ROCKWOOL Foundation Berlin
Institute for the Economy and the Future of Work (RFBerlin)

DISCUSSION PAPER SERIES 143/26

Climate Change and the Decline of Labor Share

Xincheng Qiu, Masahiro Yoshida

www.rfberlin.com

MAY 2026

Climate Change and the Decline of Labor Share

Authors

Xincheng Qiu, Masahiro Yoshida

Reference

JEL Codes: E25, Q54, O33

Keywords: climate change, labor share, automation

Recommended Citation: Xincheng Qiu, Masahiro Yoshida (2026): Climate Change and the Decline of Labor Share. RFBerlin Discussion Paper No. 143/26

Access

Disclaimer

Imprint

RFBerlin
ROCKWOOL Foundation Berlin –
Institute for the Economy
and the Future of Work

Gormannstrasse 22, 10119 Berlin
Tel: +49 (0) 151 143 444 67
E-mail: info@rfberlin.com
Web: www.rfberlin.com

Climate Change and the Decline of Labor Share*

Xincheng Qiu† Masahiro Yoshida‡

May 6, 2026

Abstract

We study the impact of climate change on the labor share. Combining newly constructed US county-industry-level labor shares with climate variables, we find that extreme temperatures reduce the labor share, with stronger effects in industries with higher climate exposure and automation potential. Extreme temperatures also accelerate robot adoption. A back-of-the-envelope calculation suggests that the within-county-industry response to climate change accounts for 15% of the decline in labor share since 2000. Over the 20th century, however, the opposing effects of decreased cold days and increased hot days offset each other, consistent with the historical stability of labor share.

Keywords: climate change, labor share, automation
JEL Codes: E25, Q54, O33

*We thank the Editor, Ayşegül Şahin, four anonymous referees, Gabriel Chodorow-Reich, Xiaomeng Cui, and seminar participants at Jinan, Lingnan, Renmin, SUFE, Waseda, and the Econometric Society World Congress in Seoul for useful comments.

†Guanghua School of Management, Peking University. Email: xincheng.qiu@gsm.pku.edu.cn.

‡Department of Political Science and Economics, Waseda University, Tokyo. Email: m.yoshida@waseda.jp.

1 Introduction

The labor share, the portion of national income accruing to workers as wages and compensation, has fallen sharply in the United States. The decline of labor share breaks its historical stability established as one of Kaldor (1961)'s stylized facts of economic growth, and has been documented across many countries (Karabarbounis and Neiman, 2014). It has sparked vigorous debate over the causes of this phenomenon, including technological change, globalization, shifts in market structure, and measurement issues (Grossman and Oberfield, 2022; Karabarbounis, 2024). This paper contributes a new perspective by identifying climate change—another prominent global secular trend—as an additional driver of the decline in labor share.

Global warming has accelerated in recent decades. Economists are increasingly concerned with its economic consequences, as frequent extreme heat events not only harm ecosystems but also disrupt production processes (Dell et al., 2012). Extreme temperatures cause discomfort for workers, leading to irritability, difficulty concentrating, and physical fatigue (Hancock et al., 2007; Pilcher et al., 2002). These adverse effects lead to reduced work efficiency (Borg et al., 2021; Lai et al., 2023), increased heat-related illness (Riley et al., 2018), higher error rates (Mazloumi et al., 2014), and more workplace injuries (Park et al., 2021). This paper starts from the premise that, while extreme heat impairs labor efficiency through human biomechanics, capital is relatively less sensitive to heat. Therefore, we hypothesize that firms are incentivized to shift factor demand and adopt labor-saving technologies in response to climate change, which in turn contributes to the decline in labor share.

To empirically test this hypothesis, we construct county-industry-level labor shares based on the local GDP data released by the Bureau of Economic Analysis (BEA) Regional Economic Accounts. We then merge them with climate variables derived from granular daily weather station records and estimate the effect of climate change on labor share. Leveraging rich cross-sectional and time-series variation in climate exposure and labor share dynamics, we include flexible fixed effects at the county, state-by-period, and industry-by-period levels. In the preferred specification, we find that an additional 10 hot days (average working-hour temperature above 77°F) and 10 cold days (average working-hour temperature below 50°F) per year reduce the labor share by 0.63 and 0.89 percentage points, respectively. These results are robust across a wide range of alternative specifications, including different temperature cutoffs, combinations of fixed effects, and an extensive set of controls to mitigate potential confounding.

The conventional narrative in climate science emphasizes that technological progress, particularly the mechanization and automation of production since the Industrial Revolution, has contributed to climate change. This paper offers the reverse perspective that climate change may in turn catalyze the adoption of labor-saving technologies. If climate change indeed contributes to the decline in the labor share, its impact should be stronger in occupations with greater heat exposure, specifically, those involving substantial outdoor activity or indoor environments without climate control, where the discomfort caused by extreme temperatures is more severe. Using data on occupational task content to measure exposure to climatic conditions, we find support for this prediction.

Next, we examine the mechanism that reduced worker efficiency incentivizes firms to adopt labor-saving technologies. This mechanism implies that workers in occupations with higher automation potential—typically those involving manual, routine, and hazardous tasks—are more susceptible to being replaced by machines. Using various measures of automation potential, we find evidence consistent with this prediction. Furthermore, drawing on two datasets from the BEA and the International Federation of Robotics (IFR), we provide direct evidence that industries more exposed to extreme temperatures adopt more industrial robots. Together, these results suggest that climate-induced automation contributes to the decline in labor share. We also discuss alternative mechanisms.

Finally, we assess the macroeconomic implications of these findings. We conduct a back-of-the-envelope calculation by multiplying the observed changes in the number of hot and cold days by their respective estimated coefficients and summing the effects. Although this calculation captures only the within-county-industry channel and abstracts from general-equilibrium adjustments and reallocation across regions and industries, it provides an informative input for a comprehensive aggregate assessment. Between 2001 and 2019, the increase in the annual number of hot days (+12.5 days) dominates the decrease in cold days (−1.2 days). Our calculation yields an implied effect of 0.58 percentage points, equivalent to 14.8% of the post-2000 decline in the labor share. By contrast, from 1950 to 2001, the opposing effects of more hot days (+9.0 days) and fewer cold days (−4.7 days) largely offset each other, consistent with the historical stability of the labor share during the 20th century.

Related Literature. This paper contributes to three strands of literature. First, it adds to the debate on the decline in labor share. Existing explanations include technological changes (Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2018), globalization (Böckerman and Maliranta, 2012; Elsby et al., 2013), shifts in market structure (De Loecker et al., 2020; Autor et al., 2020; Kehrig and Vincent, 2021), and measurement issues (Rognlie, 2015; Koh et al., 2020; Gutiérrez and Piton, 2020). This literature has rapidly become too large to be summarized comprehensively here but we refer interested readers to Grossman and Oberfield (2022) and Karabarbounis (2024) for excellent reviews. This paper highlights a novel fundamental force—climate change. Importantly, our explanation extends to both the stability of labor share in the 20th century and the decline of labor share in the 21st century.

Second, our finding builds on the expanding literature on the impact of climate on labor markets. Borg et al. (2021) review global evidence that occupational heat stress reduces labor productivity and working hours, highlighting workers' vulnerability to rising temperatures. Establishment-level studies document declines in labor efficiency in response to heat (Zhang et al., 2018; Chen and Yang, 2019; Somanathan et al., 2021; Cachon et al., 2012). Individual-level studies also document that extreme temperatures reduce labor supply (Graff Zivin and Neidell, 2014) and impair cognitive performance (Cook and Heyes, 2020; Graff Zivin et al., 2018). While these studies quantify high-frequency damages from weather shocks, our paper focuses on the low-frequency consequences of climate change. The above micro estimates are also reflected in aggregate outcomes such as national growth (Dell et al., 2012), state-level growth (Colacito et al., 2019), and county-level income (Deryugina and Hsiang, 2014). To our knowledge, this is the first paper that connects climate-induced harm to labor with the ongoing debate on the decline in the labor share.

Third, this paper advances the burgeoning literature on firms' adaptation to climate change (Grover and Kahn, 2024). Using the U.S. Census of Manufactures, Ponticelli et al. (2023) show that warming induces small plants to downsize or exit, increasing the concentration of production among large plants. Acharya et al. (2023) find that multi-establishment firms adapt to warming by reallocating employment from plants in heat-exposed locations to less exposed ones. Somanathan et al. (2021) and Adhvaryu et al. (2020) find that Indian manufacturers mitigate productivity losses on hot days through air conditioning and energy-efficient LED lighting, respectively. Moscona and Sastry (2022) document directed technological change that offsets climate damages in U.S. agriculture. This paper highlights adjustments in factor shares as an overlooked margin of climate adaptation.

The remainder of the paper is structured as follows. Section 2 describes the data sources used in the study and provides descriptive statistics. Section 3 presents the baseline results, followed by robustness checks and heterogeneity analysis. Section 4 presents evidence of the adoption of labor-saving technologies and discusses alternative mechanisms. Section 5 evaluates the macroeconomic implications of our findings and Section 6 concludes.

2 Data

2.1 Climate Data

We draw on weather station data from the Global Historical Climatology Network Daily (GHCN-Daily), managed by the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA). The GHCN-Daily database provides daily climate statistics, such as maximum and minimum daily temperature, precipitation, and snowfall, from approximately 15,000 weather stations across the US, offering a comprehensive climatic dataset with the highest frequency, resolution, and quality since the 19th century. We use data from stations with complete annual records during 1940–2019.

To aggregate station-level data to the county level, we employ the inverse-distance weighting method (e.g., Barreca et al., 2016). Specifically, for each county we select the three nearest weather stations to the county's population centroid (available from the Census Bureau) and aggregate their daily records, weighted by the inverse square of the distance from the centroid. Then, we construct an average daytime temperature for each day d as a weighted average of the maximum and minimum temperature, i.e., $T_d = \omega T_d^{\max} + (1-\omega) T_d^{\min}$. Instead of using $\omega = 0.5$ as is common in the climate literature, we assign $\omega = 0.75$ in light of our focus on regular working hours, 8 a.m. to 6 p.m. This calculation assumes a linear fluctuation of daily temperature between its minimum at 6 a.m. and its maximum at 1:30 p.m. and is derived in Appendix I.1.

Each location's exposure to climate change is measured as the change in the number of hot and cold days per year. There is no consensus on the appropriate temperature cutoffs in defining hot and cold days in the climate literature, and the choice varies depending on the context. Following the Occupational Safety and Health Administration (OSHA) guideline, we define hot days as those with an average working-hour temperature above 77°F (25°C) and cold days as below 50°F (10°C).[1] These cutoffs turn out to be the upper and lower terciles of the nationwide temperature distribution in the latest decade (see Figure A-2). Importantly, we show below that our estimates remain robust to alternative reasonable cutoff pairs (see Table A-1). Note that these cutoffs are constructed based on the average working-hour temperature; the corresponding maximum and minimum temperatures reach 89.3°F (31.8°C) and 36.1°F (2.3°C), respectively (see Figure A-3).

Figure A-4 displays the geographic distribution of hot and cold days and reveals substantial geographical variation of exposure to climate change across counties. The top panel shows the annual levels of hot days (left) and cold days (right) in 2019, and the bottom panel depicts the change in the frequency of hot days (left) and cold days (right) from 2001 to 2019. Although, not surprisingly, hot days are more concentrated in the south and cold days are more concentrated in the north, the patterns of "warming" (i.e., changes in the number of hot days) and "cooling" (i.e., changes in the number of cold days) are more geographically dispersed across the country.

[1] OSHA specifies 77°F (25°C) as a threshold where strenuous work may become unsafe (OSHA, Determinations of Whether the Work is Too Hot). For indoor workplaces, OSHA recommends temperature control in the range of 68–76°F. Chen and Yang (2019) find that industrial output declines when the daily temperature exceeds 24°C in their establishment-level analysis.

2.2 Labor Share

To measure labor share at the county level, we link two data products from the BEA Regional Economic Accounts: GDP by County and Personal Income by County. The county-level GDP data are available from 2001 onward. This period is well suited for our analysis, as it encompasses the most pronounced changes in both climate and labor share. Within each county, the BEA data allow us to construct labor shares for 16 NAICS-based industries. We thus adopt a county–industry cell as our unit of analysis. This granular approach is particularly valuable, as counties differ substantially in industrial composition, and industries display considerable heterogeneity in their labor shares.

We construct labor share as the ratio of wage compensation to GDP net of proprietors' income, where wage compensation includes both wages and salaries and associated supplements. Accurately allocating self-employment income between labor and capital poses a well-known measurement challenge. By excluding proprietors' income from the denominator, we focus on the wage employment sector. This implicitly assumes that proprietors use labor as intensively as the rest of the economy, a treatment referred to as the "economy-wide basis" measure by Kravis (1959) and the preferred approach of Karabarbounis (2024). The following paragraph details the construction of county-industry labor share and shows that variation in our measure traces back to variation in the payroll-to-value-added ratio from the Economic Census.

Measurement. The BEA produces GDP by county as the local counterpart to national GDP, using the income approach due to limited geographically detailed data for the expenditure and production approaches. The official county-industry-level GDP series begins in 2001 and was first released in December 2019. The BEA computes county l's GDP, either overall or for a specific industry k, as the sum of three components:

$$\mathrm{GDP}_{l,k} = \mathrm{COMP}_{l,k} + \mathrm{PI}_{l,k} + \mathrm{OIC}_{l,k},$$

where COMP denotes compensation of employees, PI denotes proprietors' income, and OIC denotes other income components, including consumption of fixed capital, corporate profits, rental income, net business current transfer payments, and taxes net transfers to businesses. We treat COMP as labor income and OIC capital income, while PI represents a mixture of the two. Under the economy-wide basis assumption described above, we construct the county l and industry k's labor share as

$$\text{Labor Share}_{l,k} = \frac{\mathrm{COMP}_{l,k}}{\mathrm{GDP}_{l,k} - \mathrm{PI}_{l,k}}.$$

Prior to the availability of local GDP estimates, the BEA has long published personal income statistics at the county level, covering compensation of employees and proprietors' income (the difference between earnings and compensation).[2] The BEA then allocates OIC from the state to the county level to construct local GDP estimates. To do so, it draws on the Economic Census, using county-level value added (VA) and payroll (PAY) for goods-producing industries, and county receipts and payroll for service industries, as the primary allocation factors. The county-industry-level OIC is imputed as

$$\mathrm{OIC}_{l,k} = \mathrm{OIC}_{s,k} \times \frac{\mathrm{VA}_{l,k} \times \frac{\mathrm{COMP}_{l,k}}{\mathrm{PAY}_{l,k}}}{\sum_{l' \in s} \mathrm{VA}_{l',k} \times \frac{\mathrm{COMP}_{l',k}}{\mathrm{PAY}_{l',k}}}$$

Since the Economic Census is quinquennial, the BEA interpolates geometrically between Census benchmarks and extrapolates beyond the latest Census to produce annual county-level allocation factors for OIC. Beyond this general framework, the BEA applies industry-specific sources where they better track production or receipts.[3]

Given that county GDP is estimated rather than directly observed, one may be concerned about potential biases. Note, however, that our construction of labor share reduces to

$$\text{Labor Share}_{l,k} = \frac{\mathrm{COMP}_{l,k}}{\mathrm{COMP}_{l,k} + \mathrm{OIC}_{l,k}} = \frac{1}{1 + \frac{\mathrm{OIC}_{s,k}}{\sum_{l' \in s} \mathrm{VA}_{l',k} \times \frac{\mathrm{COMP}_{l',k}}{\mathrm{PAY}_{l',k}}} \times \frac{\mathrm{VA}_{l,k}}{\mathrm{PAY}_{l,k}}}$$

Therefore, within-state variation in our measure of labor share derives from variation in

$$\frac{\mathrm{PAY}_{l,k}}{\mathrm{VA}_{l,k}},$$

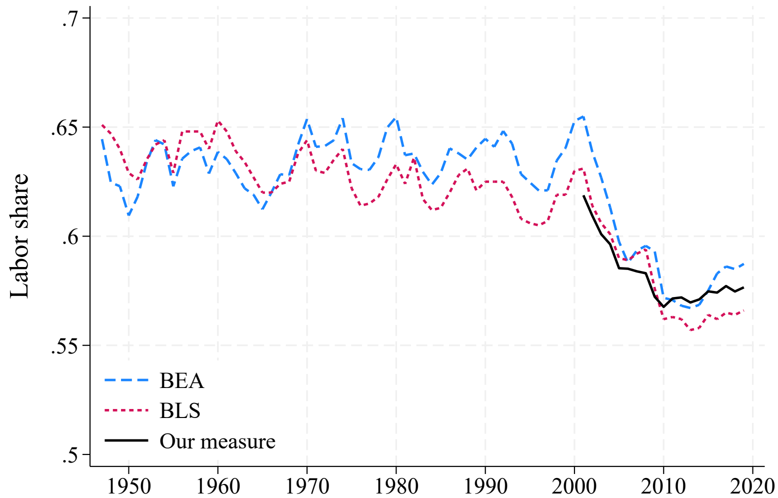
where $\mathrm{PAY}_{l,k}$ and $\mathrm{VA}_{l,k}$ are payroll and value added data from the Economic Census. This ratio is itself a measure of the labor share. Given that the Economic Census covers approximately four million establishments across the entire economy, we regard it as accurately capturing variation in labor share at the county–industry level.

