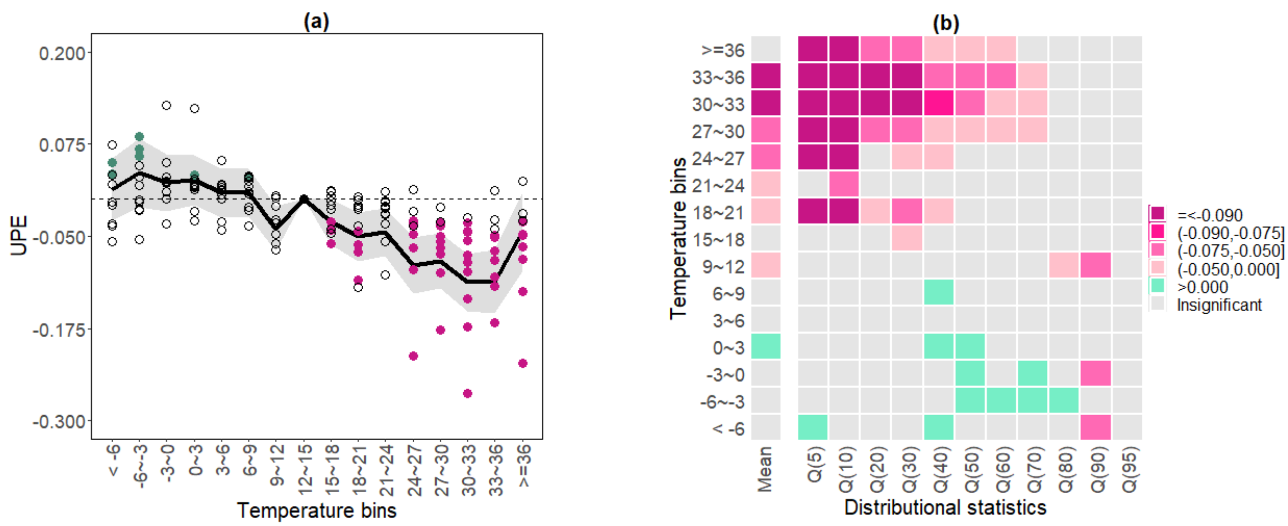

Figure G.1. UPEs of Temperature on the Mean and Quantiles of Labor Productivity (×100)

Notes: Subfigure (a) plots the estimates of UPEs on worker productivity of permanently relocating a day within a year from a [12°C, 15°C) temperature interval—the omitted reference bin—to each one of the other temperature bins on the horizontal axis. Bubbles show UPEs on the 5th, 10th, 20th, . . . , 90th, 95th productivity *percentiles* and are filled with solid color if their point estimates are statistically significant at the 5% level. The solid black line, with a 95% gray-shaded confidence band around it, corresponds to UPEs on the *mean* productivity. Subfigure (b) summarizes these UPE estimates across models in the form of a matrix, color-coded based on their sign, size and statistical significance at the 5% level. Regardless of their sign and magnitude, all statistically *in*significant estimates are shown using the same shade of gray.

[15]Because, just like worker productivity, county population can react to weather, we use its 2001 level for all time periods to avoid introducing endogeneity into the estimation. This is also reasonable since we detrend labor log-productivity prior to our analysis.

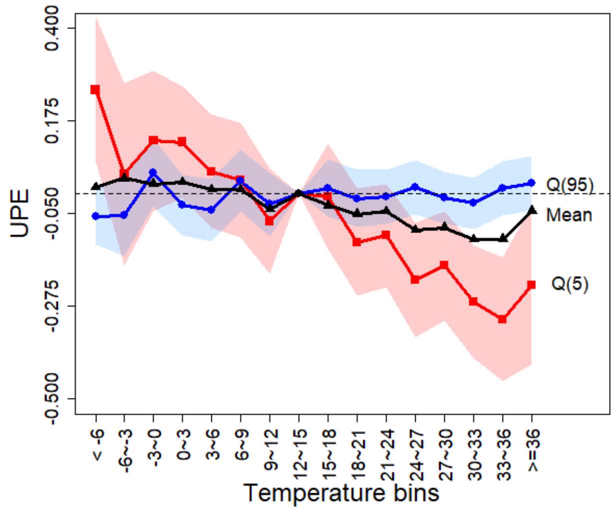

Figure G.2. UPEs of Temperature on Centrality and Tails of the Labor Productivity Distribution ($\times 100$)

Notes: The red (blue) line with a 95% shaded confidence band around it shows the estimates of UPEs on the 5th (95th) productivity percentile of permanently relocating a day within a year from a $[12°C, 15°C)$ temperature interval—the omitted reference bin—to each one of the other temperature bins on the horizontal axis. The black line shows the corresponding effects on mean productivity.