Comparison to official statistics. We aggregate our labor share measure at the county level to the national level, and compare it with the official measures of the national labor share by both the BLS and the BEA. We confirm in Figure 1 that the aggregate of our measure closely

[2]COMP is built primarily from BLS QCEW microdata tabulated by county and industry, with targeted supplements for partially or non-covered industries. PI relies on IRS tabulations for nonfarm proprietors and USDA sources for farm proprietors.

[3]Detailed industry-specific source data used to estimate GDP by county are listed in Table 3 of A Primer on Local Area Gross Domestic Product Methodology.

Figure 1: Alternative Measures of the Labor Share



Notes: This figure compares our measure of the labor share aggregated to the national level with the official measures by the BEA and the BLS.

tracks both the Bureau of Labor Statistics (BLS) and BEA labor share measures since 2001. The Bureau of Labor Statistics (BLS) headline labor share measure assumes equal wages for the self-employed and payroll-employed, and imputes proprietors' labor income by multiplying proprietors' hours by employees' hourly compensation (Giandrea and Sprague, 2017). This approach is referred to as the "labor basis" measure by Kravis (1959). However, this imputation is impractical at the county level due to the lack of data on proprietors' hours. The BLS labor share covers the nonfarm business sector and is the most commonly used series, while the Bureau of Economic Analysis (BEA) measure, instead, focuses on the nonfinancial corporate sector, thereby avoiding ambiguities related to the classification of proprietors' income as labor or capital income. Our measure, available only from 2001 onward, aligns closely with the BEA and BLS series during the overlapping period. Notably, our measure captures a similar decline in the labor share. The consistency with both official series supports the reliability of our measure.

2.3 Summary Statistics

Table 1 reports the summary statistics for the sample used in our baseline analysis. For each outcome year (2001, 2010, and 2019), the decadal averages of the number of hot and cold days are calculated at the county level, while labor shares are measured at the county-industry level. Over the study period, the median county experiences 86.7 hot days and 111.2 cold days per year, roughly corresponding to 3 and 3.5 months, respectively.

Table 1: Summary Statistics

	Mean	SD	P10	P25	Median	P75	P90	Obs
Panel A: county level by year								
hot days	90.8	49.6	29.0	50.3	86.7	126.6	158.7	9,228
cold days	106.5	53.9	28.2	61.6	111.2	150.9	174.9	9,228
Panel B: county-industry level by year								
labor share	0.673	0.204	0.396	0.554	0.685	0.828	0.923	93,452

Notes: This table reports unweighted summary statistics for the key variables in our baseline analysis. Unit of statistics for hot and cold days: outcome years (2001, 2010, 2019) × counties; Unit of statistics for labor shares: outcome years × counties × industries.

Figure 2a plots the nationwide trends in exposure to hot days and the labor share since 1950. The figure shows that warming has accelerated while the labor share has fallen sharply in the 21st century. Although such time-series correlation is only suggestive, the coincidence in timing is nonetheless striking.

Figure 2b plots the local labor share against the ten-year average number of hot days across commuting zones. Each circle represents a commuting zone, with its size proportional to the denominator of the labor share (i.e., GDP minus proprietors' income). Hotter cities, such as Atlanta, Dallas, and Houston, tend to exhibit lower labor shares. The weighted fitted line reveals a clear negative correlation, with a statistically significant negative slope of -0.021 (s.e. $= 0.004$). Of course, this cross-sectional pattern may partly reflect regional differences in industrial composition. Figure A-7 therefore plots local labor shares in the mining, construction, manufacturing, and service sectors against the decadal average number of hot days. We find a similarly negative relationship within each sector.

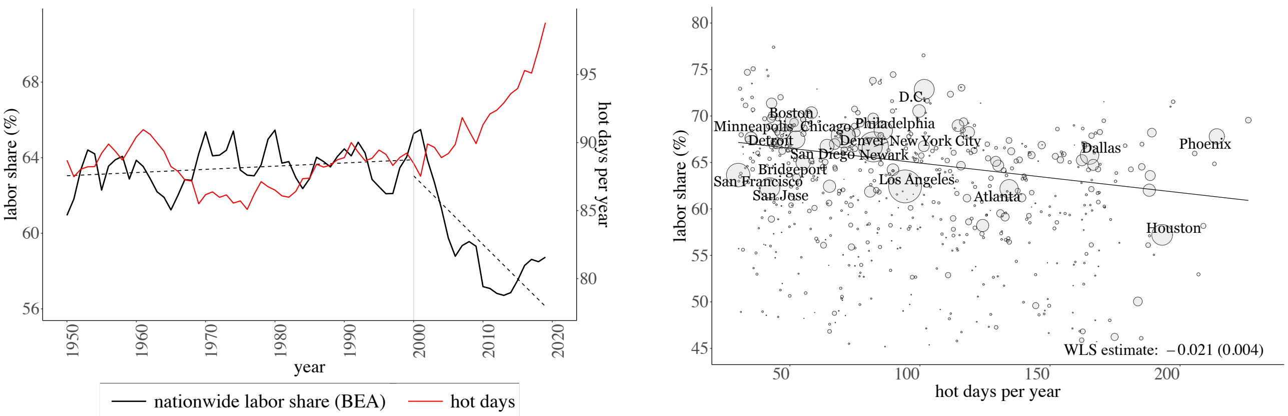
3 Empirical Analysis

3.1 Baseline Results

Model. Motivated by the observed time-series and cross-regional relationships between hotter temperatures and lower labor shares as shown in Figure 2, this section conducts a rigorous empirical analysis to identify the causal impact of climate change on the labor share. The baseline model regresses county-industry level labor share on the number of hot and cold days for each county, controlling for other climatic factors and a rich set of socioeconomic variables. Specifically, for counties (indexed by l) and industries (indexed by k) during three near-decade

Figure 2: Climate Change and Labor Share in the US

(a) Nationwide Time Trend (1950–2019) (b) Cross-Regional Relationship (2019)



Notes: Panel (a): County-level exposure to hot days is aggregated at the national level, weighted by county employment in 2000 from the County Business Patterns (Eckert et al., 2021). Hot days are defined as days with an average temperature during working hours (8 a.m. to 6 p.m.) exceeding 77°F. Aggregate labor share is taken from the headline figure provided by the Bureau of Economic Analysis. The dashed lines are trends over 1950–2000 and 2000–2019, respectively. Panel (b): This figure presents a scatterplot of the labor share against the prior decade average number of hot days per year across US commuting zones in 2019. Hot days are 2010 employment-weighted average of hot days (with working-hour temperature above 77°F) during 2010–2019 across counties. The bubble size captures the denominator of the labor share (i.e., GDP minus proprietors' income) in 2019.

intervals (indexed by $I = [\underline{I}, \overline{I}]$ for 1992–2001, 2001–2010, and 2010–2019), we consider the following regression:

$$\text{LaborShare}_{l,k,\overline{I}} = \beta^h \text{hd}_{l,I} + \beta^c \text{cd}_{l,I} + \mathbf{\Lambda C}_{l,I} + \delta_l + \delta_{s,I} + \delta_{k,I} + \varepsilon_{l,k,\overline{I}}, \tag{1}$$

where $\text{LaborShare}_{l,k,\overline{I}}$ denotes the labor share in county l and industry k in year $\overline{I}$. We focus on nonfarm, nonfinancial private industries, as is common in studies on labor share. Treatment variables $\text{hd}_{l,I}, \text{cd}_{l,I}$ are the average number of hot and cold days, respectively, in county l during period I (scaled by 10). The coefficients of interest, β^h, β^c, capture the impact of an additional 10 hot or cold days on labor share. A similar two-tail specification has been widely used by, for example, Barreca et al. (2016) and Somanathan et al. (2021). We also control for additional climate covariates $\mathbf{C}_{l,I}$, including daily precipitation on rainy days (intensive margin) and the number of days with no precipitation (extensive margin), and those with heavy snowfall (≥ 300 mm) averaged during each period I.

In addition to county fixed effects δ_l, the model allows for the inclusion of state-period fixed effects $\delta_{s,I}$, capturing any time-varying state-level institutions (e.g., unionization, taxation, minimum wage), as well as industry-period fixed effects $\delta_{k,I}$, capturing nationwide industry-specific trends (e.g., technological evolution, trade competition).[4] Thus, the estimates are identified from within-county variation, net of common shocks at the state-period and industry-period level. In the full specification, we further include a comprehensive set of controls $\mathbf{Z}_{l,k,\underline{I}}$ that may influence the labor share. As detailed in Appendix I.3, we incorporate three groups of start-of-period covariates for 1990, 2000, and 2010: industry concentration $\mathbf{S}_{l,k,\underline{I}}$ by county l and industry k that could influence market power and labor demand, demographic composition of employment $\mathbf{D}_{c,k,\underline{I}}$ by commuting zone c and industry k, and commuting zone c's local labor market characteristics $\mathbf{M}_{c,\underline{I}}$, where each commuting zone c comprises multiple counties l.

The regression is weighted by denominators of the labor share, i.e., GDP minus proprietors' income. Since temperature is spatially correlated across nearby counties, we cluster standard errors at the state level. We drop cells with missing labor shares due to missing labor incomes or GDP. To further avoid potential measurement errors, we restrict our analysis to cells with labor shares between 0 and 1.

Results. Table 2 summarizes the estimates with various sets of controls. In the preferred specification (Column 1) that includes the full set of fixed effects and extra climate variables $\mathbf{C}_{l,I}$, we find that an increase of 10 hot days in place of normal days reduces the labor share by 0.630 percentage points ($t = -3.96$). Although changes in the number of cold days are less prominent in the 21st century (see Section 5), the effect of cold days is also significantly negative: an additional 10 cold days reduces the labor share by 0.891 percentage points ($t = -2.21$). Column 2 instead drops extra climate variables $\mathbf{C}_{l,I}$ from the baseline. In addition to the baseline model, Columns 3–5 progressively add controls for industry concentration $\mathbf{S}_{l,k,\underline{I}}$, demographic composition $\mathbf{D}_{c,k,\underline{I}}$, and labor market characteristics $\mathbf{M}_{c,\underline{I}}$. Both the magnitude and precision of the estimates remain remarkably stable across these specifications. This suggests that under the flexible fixed effects at the county, state-year, and industry-year levels, climate shocks are nearly unconditionally-independent of other regional- and industry-level observables. Given the richness of the fixed effects and controls, we believe the estimates are unlikely to be confounded by other factors and interpret these within-county estimates as indicative of the causal impact of climate change. Moreover, we find that this negative effect on the labor share is driven primarily by a substantial reduction in labor income (the numerator), with a smaller reduction in GDP (the denominator) (Table A-17).

[4] We use county FEs rather than county-industry FEs to preserve sufficient variation for identification. Including county-industry FEs (approximately 3,000 × 16 parameters) would substantially reduce statistical power. Nevertheless, as shown in Table A-7), even under this more demanding specification, the estimated effects of hot days remain statistically significant.

Table 2: Climate Change and Labor Share (By County- Industry, 2001–2019)

	dependent variable: labor shares (units: percentage points)				
	Baseline				
	(1)	(2)	(3)	(4)	(5)
10 hot days	−0.630	−0.675	−0.578	−0.586	−0.587
	(0.159)	(0.178)	(0.196)	(0.195)	(0.202)
10 cold days	−0.891	−0.896	−0.837	−0.860	−0.875
	(0.403)	(0.388)	(0.418)	(0.413)	(0.414)
county FE	Yes	Yes	Yes	Yes	Yes
state × year FEs	Yes	Yes	Yes	Yes	Yes
industry × year FEs	Yes	Yes	Yes	Yes	Yes
extra climate variables	✓	–	✓	✓	✓
industry concentration	–	–	✓	✓	✓
demography	–	–	–	✓	✓
labor market	–	–	–	–	✓
N	92,803	93,445	90,330	90,311	90,311
Adjusted R^2	0.808	0.808	0.813	0.815	0.815

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. We restrict the analysis to cells with labor shares between 0 and 1. The thresholds for hot and cold days are set at 77°F and 50°F, respectively, based on average temperature during business hours (8 a.m. to 6 p.m.). Numbers of hot and cold days are averaged during each period. The regressions are weighted by the denominator of the labor share, i.e., GDP minus proprietors' income. Standard errors in parentheses are clustered at the state level.

3.2 Robustness Checks

To further validate our main result presented in Table 2, we conduct a series of robustness checks. In the interest of space, all corresponding tables are relegated to the Appendix.

Cutoffs for hot and cold days. In the baseline specification, we define hot and cold days based on thresholds of 77°F (25°C) and 50°F (10°C), respectively, which correspond to the upper and lower tertiles of the nationwide temperature distribution. To test robustness to the cutoffs, we also run specifications with alternative temperature cutoffs of 73, 75, 77, and 80°F for hot days, and 35, 40, 45, 50, and 55°F for cold days. Across these specifications, we find consistent effects of both hot and cold temperature exposure on the labor share (Table A-1).

Binning bias. A potential concern with the two-tailed specification is that changes in the frequency of hot and cold days may be systematically correlated with baseline temperature levels. As Jones et al. (2026) emphasize, regions with higher initial temperatures tend to experience larger increases in extreme heat exposure. Consequently, the estimated effects may partly reflect differential trends associated with baseline temperature rather than causal effects of temperature shocks. Following the recommendation of Jones et al. (2026), we address this concern by including linear time trends interacted with initial temperature measures. Our estimates for both hot and cold days remain similar in magnitude and statistical significance (Table A-2).

Treatment window. To capture the long-run effects of climate change, we use changes in the decadal averages of hot and cold days in the baseline specification. We also examine alternative treatment windows, ranging from 1 to 20 years (Table A-3). The adverse effect remains significant for windows of 8 years or longer. However, for windows of 5 years or shorter, the estimates for hot days are no longer statistically significant. This is consistent with the idea that technological changes and capital adjustments occur over longer horizons.

Measurement of labor share. We measure the labor share as the ratio of wage compensation to GDP excluding proprietors' income. Our measurement closely aligns with the headline figures from both the BEA and BLS (Figure 1). Alternatively, we consider the ratio of wage compensation to GDP, and the ratio of wage compensation plus proprietors' income to GDP. These proxies effectively reflect two extreme assumptions: one in which all proprietors' income is considered capital income, and the other in which it is entirely labor income. The results remain consistent, indicating that the treatment of proprietors' income has a minimal impact on the findings (Table A-4).

Leave-one-out analysis. One potential concern is that the results might be disproportionately driven by the most temperature-sensitive sectors. To address this concern, we separately drop construction/mining/utilities or transportation from the analysis. We also exclude the Southeast and South regions, the hottest and most humid areas, or the Northwest and West North Central regions, the coldest areas. Reassuringly, the estimates from each of these subsample analyses remain unchanged (Table A-5).

Labor demand shocks. Some counties exposed to climate shocks may also experience concurrent labor demand shocks. To address this concern, we conduct a series of additional leave-one-out analyses that exclude areas particularly affected by China trade shocks (Autor et al., 2013), robot exposure shocks (Acemoglu and Restrepo, 2020), and computerization shocks (Autor and Dorn, 2013). The resulting estimates reported in Table A-6 remain stable, suggesting that these labor demand shocks do not confound our findings.

3.3 Heterogeneity

Sector heterogeneity. Our baseline model identifies the average nationwide treatment effect of hot and cold days. Does the climate impact vary across sectors with different degrees of outdoor exposure? To explore this, we partition the economy into four broad sectors based on industries' dependence on outdoor operations: construction and mining, manufacturing, low-skilled services (e.g., transportation, retail, health care, restaurants), and high-skilled services (e.g., business, information). We extend Equation (1) to allow the estimated impacts of hot and cold days to vary across four broad sectors defined above. The model with sectoral heterogeneity is specified by interacting $\text{hd}_{l,I}$ and $\text{cd}_{l,I}$ with sectoral dummies to obtain sector-specific estimates:

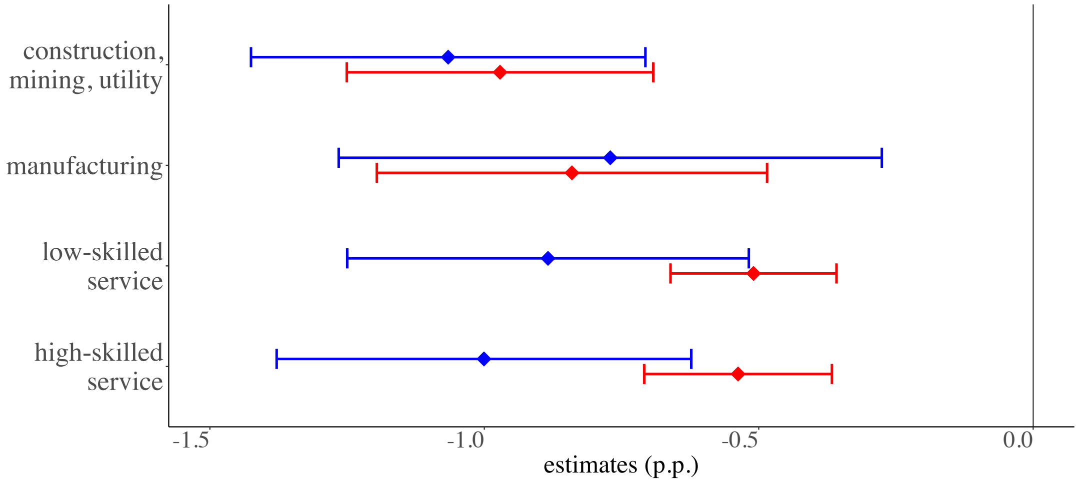
$$\text{LaborShare}_{l,k,\bar{I}} = \sum_{K} \mathbb{I}(K) \left(\beta_K^h \text{hd}_{l,I} + \beta_K^c \text{cd}_{l,I}\right) + \mathbf{\Lambda}\mathbf{C}_{l,I} + \delta_l + \delta_{s,I} + \delta_{k,I} + \varepsilon_{l,k,\bar{I}}, \tag{2}$$

where the coefficients of the interaction terms with sector K dummies, β_K^h and β_K^c, capture the sector-specific impacts of hot and cold days, respectively. Figure 3 presents these estimates. The effect of hot days tends to be larger in sectors such as construction and manufacturing, where workers are more likely to face non-climate-controlled environments. We next use O*NET measures of occupational climate exposure to formally test whether this effect increases with the degree of climate exposure.

Occupational climate exposure. Although the four-sector classification provides an intuitive illustration, we seek more systematic evidence by exploiting variation in workers' direct exposure to climatic conditions, as captured by their access to climate control. The idea is that an average temperature of 77°F can impose substantial strain on outdoor manual workers, who face continuous heat during physically demanding tasks (González-Alonso et al., 1999), whereas office workers encounter such conditions only intermittently, for instance during a one-hour lunch break.

To measure jobs' exposure to temperature, we rely on the Work Context Survey (WCS) from the O*NET (Occupational Information Network) database, sponsored by the US Department of Labor. We draw from the section on "physical and social factors that influence the nature of work" to construct four indices that capture different modes of temperature exposure for 873 O*NET-SOC occupations. We use the following questions:

Figure 3: Sectoral Heterogeneity in Climate Effects



Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. Both models inherit the climate controls and county, state-year, industry-year fixed effects from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP minus proprietors' income. The horizontal bars represent the 95% confidence intervals using standard errors clustered at the state level.

- "How often does this job require *working indoors in non-controlled environmental conditions* (e.g., warehouse without heat)?"
- "How often does this job require *working outdoors*, exposed to all weather conditions?"
- "How often does this job require *working outdoors, under cover* (e.g., structure with roof but no walls)?"
- "How often does this job require *working indoors in environmentally controlled conditions*?"

To each question, respondents answer using a 5-point scale: 5 = Every day; 4 = Once a week or more but not every day; 3 = Once a month or more but not every week; 2 = Once a year or more but not every month; 1 = Never. Combining answers 4 and 5, we compute employment shares for working at least weekly under each mode of temperature exposure. After mapping O*NET-SOC identifiers to occupation codes in the Census and the ACS, we construct a measure of occupational weather exposure, $x_{c,k,\underline{I}}$, for each commuting zone c and industry k at the start-of-period $\underline{I}$.[5]

[5] Alternatively, we use intensive-margin proxies based on the imputed weekly frequency of working under each environment across commuting zones and industries, and find similar estimates.

We extend the baseline model (1) by interacting $\mathrm{hd}_{l,I}$ and $\mathrm{cd}_{l,I}$ with $x_{c,k,\underline{I}}$:

$$\begin{aligned}\mathrm{LaborShare}_{l,k,\overline{I}} = \beta^h \mathrm{hd}_{l,I} + \beta^c \mathrm{cd}_{l,I} + \gamma^h \mathrm{hd}_{l,I} \times x_{c,k,\underline{I}} + \gamma^c \mathrm{cd}_{l,I} \times x_{c,k,\underline{I}} + \theta x_{c,k,\underline{I}} \\ + \mathbf{\Lambda C}_{l,I} + \delta_l + \delta_{k,I} + \delta_{s,I} + \varepsilon_{l,k,\overline{I}}.\end{aligned} \tag{3}$$

Recall that the outcome variable, $\mathrm{LaborShare}_{l,k,\overline{I}}$, represents the labor share for county l and industry k at the end of period $\overline{I}$, and the second line is the same as (1). Table 3 report the interaction coefficients γ^h, capturing sensitivity to hot-day effect to different modes of temperature exposure. Indoor non-controlled environments, such as manufacturing plants using fire or furnaces, or transportation warehouses where doors are frequently opened, show a large negative estimate (Column 1). The estimates remain similar when we extend the exposure measure to include outdoor environments, defined as the sum of employment shares of workers exposed at least weekly to indoor non-controlled and outdoor conditions (Column 2). Column 3 reports significantly negative interaction coefficients for exposure to outdoor environments with cover (e.g., gas stations, repair shops). In contrast, indoor controlled environments exhibit significantly positive coefficients (Column 4).[6] These results indicate that counties or industries with greater temperature exposure, particularly those without air conditioning, experience larger adverse effects on the labor share due to warming.

Hot days vs. cold days. For cold days, we do not find meaningful heterogeneity related to occupational temperature exposure, consistent with the sectoral analysis in Figure 3 that the effects of cold days appear relatively uniform. We propose several possible explanations. First, during extremely cold winters, workers in northern regions may be unable to work outdoors under heavy snowfall, leading to widespread work suspensions rather than differential impacts. Second, outdoor workers in the construction or mining sectors are often required to wear personal protective equipment (PPE) for safety, such as helmets, gloves, and poorly ventilated clothing, which provides protection against cold but exacerbates heat, thus making them more resilient to cold temperatures but vulnerable to heat. Third, exposure to cold weather may be relatively uniform across occupations because commuting typically occurs during the coldest hours of the day. Even for employees who work indoors in climate-controlled environments, commuting time represents a common channel of exposure to cold temperatures.[7]

[6] The index for each mode does not sum up to one, as the questionnaire does not measure the exact amount of time allocated to each working condition.

[7] According to 2018–19 ACS data, the average worker spends 55 minutes commuting per day, accounting for 11.5% of typical daily working hours.

Table 3: Sensitivity of Climate Impacts to Workplace Climate Exposure

	dependent variable: labor share (units: percentage points)			
	by climate exposure			
	×indoor non-controlled	×indoor non-controlled plus outdoor	× outdoor with cover	× indoor controlled
	(1)	(2)	(3)	(4)
10 hot days	−0.440	−0.481	−0.406	−1.118
	(0.159)	(0.188)	(0.206)	(0.170)
10 hot days × climate exposure	−0.773	−0.281	−1.550	0.741
	(0.277)	(0.102)	(0.676)	(0.236)
N	92,780	92,780	92,780	92,780
Adjusted R^2	0.812	0.812	0.813	0.811

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × NAICS industries. We restrict the analysis to cells with labor shares between 0 and 1. All models include the climate controls and three-fold fixed effects from the baseline specification (1) in Table 2, supplemented with task characteristics interacted with hot and cold days. The regressions are weighted by the denominator of the labor share, i.e., GDP minus proprietors' income. Standard errors in parentheses are clustered at the state level.

4 Mechanism

The previous section presents our primary contribution that documents a robust relationship between climate change and the decline in the labor share, particularly in regions with a higher share of jobs exposed to climatic conditions. This section turns to explore the mechanisms through which extreme temperatures reduce the labor share. We provide novel evidence on climate-induced automation, while noting that we do not mean to interpret it as the sole mechanism at work. Given the regional nature of our data, we acknowledge that we cannot directly test alternative mechanisms such as rising markups (De Loecker et al., 2020), the emergence of "superstar" firms (Autor et al., 2020), or the reallocation of economic activities toward establishments with lower labor shares (Kehrig and Vincent, 2021). Nevertheless, we discuss the potential role of compositional changes across establishments that may operate through these alternative channels.

4.1 Climate-Induced Automation

Automation potential. If climate change is a catalyst for automation, then regions or industries with a higher share of occupations susceptible to automation should experience a larger decline in labor share in response to extreme temperatures. To measure automation potential, we construct four occupation-level indices based on independent data sources. We then aggregate these indices to the commuting-zone-by-NAICS-industry level at the start of each period, using occupational employment shares from the 2000 Census and the 2009–2010 stacked ACS as weights. Similar to Table 3, Table 4 presents estimates showing how the effect of hot days varies with the degree of automation potential.

In Column 1, we construct an index of physical intensity based on questions from the Abilities Survey in O*NET following Peri and Sparber (2009). Specifically, we take an average of each occupation's "movement and strength" requirements. In Column 2, we build a manual-routine intensity index based on a widely used occupational characteristic from Autor et al. (2003); Autor and Dorn (2013), originally constructed from the Dictionary of Occupational Titles (DOT). In both cases, we find significantly negative interaction coefficients. Column 3 takes a more direct approach by employing the "technological exposure to robots" index developed by Webb (2019), which measures the similarity between job task descriptions and global patent profiles on robotics using natural language processing. Consistent with the previous results, we again find significantly negative coefficients, suggesting that the negative impact of extreme heat on the labor share is amplified in tasks with greater technical feasibility for robotic substitution. In Column 4, we construct an injury and illness risk proxy using questions from the WCS, measured as the average incidence of working at least weekly under nine hazardous conditions, including exposure to disease or infections, contaminants, radiation, minor burns, cuts, bites, or stings. The result confirms that occupations facing higher physical danger experience a more pronounced negative effect of hot days on labor share. This pattern is consistent with employers or labor unions prioritizing workplace safety, such as preventing injuries from cutting or burning tools or mitigating illnesses caused by contaminants or radiation. Ensuring this protection may inadvertently sacrifice labor efficiency and incur additional costs associated with sick leave, injury leave, or medical expenses, thereby strengthening firms' incentives to automate hazardous tasks.[8] Overall, after mapping these four occupational indices to the commuting-zone-by-industry level, the results in Table 4 consistently show that warming reduces labor share more in jobs with higher automation potential, lending support to the notion of climate-induced automation.

Machines and industrial robots. We now directly examine whether extreme temperatures have facilitated the adoption of labor-saving technologies and accelerated the replacement of labor with machines, focusing specifically on industrial robots (hereafter referred to simply as robots). The growing literature on robots (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020, among others) typically relies on data from IFR (2019), which defines a robot as "*an automatically controlled, reprogrammable, and multipurpose machine.*" Because IFR (2019) provides robot data only for 16 non-service industries in the US from 2004 onward, we complement these data with the National Income and Product Accounts (NIPA) from the BEA, which provide capital stocks and investments for 54 four-digit NAICS industries over a longer period from 1947 to 2015. Using NIPA capital stocks and investments in Private Nonresidential Fixed Assets, we construct a proxy for robots as a combination of *metalworking machinery* and *special industrial machinery*, which statistically aligns with the IFR series (see Appendix I.5). Although the term "robots" may evoke images of fully autonomous machines, as in the IFR definition, the BEA-based measure captures a much broader set of labor-saving equipment, and is an order of magnitude larger in terms of operating stock value and spans a much wider range of sectors including construction and services. In practice, this broader definition includes heat-resilient devices such as personal protective equipment (PPE) and machinery equipped with cooling systems that are classified under special industrial machinery.

Due to limited historical coverage of the robot data, particularly for non-manufacturing industries, we restrict the analysis to 1980–2015, a period that encompasses roughly equal lengths of both the stable and declining phases of the labor share. As neither dataset reports robot usage at the regional level, we conduct the analysis at the industry level instead. An advantage of this approach is that it is insulated from potential relocation of establishments,

[8] Using daily temperature data and universal injury records in Texas, Park et al. (2021) show that increased hot days lead to more occupational injuries.

Table 4: Sensitivity of Climate Impacts to Automation Potential

	dependent variable: labor share (units: percentage points) **by task characteristics**			
	× physical intensity	× manual routine intensity	× technological exposure to robots	× injury and illness risk
	(1)	(2)	(3)	(4)
10 hot days	−0.341	−0.535	−0.206	−0.398
	(0.202)	(0.164)	(0.175)	(0.180)
10 hot days × task characteristics	−0.585	−0.161	−0.924	−0.647
	(0.144)	(0.030)	(0.145)	(0.164)
N	92,785	92,787	92,787	92,787
Adjusted R^2	0.810	0.810	0.810	0.812

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × NAICS industries. We restrict the analysis to cells with labor shares between 0 and 1. All models include the climate controls and three-fold fixed effects from the baseline specification (1) in Table 2, supplemented with task characteristics interacted with hot and cold days. The regressions are weighted by the denominator of the labor share, i.e., GDP minus proprietors' income. Standard errors in parentheses are clustered at the state level.

which may otherwise complicate the interpretation of our within-county estimates, as discussed in Section 4.2 below. Specifically, for each nonfarm, nonfinancial industry k during period I, we estimate an industry-level analog of the baseline model (1):

$$\text{Robot}_{k,\overline{I}} = \beta^h \text{hd}_{k,I} + \beta^c \text{cd}_{k,I} + \mathbf{\Lambda C}_{k,I} + \mathbf{\Gamma Z}_{k,\underline{I}} + \phi_{g(k)}\overline{I} + \delta_k + \delta_I + \varepsilon_{k,\overline{I}}, \tag{4}$$

where $\text{Robot}_{k,\overline{I}}$ denotes various measures of robot adoption for industry k at the end of period $\overline{I}$. We construct a shift-share measure of industry k's exposure to hot and cold days during period I, $\text{hd}_{k,I}$ and $\text{cd}_{k,I}$, as follows:

$$\text{hd}_{k,I} = \sum_l \omega^l_{k,\underline{I}} \text{hd}_{l,I}, \quad \text{cd}_{k,I} = \sum_l \omega^l_{k,\underline{I}} \text{cd}_{l,I},$$

where $\text{hd}_{l,I}$ and $\text{cd}_{l,I}$ are county-level hot and cold day counts, and $\omega^l_{k,\underline{I}} = L_{k,l,\underline{I}}/L_{k,\underline{I}}$ is county l's start-of-period employment share in industry k, computed from the CBP data (Eckert et al., 2021).[9]

We also control for other climate variables, $\mathbf{C}_{k,I}$, and industry concentration, $\mathbf{Z}_{k,\underline{I}}$, computed analogously.[10] Consistent with Equation (1), the extended coverage of the NIPA data enables a long-difference specification over decade-long periods. For the IFR data, we use five-year intervals instead to maintain adequate sample size. To account for trends in rising temperatures and the secular increase in automation, we include sector-specific time trends, $\phi_{g(k)}\overline{I}$, where sectors correspond to major industry groupings: mining, utilities/construction, manufacturing, retail/wholesale, transportation, and services. The specification also incorporates two-way fixed effects δ_k and δ_I. Standard errors are clustered at the sector level.

Panel A of Table 5 reports the results using BEA data. Column 1 examines robots as a share of total capital stock and shows that both hot and cold days have a significantly positive effect. This suggests that industries more exposed to extreme temperatures systematically deploy more robots. Column 2 examines robot investment as a share of total investment and likewise finds that industries more exposed to hot and cold days allocate a larger portion of their capital investment to robots. Finally, Column 3 confirms a similarly positive effect on robot investment as a share of GDP. Overall, these results indicate that industries with greater exposure to extreme temperatures rely more on automation. We further cross-validate the analyses using IFR data in Panel B of Table 5. Although the IFR data measure robots in

[9] A conventional shift-share design interacts the regional industry composition with industry-specific national shocks to form a regional treatment exposure (Goldsmith-Pinkham et al., 2020). In contrast, our industry-level analysis of robot adoption is a reverse shift-share design that interacts the spatial distribution of industries with regional exposure to extreme temperatures to construct an industry-level treatment.

[10] Including demographic compositions and employment characteristics does not change the results. A detailed list of industry-level covariates is provided in Appendix I.3.

Table 5: Climate Change and Robot Adoption Across Industries

	Panel A: Industrial Robots from the BEA (units: percentage points)			Panel B: Industrial Robots from the IFR (units: robots/100 million USD)		
	Robot /Capital (1)	Robot Inv. /Capital Inv. (2)	Robot Inv. /GDP (3)	Robot /Capital (4)	Robot Inv. /Capital Inv. (5)	Robot Inv. /GDP (6)
10 hot days	3.996	4.564	1.052	2.708	4.514	0.524
	(1.614)	(1.230)	(0.333)	(0.356)	(1.328)	(0.101)
10 cold days	2.984	4.531	0.524	2.434	9.602	0.734
	(1.510)	(1.553)	(0.137)	(0.384)	(1.524)	(0.107)
extra climate variables	✓	✓	✓	✓	✓	✓
emp. size distribution	✓	✓	✓	✓	✓	✓
industry FE	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes
division trend	Yes	Yes	Yes	Yes	Yes	Yes
N	194	194	194	48	48	64
Adjusted R^2	0.966	0.936	0.846	0.990	0.775	0.939

Notes: The thresholds for hot and cold days are set at 77°F and 50°F, respectively, as in the baseline analysis. We focus on nonfarm, nonfinancial industries. All regressions are weighted by industry GDP. Standard errors in parentheses are clustered at the sector level. (Panel A) Unit of analysis: outcome years (1980–2010 by decade) × industries. (Panel B) Unit of analysis: outcome years (2005, 2010, 2015, 2019) × industries.

units rather than in dollars, we obtain similar results, despite the more limited variation across industries and years.