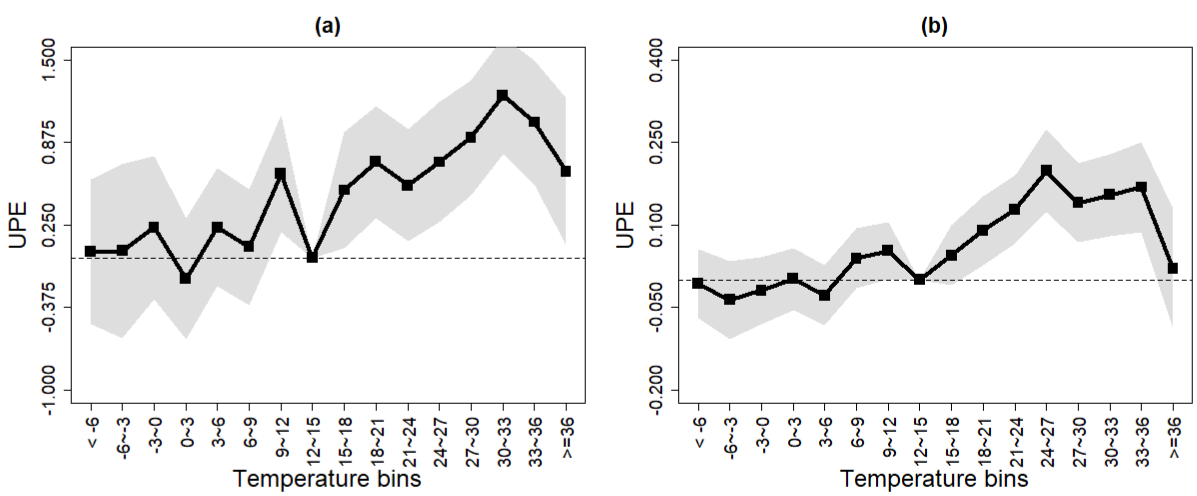

Figure G.3. UPEs of Temperature on Dispersion of the Labor Productivity Distribution ($\times 100$)

Notes: Plotted are the estimates, along with 95% confidence bands, of UPEs on the inter-decile ratio (a) and the standard deviation (b) of productivity resulting from permanently relocating a day within a year from a $[12°C, 15°C)$ temperature interval—the omitted reference bin—to each one of the other temperature bins on the horizontal axis.

Table G.1. UPEs of Temperature on Distributional Statistics of Labor Productivity ($\times 100$)

Variable	Mean	Q(5)	Q(10)	Q(20)	Q(30)	Q(40)	Q(50)	Q(60)	Q(70)	Q(80)	Q(90)	Q(95)	SD	IDR
$T_d \geq 36°C$	–0.036	–0.182*	–0.098*	–0.058*	–0.059**	–0.050**	–0.039**	–0.032*	–0.019	–0.015	–0.005	0.048	0.020	0.654*
$T_d \in [33°C, 36°C)$	–0.095**	–0.249**	–0.146**	–0.098**	–0.095**	–0.071**	–0.062**	–0.052**	–0.040**	–0.013	–0.020	0.035	0.169**	1.029**
$T_d \in [30°C, 33°C)$	–0.099**	–0.237**	–0.163**	–0.098**	–0.092**	–0.080**	–0.063**	–0.045**	–0.038**	–0.022	–0.039	0.016	0.155**	1.231**
$T_d \in [27°C, 30°C)$	–0.072**	–0.153*	–0.111**	–0.053**	–0.053**	–0.045**	–0.036**	–0.039**	–0.034*	–0.030	–0.042	0.015	0.140**	0.912**
$T_d \in [24°C, 27°C)$	–0.075**	–0.142*	–0.102**	–0.032	–0.047**	–0.033*	–0.020	–0.023	–0.017	–0.018	–0.015	0.045	0.198**	0.725**
$T_d \in [21°C, 24°C)$	–0.036*	–0.082	–0.064*	–0.018	–0.016	–0.013	–0.010	–0.006	–0.003	0.010	–0.030	0.028	0.128**	0.550*
$T_d \in [18°C, 21°C)$	–0.037*	–0.114*	–0.096**	–0.047**	–0.053**	–0.032*	0.008	0.006	0.008	–0.012	–0.024	0.015	0.090**	0.726**
$T_d \in [15°C, 18°C)$	–0.023	–0.003	–0.048	–0.035	–0.039*	–0.025	–0.001	–0.004	0.011	–0.006	–0.044	0.054	0.045	0.513*
$T_d \in [9°C, 12°C)$	–0.033*	–0.051	–0.054	–0.023	–0.026	–0.005	0.007	0.013	–0.010	–0.044*	–0.061*	–0.006	0.053*	0.637**
$T_d \in [6°C, 9°C)$	0.013	0.037	0.002	0.034	0.016	0.029*	0.025	0.014	0.011	–0.005	–0.020	0.040	0.039	0.084
$T_d \in [3°C, 6°C)$	0.009	0.005	–0.011	0.019	0.011	0.020	0.027	0.013	0.010	0.004	–0.034	–0.040	–0.028	0.232
$T_d \in [0°C, 3°C)$	0.031*	0.090	0.027	0.029	0.014	0.031*	0.033*	0.012	0.027	0.016	–0.003	0.022	0.002	–0.159
$T_d \in [-3°C, 0°C)$	0.023	0.103	0.006	0.021	–0.009	0.018	0.039*	0.028	0.038*	0.002	–0.056*	0.047	–0.019	0.229
$T_d \in [-6°C, -3°C)$	0.036	0.004	0.017	–0.015	–0.012	0.005	0.052*	0.053*	0.059*	0.068*	–0.034	0.032	–0.037	0.052
$T_d < -6°C$	0.013	0.191*	0.032	0.033	0.035	0.051**	0.028	0.001	–0.001	–0.018	–0.053*	–0.039	–0.007	0.044
Precipitation	0.011**	0.035**	0.020**	0.010**	0.008**	0.005**	0.004**	0.004**	0.003*	0.003*	0.002	0.007*	–0.016**	–0.134**
Precipitation Square/1000	–0.004**	–0.014**	–0.008**	–0.004**	–0.003**	–0.002**	–0.002**	–0.002**	–0.001**	–0.001*	0.000	–0.001	0.007**	0.049**