Overall, these results provide robust evidence that exposure to extreme temperatures accelerates the adoption of industrial robots. Climate-induced automation represents a previously underexplored form of directed technological change (Acemoglu, 2002), conceptually similar to other contexts in which rising labor costs stimulate robot adoption, such as population aging (Acemoglu and Restrepo, 2022), shortages of low-skilled immigrants (Lewis, 2011), and stricter dismissal regulations (Presidente, 2017). This finding is consistent with, and complementary to, firm-level evidence from contemporaneous work by Xiao (2024), who shows that climate-exposed public firms adapt by acquiring robotics-related human capital and developing automation-oriented technologies. This is also consistent with recent evidence from Ma (2025), who uses firm-level data and patent records across nine EU countries to show that extreme heat induces labor-saving innovation and capital reallocation.

As a placebo test, we repeat the analysis by replacing robots with general physical equipment, structures, and intellectual property products (IPP), respectively. None of these, in either stocks or investments, show significant responses (Table A-15). The pronounced impact of extreme temperature days on robots, together with the null effects on equipment and other forms of capital, suggests that the primary mechanism through which climate change reduces the labor share is automation—by substituting labor with robots across an expanding range of tasks (Acemoglu and Restrepo, 2018)—rather than general capital-labor substitution.[11] Furthermore, to explore alternative modes of technological change, we examine the response of computer capital and software, a subset of equipment and IPP, respectively, in a similar manner.[12] We find no evidence that climate change drives digitization (Table A-16), consistent with the observation that digitization mainly impacts white-collar workers and they mostly work indoors in controlled environments.

4.2 Compositional Change of Establishments

As with most cross-regional analyses, our baseline within-county estimates may also reflect compositional shifts across establishments rather than purely within-establishment adjustments. For example, in warming areas, labor-intensive plants may scale back operations, relocate to cooler regions, offshore production, or shut down entirely. While our county-industry data do not allow us to definitively confirm or rule out compositional change, we assess the importance of this channel as follows.

First, we examine the impact of climate change on local market structure, measured by the establishment size distribution in the CBP data. Applying our baseline specification to employment shares across establishment size bins, we find that extreme temperatures reduce the employment share of smaller establishments and thereby raise the Herfindahl–Hirschman Index (Table A-18). This pattern suggests that extreme temperatures affect the firm size distribution, consistent with Ponticelli et al. (2023), who document that extreme temperatures increase concentration among larger plants.

Second, we control for start-of-period employment shares across establishment size bins within each county-industry cell. As shown in Table A-19, the coefficient on hot days declines only modestly from -0.630 in Column (1) to -0.575 in Column (7), even after including the full set of controls for the firm size distribution in the CBP data and the HHI constructed from size-bin midpoints. This result suggests that, after accounting for climate-induced shifts in the firm-size

[11] The null effect on total equipment is consistent with a series of recent plant-level studies, including Chirinko et al. (2011), Herrendorf et al. (2015), Lawrence (2015), and Oberfield and Raval (2021), which find that the aggregate capital-labor elasticity of substitution is less than one, suggesting that capital and labor are generally complementary.

[12] Computer capital consists of *PCs* and *mainframes*, while software consists of *prepackaged software*, *custom software*, and *own-account software*. Aum and Shin (2024) explore the role of software in reducing the labor share.

distribution, the bulk of the climate effect on the labor share persists. This is consistent with Lipsius (2018) and Berger et al. (2022), who argue that changes in labor-market concentration have little explanatory power for the aggregate decline in the labor share.

Taken together, we find modest evidence that the climate effect is partially mediated by compositional shifts across establishments, potentially reflecting other forces behind the declining labor share, such as reallocation and changes in market structure. Unfortunately, we cannot fully disentangle or quantify the relative importance of these channels with the data we have. A more definitive assessment using establishment-level labor-share data is left for future work.

5 Back-of-the-Envelope Calculations

Armed with our estimates, we next quantify the contribution of climate change to the evolution of the labor share. Guided by Figure 2a, we separately examine the period of stable labor share (1950–2001) and the subsequent period of declining labor share (2001–2019). Figure 4a presents a histogram of climate exposure across counties, where red bars represent changes in the decadal average number of hot days and blue bars represent changes in cold days. Between 1950 and 2001, the employment-weighted median county experienced 9.0 more hot days and 4.7 fewer cold days. By contrast, from 2001 to 2019, the increase in hot days dominates, with the median county experiencing 12.5 more hot days and only 1.2 fewer cold days.

We compute the aggregate impact of climate change on the labor share from year t_0 to t_1 as

$$\Delta\widehat{\text{LaborShare}} = \underbrace{\sum_l \omega_l \beta^h (\text{hd}_{l,t_1} - \text{hd}_{l,t_0})}_{\text{effect from hot days}} + \underbrace{\sum_l \omega_l \beta^c (\text{cd}_{l,t_1} - \text{cd}_{l,t_0})}_{\text{effect from cold days}}, \tag{5}$$

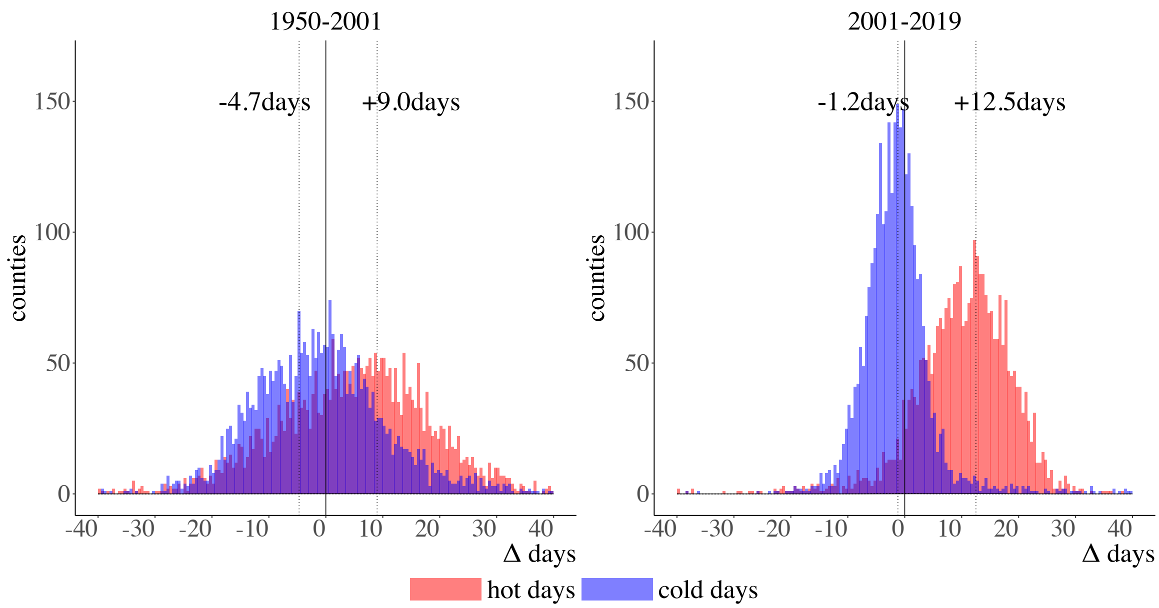
where ω_l is the GDP share of county l in 2001. The terms $\text{hd}_{l,t}$ and $\text{cd}_{l,t}$ denote the decadal averages of hot and cold days, respectively. We also compute implied impacts separately by sector, using sector-specific estimates for construction/mining, manufacturing, low-skilled services (e.g., transportation, retail, healthcare, restaurants), and high-skilled services, as reported in Figure 3. For each sector, we apply the corresponding estimate in a formula analogous to Equation (5) (see Appendix IV).

Figure 4b reports the implied nationwide impacts of climate change on the labor share, both overall and by sector, for the periods 1950–2001 and 2001–2019. Extrapolating our estimates back to the earlier period, we find that the adverse effect of the increase in hot days (+9.0 days) has been largely offset by the decrease in cold days (−4.7 days) (Panel (b), left).[13] In

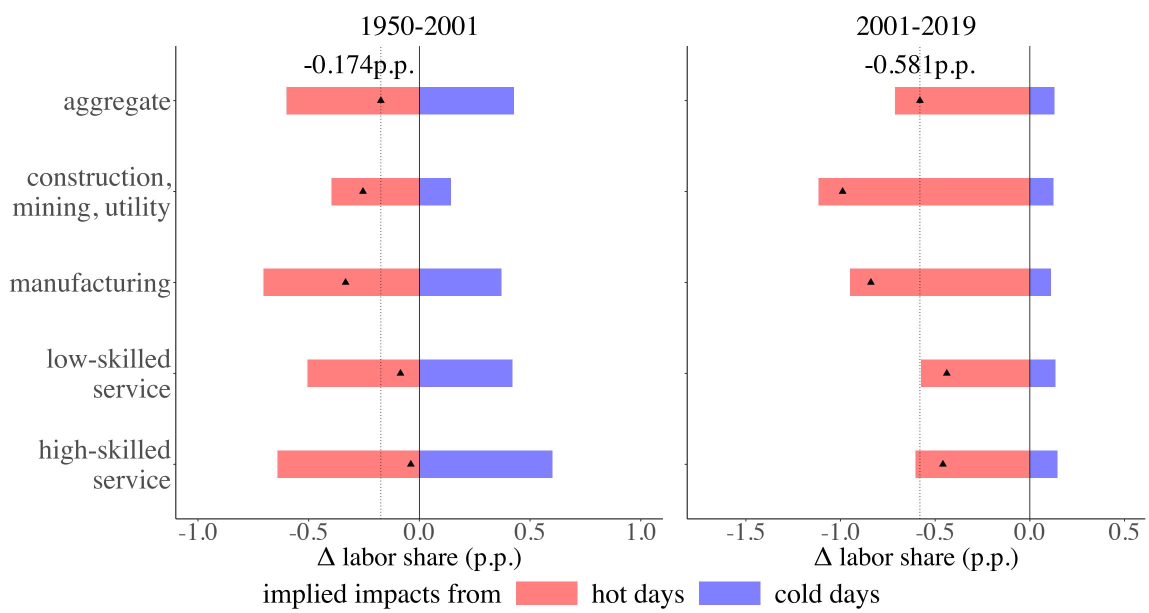
[13] Since county-industry labor share data are unavailable for 1950–2001, we simulate counterfactual impacts

Figure 4: Implied Impacts of Climate Change on Labor Share (1950-2001 vs. 2001-2019)

(a) Histogram of County Exposure of Climate Change



(b) Implied Climate Impacts



Notes: Panel (a): Hot days are defined as those with an average temperature during working hours (8 a.m. to 6 p.m.) over 77°F, and cold days below 50°F. Changes in the decadal average number of days (1941–1950 for 1950, 1992–2001 for 2001, 2010–2019 for 2019) are grouped into 0.5-day bins. Panel (b): Aggregate effects are calculated using the full specification (1) from Table 2, weighted by county × industry cell-level GDP excluding proprietors' income. Sector-level impacts are derived from sector-specific estimates. Black triangles mark the net effects of hot and cold days.

contrast, from 2001 to 2019, the pronounced increase in hot days dramatically outweighs the modest decrease in cold days. Our calculations indicate that climate change accounts for 14.8% of the observed declining trend in the labor share during this period.[14] Overall, the evolution of temperature aligns with both the stability of the labor share before 2000 and its subsequent decline. Robustness checks with alternative specifications yield similar assessments (Appendix IV).

Our findings contribute to a unified explanation for both the earlier stability of the labor share and its subsequent decline. To account for the historical stability of the labor share, Acemoglu and Restrepo (2018) introduce the creation of new tasks as a countervailing force to automation that depresses the labor share. Hubmer (2023) argues that postwar economic growth raises the labor share through an income effect, as higher-income households consume more labor-intensive goods. Our climate-based perspective complements these views: the positive impact of a decrease in the number of cold days effectively offsets the negative impact of an increase in the number of hot days in the twentieth century, helping to sustain the aggregate labor share.

Within, Between, and Interaction. The change in the aggregate labor share can be decomposed into

$$\Delta\text{LaborShare} = \Delta\Big(\sum_l \omega_l \text{LS}_l\Big) = \underbrace{\sum_l \omega_l \Delta\text{LS}_l}_{\text{(a) within}} + \underbrace{\sum_l \Delta\omega_l \text{LS}_l}_{\text{(b) between}} + \underbrace{\sum_l \Delta\omega_l \Delta\text{LS}_l}_{\text{(c) interaction}}. \tag{6}$$

Because our back-of-the-envelope calculation relies on estimates that difference out county fixed effects, it identifies only the within-county component of the climate effect. Climate-induced changes in the between-county and interaction components could in principle either amplify or attenuate the overall impact. Consider an extreme example in which high-labor-share establishments in warming counties relocate to cooler counties. The within-county estimator would register a negative effect: the reweighting of GDP shares toward cooler destination counties would be captured by the interaction component and would fully offset the within-county change.

The sign and magnitude of between-county and interaction components are ultimately empirical questions, and we therefore directly test the climate impact of these two components. Table A-20 shows little evidence that climate change affects county weights (ω_l), implying that the climate impact on the between-county component is negligible. We do find some evidence

under the assumption that effects of hot and cold days on the labor share are stable across periods.

[14]To remove cyclical fluctuations, we measure the decline in the aggregate labor share as the decrease in its linear trend (−3.92 p.p.), based on the same county-level data used in the estimation for internal consistency. The raw decline is −4.80 p.p., of which our within-county climate effect accounts for 12.1%.

that hot days reduce the interaction component (Table A-21), consistent with the force emphasized by Kehrig and Vincent (2021). Taken together, these results indicate that climate-induced county-level reallocation is unlikely to overturn our within-county estimates of the climate effect on the labor share.

Caveat: Aggregation and the Missing Intercept. Our back-of-the-envelope calculation follows a long tradition in applied research of scaling cross-sectional estimates to the aggregate level using national changes in the treatment variable (e.g., Autor et al., 2013; Mian and Sufi, 2014; Chodorow-Reich, 2014). This exercise, however, does not provide a complete quantification of the aggregate impact. As emphasized by Nakamura and Steinsson (2018), cross-sectional estimates with fixed effects identify relative effects across locations but are silent on adjustments absorbed by those fixed effects.

A few examples illustrate the concern. First, general-equilibrium responses that affect all units uniformly, such as nationwide shifts in production techniques, prices, or interest rates in response to warming, are absorbed by time fixed effects and do not enter the calculation in equation (5). Second, warming may induce heat-sensitive, labor-intensive activities to relocate from hotter to cooler states; for instance, indoor non-climate-controlled warehousing operations may shift from Sun Belt states like Arizona and Texas toward northern regions. Such reallocation is absorbed by the state-year fixed effects $\delta_{s,I}$. Third, warming may shift production techniques differentially across industries. For example, the automobile industry may disproportionately accelerate the adoption of labor-saving technologies in response to rising temperatures. Such industry-specific responses are absorbed by industry-year fixed effects $\delta_{k,I}$. Our back-of-the-envelope calculation does not capture these channels. We therefore interpret the implied magnitude as illustrative of the within-county-industry channel rather than as a formal quantification of climate change's contribution to the decline in the aggregate labor share.

6 Conclusion

The 21st century has witnessed an unprecedented decline in the labor share alongside a concerning rise in global temperatures. This paper connects these two phenomena through the lens of directed technological change. Leveraging granular county-level exposure to extreme temperatures in the US as a natural experiment, we identify climate change as an overlooked structural force behind the declining labor share. Our results suggest that climate change has accelerated automation, and consequently, contributed to a redistribution of income from labor toward owners of capital and technology. Applying our within-county estimates to national temperature trends, we find that the within-county channel can account for roughly 15% of the decline in the labor share since 2000, while the offsetting effects of fewer cold days and more hot days over the 20th century are consistent with the historical stability of the labor share.

While our cross-sectional design isolates the within-county-industry channel, the aggregate contribution of climate change to the labor share also depends on general-equilibrium responses and reallocation across locations and industries that our fixed effects absorb. Quantifying this aggregate contribution is an important avenue for future research. Our findings nonetheless contribute a new perspective to the ongoing debate on the determinants of the declining labor share and to the growing literature on the macroeconomic impacts of climate change.

References

Acemoglu, Daron, "Directed Technical Change," *The Review of Economic Studies*, 2002, *69* (4), 781–809.

_ **and Pascual Restrepo**, "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment," *American Economic Review*, 2018, *108* (6), 1488–1542.

_ **and** _ , "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 2020, *128* (6), 2188–2244.

_ **and** _ , "Demographics and Automation," *The Review of Economic Studies*, 2022, *89* (1), 1–44.

Acharya, Viral V, Abhishek Bhardwaj, and Tuomas Tomunen, "Do Firms Mitigate Climate Impact on Employment? Evidence from US Heat Shocks," Working Paper 31967, National Bureau of Economic Research December 2023.

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham, "The Light and the Heat: Productivity CoBenefits of EnergySaving Technology," *The Review of Economics and Statistics*, 2020, *102* (4), 779–792.

Aum, Sangmin and Yongseok Shin, "Is Software Eating the World?," Working Paper 32591, National Bureau of Economic Research June 2024.

Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen, "The Fall of the Labor Share and the Rise of Superstar Firms," *The Quarterly Journal of Economics*, 2020, *135* (2), 645–709.

Autor, David H and David Dorn, "The Growth of Low-skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 2013, *103* (5), 1553–1597.

Autor, David H., David Dorn, and Gordon H. Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, October 2013, *103* (6), 2121–68.

Autor, David H, Frank Levy, and Richard J Murnane, "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 2003, *118* (4), 1279–1333.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro, "Adapting to Climate Change: The Remarkable Decline in the US Temperature-mortality relationship over the Twentieth Century," *Journal of Political Economy*, 2016, *124* (1), 105–159.

Berger, David, Kyle Herkenhoff, and Simon Mongey, "Labor Market Power," *American Economic Review*, 2022, *112* (4), 1147–1193.

Böckerman, Petri and Mika Maliranta, "Globalization, Creative Destruction, and Labour Share Change: Evidence on the Determinants and Mechanisms from Longitudinal Plant-Level Data," *Oxford Economic Papers*, 2012, *64* (2), 259–280.

Borg, David N., George Havenith, Shane K. Maloney, Yan Hong, and Ollie Jay, "Occupational heat stress and economic burden: A review of global evidence," *The Lancet Planetary Health*, 2021, *5* (8), e572–e581.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel, "Global Non-linear Effect of Temperature on Economic Production," *Nature*, 2015, *527* (7577), 235–239.

Cachon, Gerard P, Santiago Gallino, and Marcelo Olivares, "Severe Weather and Automobile Assembly Productivity," Technical Report 2012.

Chen, Xiaoguang and Lu Yang, "Temperature and Industrial Output: Firm-level Evidence from China," *Journal of Environmental Economics and Management*, 2019, *95*, 257–274.

Chirinko, Robert S., Steven M. Fazzari, and Andrew P. Meyer, "A New Approach to Estimating Production Function Parameters: The Elusive CapitalLabor Substitution Elasticity," *Journal of Business & Economic Statistics*, oct 2011, *29* (4), 587–594.

Chodorow-Reich, Gabriel, "The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis," *The Quarterly Journal of Economics*, 2014, *129* (1), 1–59.

Colacito, Riccardo, Bridget Hoffmann, and Toan Phan, "Temperature and Growth: A Panel Analysis of the United States," *Journal of Money, Credit and Banking*, 2019, *51* (2-3), 313–368.

Cook, Nikolai and Anthony Heyes, "Brain Freeze: Outdoor Cold and Indoor Cognitive Performance," *Journal of Environmental Economics and Management*, 2020, *101*, 102318.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger, "The Rise of Market Power and the Macroeconomic Implications," *The Quarterly Journal of Economics*, 2020, *135* (2), 561–644.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken, "Temperature Shocks and Economic Growth: Evidence from the Last Half Century," *American Economic Journal: Macroeconomics*, 2012, *4* (3), 66–95.

Deryugina, Tatyana and Solomon M Hsiang, "Does the Environment Still Matter? Daily Temperature and Income in the United States," Technical Report, National Bureau of Economic Research 2014.

Eckert, Fabian, Peter K. Fort Teresa C.and Schott, and Natalie J. Yang, "Imputing Missing Values in the US Census Bureau's County Business Patterns," *NBER Working Paper*, 2021, *26632.*

Elsby, Michael WL, Bart Hobijn, and Ayşegül Şahin, "The Decline of the US Labor Share," *Brookings Papers on Economic Activity*, 2013, *2013* (2), 1–63.

Garimella, Suresh V. and Matt Hughes, "Physicists Explain How Heat Kills Machines and Electronics," *Scientific American*, September 5 2023.

Giandrea, Michael D and Shawn A Sprague, "Estimating the US Labor Share," *Monthly Labor Review*, 2017.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik Instruments: What, When, Why, and How," *American Economic Review*, 2020, *110* (8), 2586–2624.

González-Alonso, José, Christina Teller, Signe L Andersen, Frank B Jensen, Tino Hyldig, and Bodil Nielsen, "Influence of body temperature on the development of fatigue during prolonged exercise in the heat," *Journal of applied physiology*, 1999, *86* (3), 1032–1039.

Graetz, Georg and Guy Michaels, "Robots at Work," *Review of Economics and Statistics*, 2018, *100* (5), 753–768.

Grossman, Gene M and Ezra Oberfield, "The Elusive Explanation for the Declining Labor Share," *Annual Review of Economics*, 2022, *14* (1), 93–124.

Grover, Arti and Matthew E Kahn, "Firm Adaptation to Climate Change," Working Paper 32848, National Bureau of Economic Research 2024.

Gutiérrez, Germán and Sophie Piton, "Revisiting the Global Decline of the (Non-housing) Labor Share," *American Economic Review: Insights*, 2020, *2* (3), 321–338.

Hancock, Peter A, Jennifer M Ross, and James L Szalma, "A meta-analysis of performance response under thermal stressors," *Human factors*, 2007, *49* (5), 851–877.

Herrendorf, Berthold, Christopher Herrington, and Ákos Valentinyi, "Sectoral Technology and Structural Transformation," *American Economic Journal: Macroeconomics*, oct 2015, *7* (4), 104–133.

Hubmer, Joachim, "The Race Between Preferences and Technology," *Econometrica*, 2023, *91* (1), 227–261.

IFR, "World Robotics: Industrial Robots," Technical Report 2019.

Jones, Benjamin, Jacob Moscona, Benjamin A Olken, and Cristine von Dessauer, "With or Without U? Binning Bias and the Causal Effects of Temperature Extremes," Working Paper 34671, National Bureau of Economic Research January 2026.

Kaldor, Nicholas, "Capital Accumulation and Economic Growth," in "The Theory of Capital: Proceedings of a Conference Held by the International Economic Association" Springer 1961, pp. 177–222.

Karabarbounis, Loukas, "Perspectives on the Labor Share," *Journal of Economic Perspectives*, 2024, *38* (2), 107–136.

_ **and Brent Neiman**, "The Global Decline of the Labor Share," *The Quarterly Journal of Economics*, 2014, *129* (1), 61–103.

Kehrig, Matthias and Nicolas Vincent, "The Micro-Level Anatomy of the Labor Share Decline," *The Quarterly Journal of Economics*, 2021, *136* (2), 1031–1087.

Koh, Dongya, Raül Santaeulàlia-Llopis, and Yu Zheng, "Labor Share Decline and Intellectual Property Products Capital," *Econometrica*, 2020, *88* (6), 2609–2628.

Kravis, Irving B, "Relative Income Shares in Fact and Theory," *The American Economic Review*, 1959, *49* (5), 917–949.

Lai, Wangyang, Yun Qiu, Qu Tang, Chen Xi, and Peng Zhang, "The Effects of Temperature on Labor Productivity," *Annual Review of Resource Economics*, 2023, *15* (1), 213–232.

Lawrence, Robert Z., "Recent Declines in Labors Share in US Income: A Preliminary Neoclassical Account," Technical Report Working Paper 21296, National Bureau of Economic Research 2015.

Lewis, Ethan, "Immigration, Skill Mix, and Capital Skill Complementarity," *The Quarterly Journal of Economics*, 2011, *126* (2), 1029–1069.

Lipsius, Ben, "Labor Market Concentration Does Not Explain the Falling Labor Share." Ph.d. dissertation, University of Michigan 2018. Essay from the dissertation; also available as job market paper.

Ma, Enjie Jack, "Extreme Heat and Directed Innovation," *working paper*, 2025.

Mazloumi, Adel, Farideh Golbabaei, Somayeh Mahmood Khani, Zeinab Kazemi, Mostafa Hosseini, Marzieh Abbasinia, and Somayeh Farhang Dehghan, "Evaluating effects of heat stress on cognitive function among workers in a hot industry," *Health promotion perspectives*, 2014, *4* (2), 240.

Mian, Atif and Amir Sufi, "What explains the 2007–2009 drop in employment?," *Econometrica*, 2014, *82* (6), 2197–2223.

Moscona, Jacob and Karthik A Sastry, "Does Directed Innovation Mitigate Climate Damage? Evidence from U.S. Agriculture," *The Quarterly Journal of Economics*, 10 2022, *138* (2), 637–701.

Nakamura, Emi and Jón Steinsson, "Identification in macroeconomics," *Journal of Economic Perspectives*, 2018, *32* (3), 59–86.

Oberfield, Ezra and Devesh Raval, "Micro Data and Macro Technology," *Econometrica*, 2021, *89* (2), 703–732.

Park, Jisung, Nora Pankratz, and Arnold Behrer, "Temperature, Workplace Safety, and Labor Market Inequality," Technical Report 2021.

Peri, Giovanni and Chad Sparber, "Task Specialization, Immigration, and Wages," *American Economic Journal: Applied Economics*, 2009, *1* (3), 135–169.

Pilcher, June J., Eric Nadler, and Caroline Busch, "Effects of hot and cold temperature exposure on performance: a meta-analytic review," *Ergonomics*, 2002, *45* (10), 682–698.

Ponticelli, Jacopo, Qiping Xu, and Stefan Zeume, "Temperature and Local Industry Concentration," Working Paper 31533, National Bureau of Economic Research August 2023.

Presidente, Giorgio, "Labor Services At Will: Regulation of Dismissal and Investment in Industrial Robots," *mimeo*, 2017.

Riley, Kevin, Holly Wilhalme, Linda Delp, and David Eisenman, "Mortality and Morbidity during Extreme Heat Events and Prevalence of Outdoor Work: An Analysis of Community-Level Data from Los Angeles County, California," *International Journal of Environmental Research and Public Health*, 2018, *15* (4), 580.

Rognlie, Matthew, "Deciphering the Fall and Rise in the Net Capital Share: Accumulation or Scarcity?," *Brookings Papers on Economic Activity*, 2015, *2015* (1), 1–69.

Somanathan, Eswaran, Rohini Somanathan, Anant Sudarshan, and Meenu Tewari, "The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing," *Journal of Political Economy*, 2021, *129* (6), 1797–1827.

Webb, Michael, "The Impact of Artificial Intelligence on the Labor Market," *Available at SSRN 3482150*, 2019.

Xiao, Zhanbing, "Labor Exposure to Climate Risk, Productivity Loss, and Capital Deepening," *Working Paper*, 2024.

Zhang, Peng, Olivier Deschenes, Kyle Meng, and Junjie Zhang, "Temperature Effects on Productivity and Factor Reallocation: Evidence from a Half Million Chinese Manufacturing Plants," *Journal of Environmental Economics and Management*, 2018, *88*, 1–17.

Zivin, Joshua Graff and Matthew Neidell, "Temperature and the Allocation of Time: Implications for Climate Change," *Journal of Labor Economics*, 2014, *32* (1), 1–26.

_ , Solomon M Hsiang, and Matthew Neidell, "Temperature and human capital in the short and long run," *Journal of the Association of Environmental and Resource Economists*, 2018, *5* (1), 77–105.

APPENDICES FOR ONLINE PUBLICATION

Climate Change and the Decline of Labor Share

Xincheng Qiu and Masahiro Yoshida

May 6, 2026

I Additional Data Details

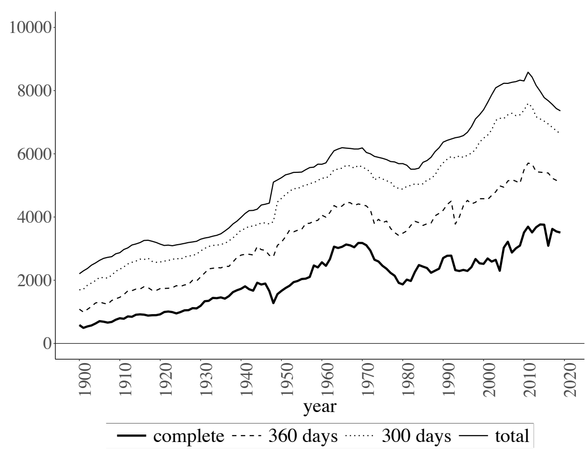
I.1 Climate Data

Weather stations. The left panel of Figure A-1 shows the long-run trend in the number of weather stations operating in the US from 1900 to 2019. It plots four lines based on the completeness of stations' daily records each year, including the number of stations with complete daily records, with at least 360 days of records per year, with at least 300 days of records per year, as well as the total number of weather stations. The number of stations in operation generally increases over time.

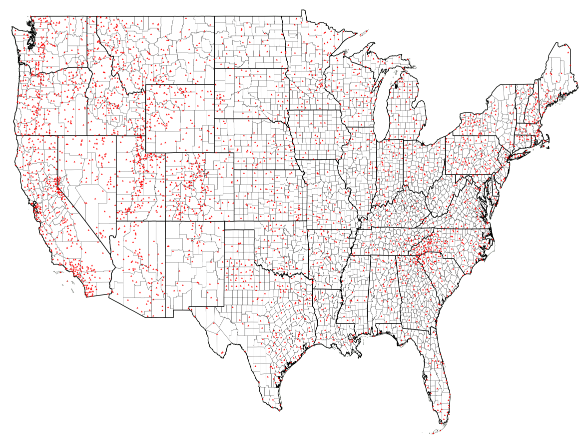
The right panel of Figure A-1 depicts the geographic distribution of stations with complete records in 2019. Each dot represents a weather station, and the boundaries mark county borders. The map shows dense coverage of weather stations overall, particularly in populous areas along the East and West Coasts and in the Midwest, although coverage is sparser in less-populated mountainous regions.

Figure A-1: Weather Stations in the US Mainland

(a) Number of Weather Stations (1900–2019)



(b) Map of Weather Stations (in 2019)



Notes: Panel (a) plots the number of weather stations in the US mainland from the Global Historical Climatology Network Daily (GHCN-Daily), provided by the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA). Panel (b) plots the geographic distribution of weather stations (red triangles), where county and state borders are depicted by thin and thick lines, respectively.

Daily records, such as minimum and maximum temperature, precipitation, and snowfall, from 3 weather stations closest to county population centroids in 2020 are aggregated using an inverse-distance weighting method. Figure A-2 illustrates the distributions of the decadal average working-hour temperature in 2001 vs. 2019. Each bar represents the annual number of days with work-hour temperatures falling into each 1°F-bin, weighted by employment at the start of each period. The figure depicts a noticeable shift in average temperature distribution to the right, with a higher concentration of days in higher temperature bins in 2019 compared to 2001, highlighting the warming trend. The dashed lines mark the cutoffs used in the baseline analysis to define hot and cold days, 77°F and 50°F, aligned with the thresholds for the top and bottom terciles, respectively, in the latest decade, 2010–2019.

Linear interpolation. Let t denote hours from 6 a.m. (so $t = 0$ at 6 a.m., $t = 7.5$ at 1:30 p.m., and so on). The piecewise-linear daily temperature path is

$$T(t) = \begin{cases} T^{\min} + (T^{\max} - T^{\min})\, \dfrac{t}{7.5}, & 0 \le t \le 7.5, \\ T^{\max} - (T^{\max} - T^{\min})\, \dfrac{t - 7.5}{16.5}, & 7.5 \le t \le 24. \end{cases}$$

The interval 8 a.m.–6 p.m. corresponds to $t \in [2, 12]$, of length 10 hours, and crosses the peak at $t = 7.5$. The average temperature during this interval is

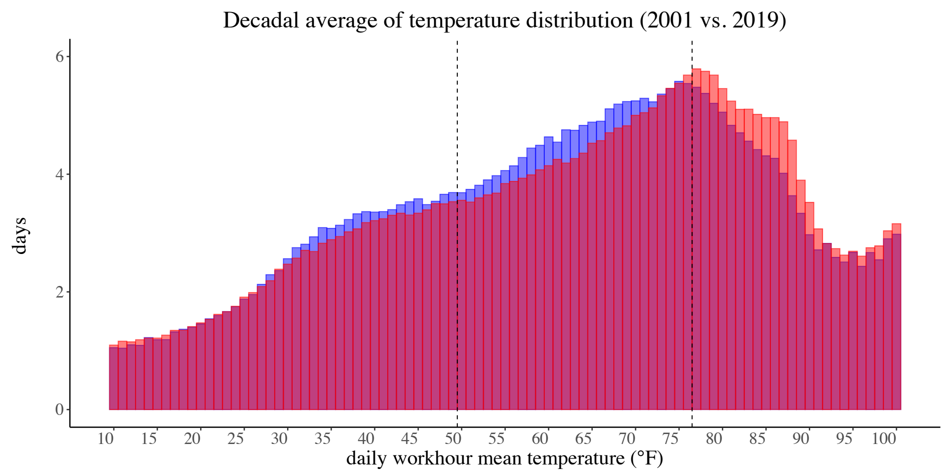
$$\bar{T} = \frac{1}{10}\left[\int_2^{7.5} T(t)\, dt + \int_{7.5}^{12} T(t)\, dt\right].$$

Since each segment is linear, each integral equals segment length times the average of endpoint values. Note that $T(2) = T^{\min} + \frac{2}{7.5}(T^{\max} - T_{\min}) \approx 0.27\, T^{\max} + 0.73\, T^{\min}$, $T(7.5) = T^{\max}$, and $T(12) = T^{\max} - \frac{4.5}{16.5}(T^{\max} - T^{\min}) \approx 0.73\, T^{\max} + 0.27\, T^{\min}$. Therefore,

$$\bar{T} = \frac{1}{10}\left[5.5 \cdot \tfrac{1}{2}(T(2) + T(7.5)) + 4.5 \cdot \tfrac{1}{2}(T(7.5) + T(12))\right] \approx 0.74\, T^{\max} + 0.26\, T^{\min}.$$

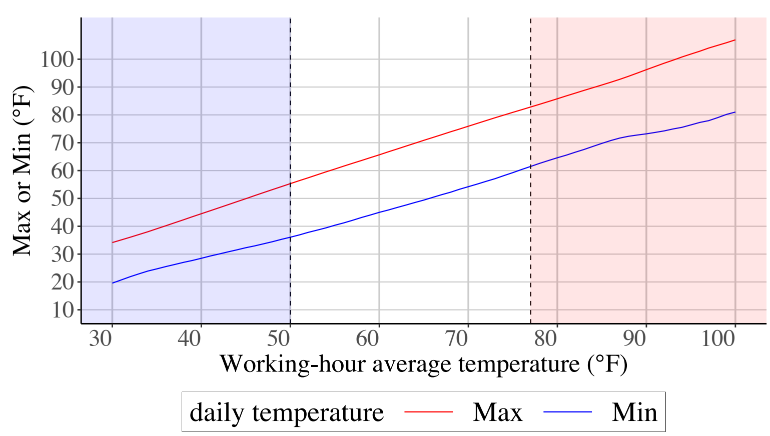
Relationship between daily mean, maximum, and minimum temperatures. Figure A-3 plots daily maximum and minimum temperatures against the average working-hour temperature. The red region marks hot days (≥77°F), and the blue region marks cold days (<50°F).