Notes: Reported are the coefficient estimates from RIF fixed-effects regressions in (2) estimated for the following distributional statistics v of labor productivity: i) mean, ii) 5th, 10th, 20th, …, 90th and 95th percentiles, iii) standard deviation and iv) the 90th-to-10th inter-decile ratio (IDR). County and year effects are included throughout. The omitted reference category is $T_d \in (12°C, 15°C]$. Statistical significance is determined using robust standard errors clustered at the climate division and year level. $^{**}p < 0.01$, $^{*}p < 0.05$.

Table G.2. Projected Labor Productivity Damages due to Climate Change by the Mid-Century

Distributional Statistic	*Future Climate Scenarios* HadGEM2-ES365 RCP 4.5	HadGEM2-ES365 RCP 8.5	NorESM1–M RCP 4.5	NorESM1–M RCP 8.5
Q(5)	**–0.091**	**–0.100**	**–0.074**	**–0.091**
	(0.028)	(0.037)	(0.018)	(0.023)
Q(10)	**–0.037**	**–0.039**	**–0.032**	**–0.040**
	(0.013)	(0.017)	(0.008)	(0.011)
Q(20)	**–0.029**	**–0.030**	**–0.025**	**–0.031**
	(0.008)	(0.010)	(0.005)	(0.007)
Q(30)	**–0.025**	**–0.027**	**–0.023**	**–0.028**
	(0.006)	(0.008)	(0.004)	(0.005)
Q(40)	**–0.025**	**–0.026**	**–0.021**	**–0.027**
	(0.005)	(0.007)	(0.004)	(0.005)
Q(50)	**–0.025**	**–0.027**	**–0.021**	**–0.026**
	(0.005)	(0.006)	(0.003)	(0.004)
Q(60)	**–0.018**	**–0.019**	**–0.015**	**–0.019**
	(0.004)	(0.005)	(0.003)	(0.004)
Q(70)	**–0.014**	**–0.014**	**–0.012**	**–0.015**
	(0.004)	(0.005)	(0.003)	(0.004)
Q(80)	–0.006	–0.007	–0.004	–0.005
	(0.005)	(0.006)	(0.004)	(0.005)
Q(90)	0.011	0.013	0.006	0.008
	(0.007)	(0.008)	(0.005)	(0.006)
Q(95)	0.011	0.012	0.006	0.010
	(0.010)	(0.012)	(0.007)	(0.009)
Mean	**–0.018**	–0.015	**–0.017**	**–0.021**
	(0.008)	(0.011)	(0.005)	(0.007)

Notes: Reported are logarithmic differences between historical 2001–2019 labor productivity mean/quantile estimates and their 2040–2059 analogues predicted using two global climate models—HadGEM2-ES365 and NorESM1-M—and two warming scenarios: medium (RCP4.5) and the warmest (RCP8.5). A negative (positive) difference indicates that the future worker productivity is smaller (larger) than the historical value. Robust standard errors are clustered at the climate division and year level. Statistically significant (at the 5% level) predictions are boldface.