Figure A-2: Exposure to Climate Change in the US



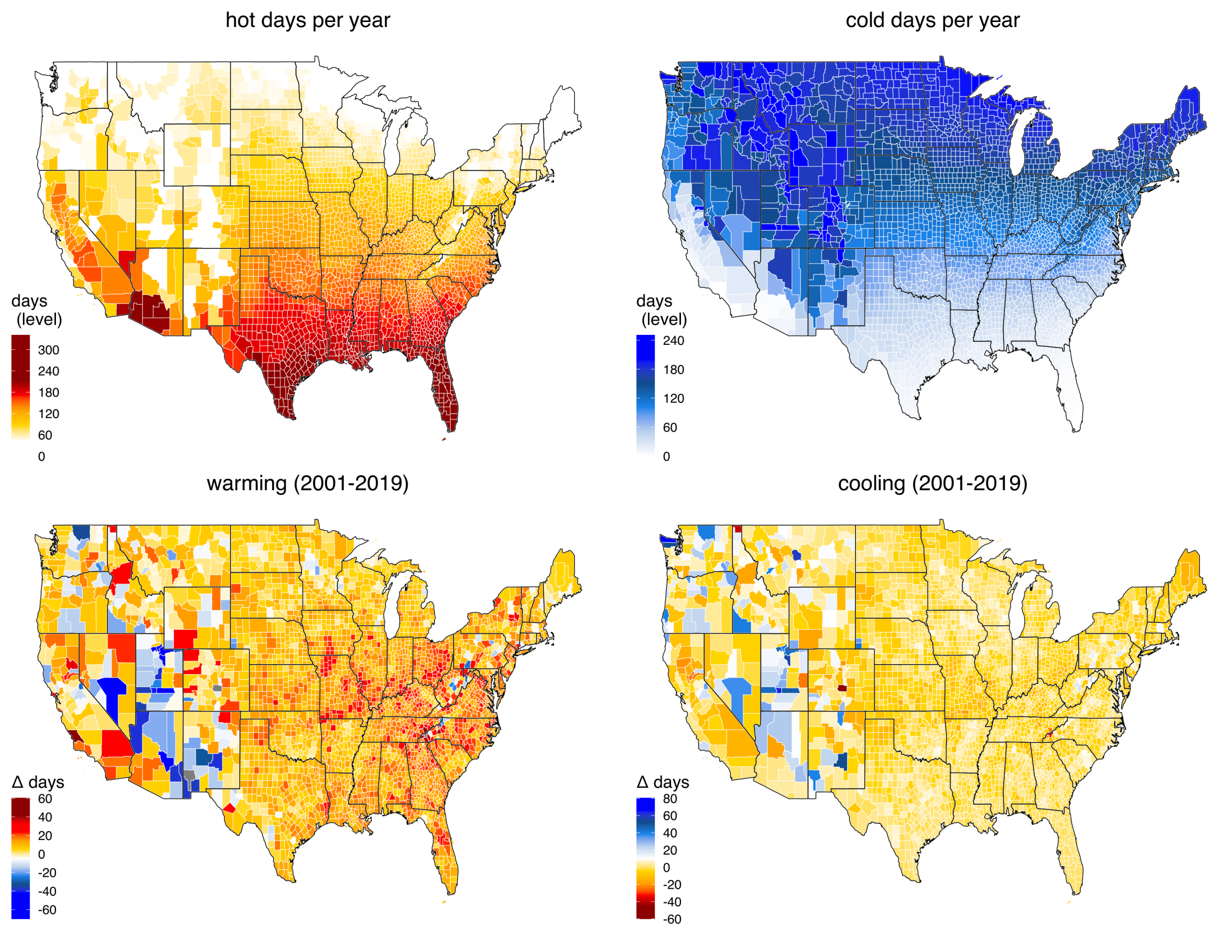
Notes: Blue: 2001 (1992–2001); Red: 2019 (2010–2019). Each histogram illustrates nationwide climate exposure across each 1°F bin, which is aggregated from the annual number of days with county-level working hour (8 a.m.–6 p.m.) temperature falling into each bin. In the periods of 1992–2001 and 2010–2019, aggregation weights are based on start-of-period employment levels from 1992 and 2010, respectively. The sum of days are normalized to 365 days. The dotted lines show our baseline thresholds for hot and cold days, 77°F and 50°F.

Figure A-3: Working-Hour Average Temperature vs. Maximum and Minimum Temperature



Notes: Nationwide daily temperature is aggregated from county-level daily temperature during 2001–2019, weighted by contemporaneous employment levels. The dotted lines mark the cutoffs used in the baseline analysis to define hot and cold days, 77°F and 50°F.

Figure A-4: Hot and Cold Days across US Counties

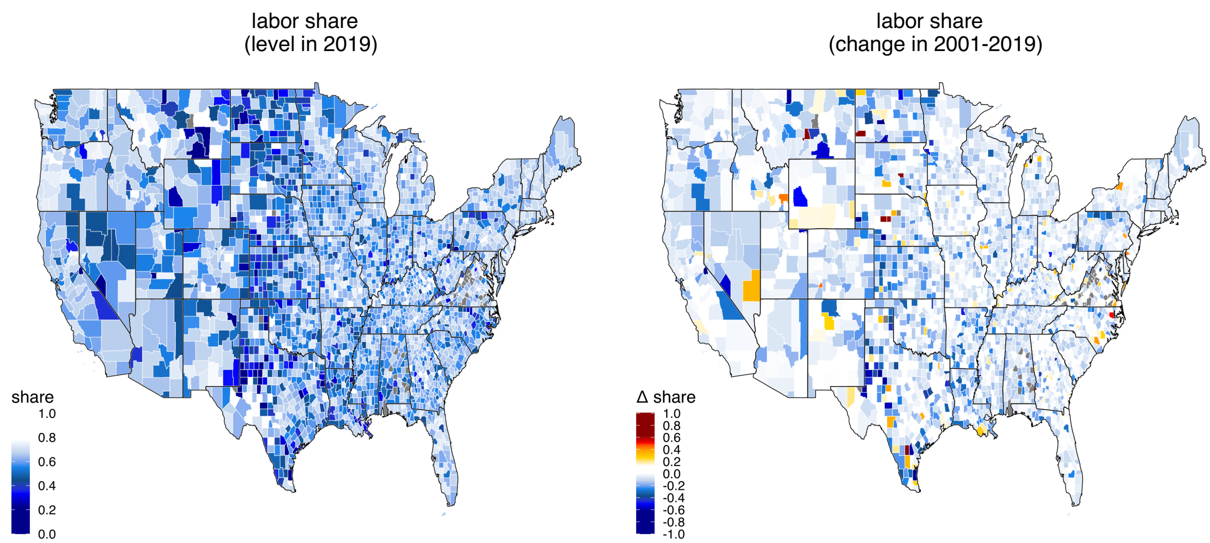


Notes: Top Panel: level in 2019; Bottom Panel: change from 2001 to 2019. Thresholds for hot and cold days are set to 77°F and 50°F based on the average temperature during working hours (8 a.m.–6 p.m.), with a weighting factor of 0.75 applied to the daily maximum temperature. The decadal averages of annual hot and cold days are calculated for the periods 1992–2001 to represent the year 2001, and 2010–2019 to represent the year 2019.

I.2 Labor Share Data

Heatmap. Figure A-5 depicts the level of labor share across counties in 2019 (left) and the change in labor share between 2001 and 2019 (right). It reveals significant spatial variation in both the level and the change in labor share. The decline in the labor share is prevalent, as is evident from the right panel.

Figure A-5: Labor Shares across US Counties



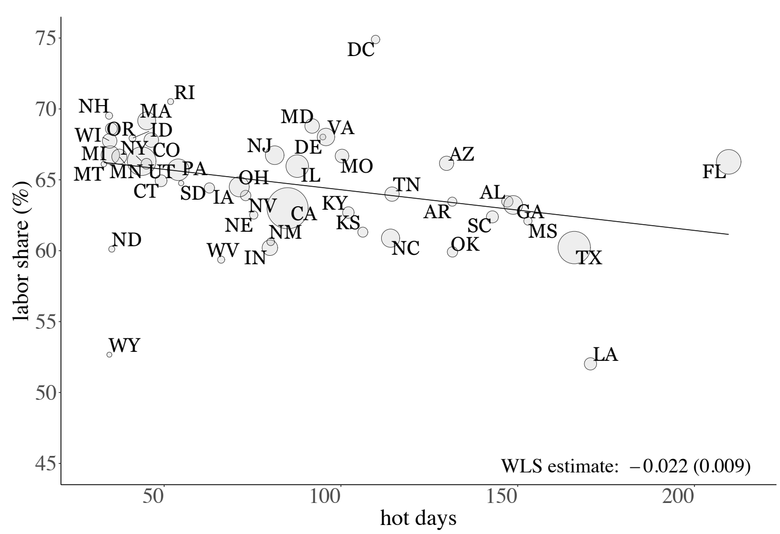
Notes: Labor share is calculated as the ratio of wage compensation to GDP net of proprietors' income, obtained from the BEA Regional Economic Accounts. Bold lines indicate state borders.

Linking data. We merge local climate data with local labor share data based on county FIPS codes. Note that the BEA Regional Economic Accounts record local economic activities in Virginia as 23 combination areas (FIPS 51901–51958), to which we manually merge the 51 Virginia counties (FIPS 51003–51735). The dataset comprises a panel of 3,080 counties in the US mainland. Due to missing data, four small counties with populations below 1,000—Petroleum, MT (FIPS 30069), Loup, NE (FIPS 31115), Loving, TX (FIPS 48301), and Roberts, TX (FIPS 48393)—are dropped, resulting in 3,076 counties in the analysis.

The 16 NAICS-based industries in the BEA data include 21 (mining, quarrying, and oil and gas extraction), 22 (utilities), 23 (construction), 31–33 (manufacturing), 42 (wholesale trade), 44–45 (retail trade), 48–49 (transportation and warehousing), 51 (information), 54 (professional, scientific, and technical services), 55 (management of companies and enterprises), 56 (administrative and support and waste management and remediation services), 61 (educational services), 62 (health care and social assistance), 71 (arts, entertainment, and recreation), 72 (accommodation and food services), 81 (other services). We use nonfarm, nonfinancial private industries; 11 (agriculture, forestry, fishing and hunting), 52 (finance and insurance), 53 (real estate and rental and leasing), and 92 (public administration) are excluded. We drop county-by-industry observations with missing labor share. Moreover, we restrict our analysis to cells with labor shares falling within the range $(0, 1)$.

Statewide relationship. Figure A-6 shows the relationship between the decadal average number of hot days per year and the average labor share across US states in 2019. Each circle corresponds to a state, with the size of each bubble representing the denominator of the labor share (i.e., GDP net of proprietors' income). One can see that states exposed to more hot days per year typically have a lower labor share. This negative correlation between hot days and labor share, indicated by the downward-sloping GDP-weighted fitted line, is significant, with an estimated slope of -0.022 and a standard error of 0.009.

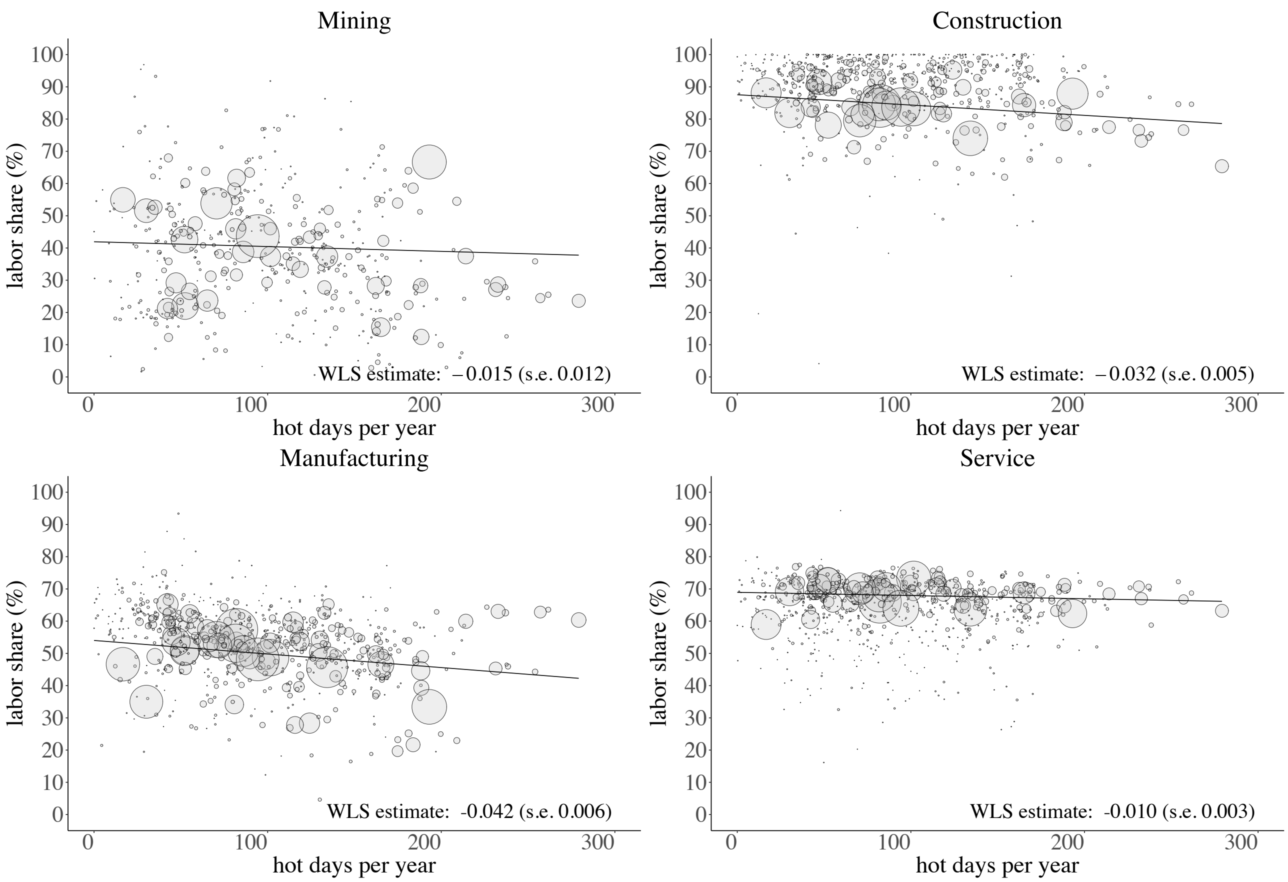
Figure A-6: Hot Days and Labor Shares across US States (2019)



Notes: This figure presents a scatterplot of the statewide labor share against the prior decade average of hot days per year across US states in 2019. Hot days is the employment-weighted average annual number of hot days with working-hour temperature above 77°F over 2010–2019, where the weights use county employment in 2010. Bubble size is proportional to GDP net of proprietors' income (the denominator of the labor share) in 2019.

Bubble plots within sectors. Figure A-7 illustrates cross-regional bubble plots, constructed separately for each sector, showing the relationship between the sectoral exposure to hot days and labor share in 2019. Each plot indicates a significantly negative association, suggesting that this spatial relationship holds within sectors.

Figure A-7: Bubble Plots within Sectors (commuting zones in 2019)



Notes: Each panel shows a bubble plot for one sector.

I.3 Covariates

In a full specification, we add a comprehensive set of demographic and socioeconomic controls that may independently affect labor share. These covariates are organized into three groups.

Industry concentration. To capture market structure dynamics that could influence the labor share, the first group includes the start-of-period $\underline{I}$'s measures of industry concentration:

- Herfindahl–Hirschman Index (HHI)
- employment share of large establishments with over 1,000 employees

These variables are constructed at the level of 16 industries by 3,080 counties, using the County Business Patterns (CBP) Database in 1990, 2000, and 2010.

Demography. The second group contains the start-of-period $\underline{I}$'s demographic variables of employment, a vector of employment shares by:

- educational attainment: less than high school, high school graduate, college graduate, above college ("some college" as the omitted reference category)
- age bins: 16–24, 25–34, 35–44, 45–54, 55–64 ("65 and above" as the omitted reference category)
- race and ethnicity groups: non-Hispanic White, non-Hispanic Black, Hispanic ("non-Hispanic Asian" and "other races" as the omitted reference categories)
- other demographic variables: immigration status (foreign-born, non-citizens), gender, veteran status

These variables are constructed at the level of 16 industries by 722 commuting zones using data from the 1990 and 2000 Population Census and the 2009–2010 stacked American Community Survey.

Labor market variables. The third group includes the start-of-period $\underline{I}$'s regional labor market variables:

- per capita non-labor income and welfare income
- population share of those who rent a house
- unemployment ratio of population
- log of population density

These variables are constructed at the level of 722 commuting zones, using data from the 1990 and 2000 Census, and the 2009–2010 stacked American Community Survey.

I.4 Occupation Characteristics

Physical intensity. We borrow the occupation-level physical intensity from Peri and Sparber (2009). The index is the average of the following variables of the O*NET Ability Survey:

- **Limb, hand, and finger dexterity**
  - 1.A.2.a.1: arm-hand steadiness
  - 1.A.2.a.2: manual dexterity
  - 1.A.2.a.3: finger dexterity
  - 1.A.2.b.1: control precision
  - 1.A.2.b.4: rate control
  - 1.A.2.c.1: reaction time
  - 1.A.2.c.2: wrist-finger speed
  - 1.A.2.c.3: speed of limb movement
- **Body coordination and flexibility**
  - 1.A.3.c.1: extent flexibility
  - 1.A.3.c.2: dynamic flexibility
  - 1.A.3.c.3: gross body coordination
  - 1.A.3.c.4: gross body equilibrium
- **Strength**
  - 1.A.3.a.1: static strength
  - 1.A.3.a.2: explosive strength
  - 1.A.3.a.3: dynamic strength
  - 1.A.3.a.4: trunk strength
  - 1.A.3.b.1: stamina

As noted in Peri and Sparber (2009), even when sensory-perception skills are included, comprising general perception, visual perception, and hearing perception, the results remain unchanged.

Manual routine intensity. Following Autor et al. (2003) and Autor and Dorn (2013), we use occupational task requirements from the fourth edition of the US Department of Labor's Dictionary of Occupational Titles (DOT) to measure the routine, abstract, and manual task content for each occupation. The data can be downloaded from David Dorn's website. Tasks are rated on a scale from zero to ten. We compute manual routine intensity as log(Routine) + log(Manual).

Technological exposure to robots. Webb (2019) develops a new method to measure occupational exposure to automation based on the overlap between the text of relevant patents, which describes technological capabilities, and the text of job descriptions, which describes tasks to be done by workers. He uses natural language processing to extract verbs from both sources. Data on each occupation's exposure to robots, software and AI can be downloaded from Michael Webb's website.

Injury and illness risk. We compute for each occupation the fraction of employees working at least weekly under nine hazardous conditions at Work Context Survey, using questions 4.C.2.b.1.c–4.C.2.c.1.f.

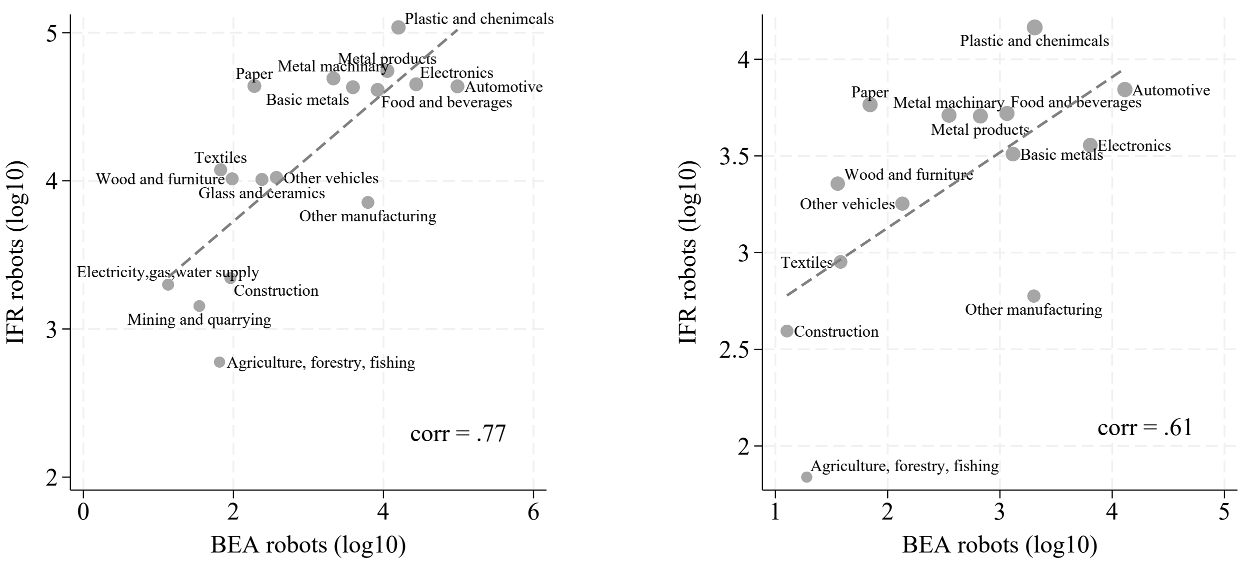
- **Frequency in Environmental Conditions**: "How often during a usual work period is the worker exposed to the following conditions?"
  - 4.C.2.b.1.c: Extremely Bright or Inadequate Lighting
  - 4.C.2.b.1.d: Exposed to Contaminants
  - 4.C.2.b.1.f: Exposed to Whole Body Vibration
- **Job Hazards**: "How often does this job require the worker to be exposed to the following hazards?"
  - 4.C.2.c.1.a: Exposed to Radiation
  - 4.C.2.c.1.b: Exposed to Disease or Infections
  - 4.C.2.c.1.c: Exposed to High Places
  - 4.C.2.c.1.d: Exposed to Hazardous Conditions
  - 4.C.2.c.1.e: Exposed to Hazardous Equipment
  - 4.C.2.c.1.f: Exposed to Minor Burns, Cuts, Bites, or Stings

I.5 Industrial Robots

Figure A-8 validates the BEA robot measure, a combination of *metalworking machinery* and *special industrial machinery*, by comparing it with the IFR robot measure in terms of both stock and investment. Following Graetz and Michaels (2018), we use the perpetual inventory method to estimate robot stocks, applying a depreciation rate of 10%, given the initial value of the stock measure in 2004 provided by the IFR. This approach mirrors the EUKLEMS procedure for computing the stock of ICT capital. Our findings are robust to alternative depreciation rates of 5% or 15%, or to directly using the IFR-reported stocks. Panel (a) of Figure A-8 plots the BEA robot stock (in million USD) against the IFR robot stock (in units), revealing a strong positive correlation of 0.77. This indicates that the BEA measure we construct aligns well with the established IFR robot data. The close clustering of industries along the fitted line further supports the reliability of the BEA robot stock measure we construct as a proxy for robot deployment. Panel (b) compares the BEA robot investment measure (in million USD) with the IFR robot investment measure (in units), showing a positive correlation of 0.61, which again underscores their alignment. Overall, both panels confirm the reliability of the BEA proxy for capturing robotization trends in the US.

Figure A-8: Measurement: BEA Robots vs. IFR Robots

(a) Stock (b) Investment



Notes: This figure compares the BEA robot measure (in million USD) with the IFR robot measure (in units) in terms of both stock (a) and investment (b). The dashed lines represent the fitted lines, with correlations of 0.77 and 0.61 for stock and investment, respectively. The size of each bubble captures log10 of BEA robots.

II Additional Analyses

II.1 Robustness Checks

This subsection presents a series of robustness checks to validate the paper's main findings.

Temperature thresholds. Table A-1 evaluates the robustness of our results to different temperature cutoffs. Specifically, we examine how varying the cutoffs for hot days at 73, 75, 77, and 80°F, and for cold days at 35, 40, 45, 50, and 55°F, affects the estimated impacts on labor share. Columns 1–4 report results for hot days defined by progressively higher temperature cutoffs, and Columns 5–8 report results for cold days defined by progressively lower temperature cutoffs. The results remain broadly consistent across different specifications with alternative cutoff pairs. However, the coefficients for hot days above 80°F in column 4, as well as for cold days below 45°F, are estimated with less precision. This is likely due to limited statistical power arising from the relative rarity of these extremely high temperature events. See the nonlinear temperature effects using more granular temperature bins below for more details.

Binning bias. Table A-2 augments the baseline specification with linear time trends interacted with climate normals, isolating variation in temperature extremes that is orthogonal to climate-normal–specific trends. Column 1 reproduces the baseline estimates for reference. Column 2 controls for county-specific linear trends as a simple solution suggested by Jones et al. (2026). Columns 3–5 interact a linear time trend with the number of hot days, cold days, and their difference in the 1990s, respectively, each serving as a proxy for baseline temperature. Column 6 instead interacts the time trend with a vector of indicators for 10°F temperature bins, with the (67–77°F) range as the omitted reference. Column 7 uses the latitude of the county centroid as an alternative proxy of climate normals. Across all specifications, the estimates for hot and cold days remain similar in magnitude and statistical significance.

Treatment window. Table A-3 reports the results of robustness checks using different treatment windows (from 1 to 20 years). To compare models with alternative treatment windows, we create extra climate variables $\mathbf{C}_l$ averaged for each time window. The estimates remain broadly consistent across all specifications in columns 1–5. However, the effects are smaller in magnitude and less significant for shorter treatment windows ($\leq$5 years) and become stronger as the window lengthens (>10 years). We thus conclude that long-term climate change, rather than temporary weather shocks, is driving the changes in labor shares. This is consistent with the theory that technological change and capital adjustments take place over the long run.

Table A-1: By Temperature Thresholds

	dependent variable: labor share (units: percentage points)							
			Baseline					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
10 hot days $\geq$73°F	−0.596							
	(0.129)							
>75°F		−0.571						
		(0.131)						
>77°F			−0.630		−0.563	−0.473	−0.416	−0.460
			(0.159)		(0.149)	(0.183)	(0.185)	(0.135)
>80°F				−0.411				
				(0.257)				
10 cold days <50°F	−0.888	−0.877	−0.891	−0.758				
	(0.397)	(0.394)	(0.403)	(0.497)				
<55°F					−0.647			
					(0.236)			
<45°F						−0.447		
						(0.389)		
<40°F							−0.243	
							(0.412)	
<35°F								−0.568
								(0.519)
N	92,803	92,803	92,803	92,803	92,803	92,803	92,803	92,803
Adjusted R^2	0.808	0.808	0.808	0.808	0.808	0.808	0.808	0.808

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. All models inherit the climate controls and county, state-year, industry-year fixed effects in specification (1) from Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. Standard errors in parentheses are clustered at the state level.

Table A-2: Controlling for Time Trends by Climate Normals

	dependent variable: labor share (units: percentage points)						
	baseline						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
10 hot days	−0.630	−0.694	−0.619	−0.634	−0.634	−0.647	−0.682
	(0.159)	(0.215)	(0.155)	(0.155)	(0.156)	(0.153)	(0.184)
10 cold days	−0.891	−0.431	−0.846	−0.903	−0.895	−0.787	−0.921
	(0.403)	(0.219)	(0.351)	(0.394)	(0.381)	(0.323)	(0.405)
trend ×(10 hot days in 90s)			0.000087				
			(0.000061)				
trend×(10 cold days in 90s)				−0.000020			
				(0.000054)			
trend× (10 hot days − 10 cold days in 90s)					0.000046		
					(0.000040)		
trend ×bin 1 in 90s						−0.000747	
						(0.000502)	
trend ×bin 2 in 90s						0.001319	
						(0.000722)	
trend ×bin 3 in 90s						−0.000796	
						(0.000350)	
trend ×bin 4 in 90s						0.000590	
						(0.000338)	
trend ×bin 5 in 90s						−0.000090	
						(0.000074)	
trend ×bin 6 in 90s						0.000040	
						(0.000184)	
trend ×bin 8 in 90s						0.000120	
						(0.000213)	
trend ×bin 9 in 90s						−0.000007	
						(0.000182)	
trend ×bin 10 in 90s						0.000620	
						(0.000177)	
trend × latitude (°)							−0.000133
							(0.000103)
county linear trend	-	Y	-	-	-	-	-
N	92,803	92,803	92,803	92,803	92,803	92,803	92,803
Adjusted R^2	0.808	0.824	0.808	0.808	0.808	0.808	0.808

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. Temperature bins (bin 1–bin 10) are defined in 10°F intervals, with the 67–77°F range as the omitted reference (bin 7). Models inherit the climate controls and county, state-year, industry-year fixed effects from specification (1) at Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. The standard errors are clustered at the state level.

Table A-3: By Treatment Window

	dependent variable: labor share (units: percentage points)							
					Baseline			
	1 year	3 year	5 year	8 year	10 year	12 year	15 year	20 year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
10 hot days	−0.104	−0.145	−0.064	−0.336	−0.630	−0.623	−0.809	−1.125
	(0.159)	(0.107)	(0.177)	(0.159)	(0.159)	(0.203)	(0.258)	(0.522)
10 cold days	−0.212	−0.613	−0.550	−0.764	−0.891	−0.923	−1.589	−2.088
	(0.231)	(0.318)	(0.157)	(0.257)	(0.403)	(0.502)	(0.920)	(0.757)
climate variables	✓	✓	✓	✓	✓	✓	✓	✓
N	92,803	92,803	92,803	92,803	92,803	92,803	92,803	92,803
Adjusted R^2	0.808	0.808	0.808	0.808	0.808	0.808	0.808	0.808

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. All models inherit the county, state-year, industry-year fixed effects from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. Standard errors in parentheses are clustered at the state level.

Measurements of labor shares. Table A-4 presents robustness checks using alternative proxies of labor share. Column 1 repeats the baseline specification. Column 2 uses the simple ratio of labor income to GDP, without excluding proprietors' income in the denominator, representing an extreme assumption that all proprietors' income is attributed to capital income. Column 3 adopts the ratio of wage compensation plus proprietors' income to GDP, representing the opposite extreme assumption that all proprietors' income is attributed to labor income. The results are similar, suggesting that the treatment of proprietors' income has little influence on the findings.

Table A-4: By Measurements of Labor Shares

	dependent variables: labor shares (units: percentage points)		
	Baseline	No adjustment of proprietors' income	Proprietors' income added to labor income
	(1)	(2)	(3)
10 hot days	−0.630	−0.653	−0.499
	(0.159)	(0.148)	(0.150)
10 cold days	−0.891	−0.925	−0.792
	(0.403)	(0.483)	(0.375)
N	92,803	99,743	93,570
Adjusted R^2	0.808	0.729	0.802

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. All models inherit the climate controls and county, state-year, industry-year fixed effects from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. Standard errors in parentheses are clustered at the state level.

Leave-one-out analysis. To assess whether our results are driven by specific industries or regions, we conduct a series of robustness checks that drop, one at a time, the most temperature-sensitive or automatable industries and the most temperature-sensitive regions. Column 1 of Table A-5 reproduces the baseline estimates for reference and comparison. Columns 2–3 rerun the analysis, each time excluding one of the most outdoor-intensive industries: construction-mining-utilities, and transportation. The results confirm that no single industry disproportionately drives the observed effects.

Additionally, we assess the influence of specific regions. The NOAA climate regions, ranked by the number of hot days in 2019, are as follows: Southeast, South, Southwest, West, Central, Northeast, East North Central, West North Central, and Northwest. In columns 4–5, we exclude the two hottest regions and the two coldest regions, respectively. The results are barely changed, confirming that the findings are not driven by any particular region.

Table A-5: Dropping Industries and Regions

	dependent variable: labor share (units: percentage points)				
	Baseline	Drop construction, mining, utilities	Drop transportation	Drop Southeast & South	Drop Northwest & West North Central
	(1)	(2)	(3)	(4)	(5)
10 hot days	−0.630	−0.516	−0.591	−0.611	−0.702
	(0.159)	(0.215)	(0.175)	(0.149)	(0.137)
10 cold days	−0.891	−0.858	−0.808	−0.848	−1.017
	(0.403)	(0.472)	(0.364)	(0.419)	(0.370)
N	92,803	80,976	86,953	58,382	81,970
Adjusted R^2	0.808	0.824	0.819	0.820	0.809

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. All models inherit the climate controls and county, state-year, industry-year fixed effects from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. Standard errors in parentheses are clustered at the state level.

Confounding labor demand shocks. Table A-6 reports the estimates from subsamples excluding CZs that were severely affected by a particular labor demand shock. Computer shocks are changes in exposure to PCs per employee over 1980–2000, borrowed from Autor and Dorn (2013). Robot shocks are changes in industrial robots per employee over 2004–2014, constructed from Acemoglu and Restrepo (2020). China shocks are proxies for international trade competition from China over 1990–2007, constructed from Autor et al. (2013). A set of CZs particularly affected by these shocks is specified by percentiles (25 pct. or 33 pct.) of CZ-level shocks. As each shock is measured at the commuting-zone level, we drop all counties belonging to commuting zones that are exposed to the relevant shock. In Column (8), the Rust Belt consists of 6 states: Illinois, Indiana, Michigan, Ohio, Pennsylvania, West Virginia. Excluding these areas does not materially affect the main estimates.

Table A-6: Dropping Regions under Intense Labor Demand Shocks

	dependent variable: labor share (units: percentage points)							
		drop		drop		drop		drop
	Baseline	czones (< 25 pct.)	czones (< 33 pct.)	czones (< 25 pct.)	czones (< 33 pct.)	czones (< 25 pct.)	czones (< 33 pct.)	Rust Belt
		hit by **computer shocks**		hit by **robot shocks**		hit by **China shocks**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
10 hot days	−0.630	−0.675	−0.678	−0.591	−0.725	−0.548	−0.531	−0.648
	(0.159)	(0.166)	(0.163)	(0.146)	(0.128)	(0.137)	(0.152)	(0.153)
10 cold days	−0.891	−0.915	−0.945	−0.887	−1.002	−0.895	−0.878	−0.780
	(0.403)	(0.401)	(0.401)	(0.373)	(0.374)	(0.380)	(0.406)	(0.461)
N	92,803	74,034	66,712	78,083	70,186	79,508	72,373	76,304
Adjusted R^2	0.808	0.809	0.810	0.804	0.795	0.803	0.805	0.808

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. All models inherit the climate controls and county, state-year, industry-year fixed effects from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. Standard errors in parentheses are clustered at the state level.

Fixed effects. The baseline specification in Table 2 includes county, state-year, and industry-year fixed effects. To ensure that this combination does not over-saturate the model, Table A-7 explores alternative ways of controlling for the underlying dynamics of warming and the declining labor shares. Column 1 reproduces the baseline estimates for reference. Column 2 replaces industry-year fixed effects with industry fixed effects only. Columns 3–5 instead absorb industry-level dynamics through linear trends: Column 3 includes industry-specific time trends in place of industry-year fixed effects, while Columns 4 and 5 add industry fixed effects together with sector-specific and industry-specific time trends, respectively. Columns 6 and 7 impose more demanding specifications by replacing the baseline county fixed effects with county-by-sector and county-by-industry fixed effects, respectively. The results are robust across all specifications, regardless of how industry-level dynamics are absorbed.

Table A-7: Inclusion of Fixed Effects

	dependent variable: labor share (units: percentage points)						
	Baseline						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
10 hot days	−0.630	−0.557	−0.984	−0.540	−0.586	−0.427	−0.394
	(0.159)	(0.157)	(0.195)	(0.145)	(0.148)	(0.131)	(0.141)
10 cold days	−0.891	−0.883	−0.984	−0.878	−0.855	−0.544	−0.507
	(0.403)	(0.454)	(0.353)	(0.431)	(0.387)	(0.373)	(0.365)
county FE	Y	Y	Y	Y	Y	-	-
state-year FE	Y	Y	Y	Y	Y	Y	Y
NAICS-year FE	Y	-	-	-	-	Y	Y
county-sector FE	-	-	-	-	-	Y	-
county-NAICS FE	-	-	-	-	-	-	Y
NAICS FE	-	Y	-	Y	Y	-	-
NAICS trend	-	-	Y	-	Y	-	-
sector trend	-	-	-	Y	-	-	-
N	92,803	92,803	92,803	92,803	92,803	92,803	92,803
Adjusted R^2	0.808	0.794	0.591	0.798	0.803	0.887	0.924

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. All models inherit the climate controls from specification (1) in Table 2. We group industries into six broad sectors: mining, construction-utilities, manufacturing, retail/wholesale, transportation, and services. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. Standard errors in parentheses are clustered at the state level.

Nonlinear effects of extreme temperatures. Table A-8 reports the effects of extreme temperatures using finer bins, with 50°F to 77°F as the normal-range reference. Hot days between 77°F and 90°F and cold days between 40°F and 50°F, have significantly adverse effects on the labor share. For the most extreme bins, however, the effects seem smaller. We consider three potential reasons.

First, under extreme heat, capital efficiency may decline alongside labor efficiency, dampening the marginal effect on the labor share. Garimella and Hughes (2023) document that extreme heat reduces machine performance through decreased efficiency and utilization under heat stress. Consistent with this view, Zhang et al. (2018) provide firm-level evidence from Chinese manufacturers that both labor-intensive and capital-intensive firms suffer TFP losses under extreme high temperatures, suggesting that capital can be as exposed to extreme heat damage as labor.

Second, employers and workers may adopt countermeasures in response to severe temperatures, such as air conditioning, flexible working hours, or work suspensions on extremely hot days. Some states have also introduced regulatory measures, such as the Heat Illness Prevention Standards (HIPS) adopted by California (2006) and Washington (2008). Adaptation is particularly likely in southern states with high baseline exposure, where workers and firms have long been accustomed to severe heat. We examine this possibility directly in the next exercise.

Third, the coefficients on the most extreme temperature bins are estimated with limited statistical power due to the rarity and the spatial concentration of these observations. Within our fixed-effects structure, the coefficient on each bin is identified from within-state-year variation across counties. Yet extreme days are rare and geographically concentrated: during 2010–2019, nearly 70% of US counties averaged fewer than 10 days at or above 90°F per year, with the remaining counties overwhelmingly located in Arizona and Texas. Since our specification relies more on spatial than intertemporal variation, most states exhibit little within-state variation at the most extreme bins, leaving the coefficient identified from a narrow set of locations. These estimates should therefore be interpreted with caution.

Table A-8: The Impacts of Severe Temperature

	dependent variable: labor share (units: percentage points)							
	Baseline							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
hot days $\geq$ 77°F	−0.630					−0.618	−0.617	−0.593
	(0.159)					(0.163)	(0.169)	(0.158)
[77, 80) °F		−1.494	−1.375					
		(0.690)	(0.746)					
hot days $\geq$ 80°F		−0.415						
		(0.169)						
[80, 85) °F			−0.673					
			(0.407)					
[77, 85) °F				−0.948				
				(0.281)				
hot days $\geq$ 85°F			−0.292	−0.284				
			(0.174)	(0.180)				
[77, 90) °F					−0.595			
					(0.211)			
hot days $\geq$ 90°F					−0.764			
					(0.768)			
cold days $<$ 50°F	−0.891	−0.821	−0.810	−0.828	−0.897			
	(0.403)	(0.378)	(0.362)	(0.361)	(0.413)			
$[45, 50)$ °F						−1.877	−1.870	
						(0.852)	(0.800)	
cold days $<$ 45°F						−0.575		
						(0.326)		
$[40, 45)$ °F							−1.228	
							(0.505)	
cold days $<$ 40°F							−0.416	
							(0.354)	
$[40, 50)$ °F								−1.635
								(0.612)
$[30, 40)$ °F								−0.597
								(0.513)
cold days $<$ 30°F								−0.124
								(0.646)
N	92,803	92,803	92,803	92,803	92,803	92,803	92,803	92,803
Adjusted R^2	0.808	0.808	0.808	0.808	0.808	0.808	0.808	0.808

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. All models inherit the climate controls and county, state-year, industry-year fixed effects from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. Standard errors in parentheses are clustered at the state level.

Adaptation. Under the most extreme heat, firms may adapt to maintain operations by installing air-conditioning systems or adopting flexible working-hour arrangements. At the regulatory level, OSHA issues guidelines for working under extreme heat. Some states, such as California and Washington, have implemented the Heat Illness Prevention Standard (HIPS) to restrict outdoor operations on extremely hot days. Workers may also engage in defensive avoidance behaviors such as reducing working hours (Graff Zivin and Neidell, 2014) or increasing absenteeism (Somanathan et al., 2021) in response to extreme heat.

To detect evidence of adaptation, Table A-9 examines heterogeneous climate impacts by exploiting both intertemporal and spatial variation. By interacting temperature exposure with a linear time trend, Columns 2–3 find weak evidence of dynamic acclimatization to hot days, but little evidence for cold days. By interacting temperature exposure with the historical climate baseline from the 1990s, Columns 4–7 document cross-sectional evidence of spatial adaptation for cooling, but not for warming: initially hotter areas experience even greater damages from both hot and cold days, whereas initially colder areas exhibit milder effects. The limited evidence of adaptation aligns with macroeconomic studies on climate and growth (Burke et al., 2015; Dell et al., 2012).

Table A-9: Heterogeneity by Time and Space

	dependent variable: labor share (units: percentage points)						
		dynamic acclimatization		spatial heterogeneity			
	baseline		stack years				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
10 hot days	−0.630	−0.722	−0.461	−0.128	−0.589	−0.727	−0.426
	(0.159)	(0.184)	(0.174)	(0.340)	(0.333)	(0.160)	(0.145)
10 cold days	−0.891	−0.877	−0.345	−1.737	−0.474	−1.729	−0.958
	(0.403)	(0.370)	(0.226)	(0.246)	(0.485)	(0.221)	(0.264)
10 hot days × 10 hot days in 90s				−0.036	−0.013		
				(0.034)	(0.037)		
10 hot days × 10 cold days in 90s						0.067	
						(0.031)	
10 cold day × 10 cold days in 90s				0.126		0.162	
				(0.043)		(0.043)	
10 cold days × 10 hot days in 90s					−0.083		
					(0.055)		
10 hot days × (10 hot days - 10 cold days) in 90s							−0.036
							(0.020)
10 cold days × (10 hot days - 10 cold days) in 90s							−0.119
							(0.039)
10 hot days × years passed		0.010	0.007				
		(0.007)	(0.004)				
10 cold days × years passed		0.007	0.0002				
		(0.007)	(0.005)				
N	92,803	92,803	589,117	92,803	92,803	92,803	92,803
Adjusted R^2	0.808	0.808	0.825	0.808	0.808	0.808	0.808

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. Both models inherit the climate controls and county, state-year, industry-year fixed effects from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. The standard errors are clustered at the state level.

State-industry level analysis. Table A-10 reports the estimates from the state-industry-level aggregate analysis using a standard two-way fixed effects specification. Aggregating the unit of analysis from counties to states drastically reduces spatial variation in the data; therefore, we stack all available years to ensure sufficient variation for the analysis. The effects of hot days remain largely robust across reasonable cutoffs, the inclusion of additional climate variables, and the adoption of more stringent industry-year fixed effects.

Table A-10: State-Industry Level Analysis

	dependent variable: labor share (units: percentage points)				
	(1)	(2)	(3)	(4)	(5)
10 hot days	−0.640	−0.625	−0.796		−0.595
($\geq 77°F$)	(0.368)	(0.347)	(0.381)		(0.357)
10 hot days				−0.715	
($\geq 80°F$)				(0.383)	
10 cold days	−0.279	−0.403			−0.325
($< 50°F$)	(0.519)	(0.485)			(0.453)
10 cold days			−1.469	−1.392	
($< 40°F$)			(0.481)	(0.477)	
state-NAICS FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	-
NAICS-year FE	-	-	-	-	Y
climate variables	✓	–	✓	✓	✓
N	14,026	14,026	14,026	14,026	14,026
Adjusted R^2	0.971	0.971	0.971	0.971	0.983

Notes: Unit of analysis: outcome years (2001–2019) × states × industries. All models except (2) inherit the climate controls from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. Standard errors in parentheses are clustered at the state level.

II.2 Heterogeneity

In Table 3, we measure climate exposure using $x_{c,k,\underline{I}}$, which captures period-specific changes in regional occupational composition. While this measure more accurately reflects local exposure, it may raise endogeneity concerns: occupational composition could itself respond to prior temperature shocks. To address this, Table A-11 reports results using alternative measures based on predetermined and/or nationwide variation. Specifically, we consider sector-wide exposure fixed at its 1990 level, $x_{k,1990}$ (Panel a); sector-wide exposure that varies over time but is measured at the national level, $x_{k,\underline{I}}$ (Panel b); and county–industry exposure fixed at its 1990 level, $x_{c,k,1990}$ (Panel c). Relative to Table 3, the estimates remain similar in magnitude and statistically significant.

Table A-11: Alternative Construction of Climate Exposure

	dependent variable: labor share (units: percentage points)			
	×indoor non-controlled	×indoor non-controlled plus outdoor	× outdoor with cover	× indoor controlled
	(a) by climate exposure (sector-wide in 1990)			
	(1)	(2)	(3)	(4)
10 hot days	−0.434	−0.507	−0.511	−0.991
	(0.170)	(0.173)	(0.195)	(0.177)
10 hot days	−0.848	−0.269	−1.060	0.560
× climate exposure	(0.455)	(0.078)	(0.503)	(0.233)
N	92,803	92,803	92,803	92,803
Adjusted R^2	0.810	0.809	0.809	0.808
	(b) by climate exposure (sector-wide)			
	(1)	(2)	(3)	(4)
10 hot days	−0.388	−0.460	−0.465	−1.166
	(0.154)	(0.185)	(0.226)	(0.189)
10 hot days	−0.978	−0.339	−1.333	0.804
× climate exposure	(0.303)	(0.098)	(0.851)	(0.272)
N	92,803	92,803	92,803	92,803
Adjusted R^2	0.810	0.809	0.809	0.809
	(c) by climate exposure (in 1990)			
	(1)	(2)	(3)	(4)
10 hot days	−0.439	−0.497	−0.476	−1.045
	(0.169)	(0.164)	(0.179)	(0.166)
10 hot days	−0.798	−0.277	−1.322	0.635
× climate exposure	(0.578)	(0.148)	(0.512)	(0.121)
N	92,763	92,763	92,763	92,763
Adjusted R^2	0.811	0.810	0.811	0.809

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. Both models inherit the climate controls and county, state-year, industry-year fixed effects from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. The standard errors are clustered at the state level.

III Mechanism

This section presents robustness checks for the analyses in Section 4.1.

Automation potential. To address the endogeneity concern raised in Section II.2, Table A-12 reports results using alternative measures of automation potential based on predetermined and/or national variation. Relative to Table 4, the estimates remain similar in magnitude and statistically significant.

Table A-12: Alternative construction of automation potential

	dependent variable: labor share (units: percentage points)			
	× physical intensity	× manual routine intensity	× technological exposure to robots	× injury and illness risk
	(a) by task characteristics (sector-wide in 1990)			
	(1)	(2)	(3)	(4)
10 hot days	−0.388	−0.565	−0.352	−0.433
	(0.203)	(0.167)	(0.207)	(0.190)
10 hot days × task characteristics	−0.520	−0.177	−0.636	−0.564
	(0.237)	(0.035)	(0.317)	(0.286)
N	92,803	92,803	92,803	92,803
Adjusted R^2	0.809	0.809	0.808	0.809
	(b) by task characteristics (sector-wide)			
	(1)	(2)	(3)	(4)
10 hot days	−0.323	−0.554	−0.233	−0.383
	(0.202)	(0.173)	(0.184)	(0.174)
10 hot days × task characteristics	−0.623	−0.167	−0.887	−0.678
	(0.137)	(0.029)	(0.139)	(0.138)
N	92,803	92,803	92,803	92,803
Adjusted R^2	0.809	0.809	0.808	0.809
	(c) by task characteristics (in 1990)			
	(1)	(2)	(3)	(4)
10 hot days	−0.370	−0.573	−0.311	−0.410
	(0.210)	(0.167)	(0.216)	(0.198)
10 hot days × task characteristics	−0.543	−0.167	−0.725	−0.592
	(0.331)	(0.054)	(0.421)	(0.434)
N	92,761	92,763	92,763	92,763
Adjusted R^2	0.810	0.810	0.809	0.810

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. Both models inherit the climate controls and county, state-year, industry-year fixed effects from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. The standard errors are clustered at the state level.

Industry-level covariates. In parallel with our baseline analysis, we construct industry-level covariates, including other climate variables $\mathbf{C}_{k,I}$ and industrial concentration $\mathbf{S}_{k,\underline{I}}$, for both analyses using the BEA and IFR data. Controlling for demographic composition $\mathbf{D}_{k,\underline{I}}$, and other employment characteristics $\mathbf{M}_{k,\underline{I}}$ does not qualitatively change the results.

- $\mathbf{C}_{k,I}$ includes the average of daily precipitation on rainy days (intensive margin), the number of non-rainy days (extensive margin), and the number of days with heavy snowfall ($\geq$ 300 mm). (Source: GHCN-Daily)
- $\mathbf{S}_{k,\underline{I}}$ includes Herfindahl–Hirschman Index (HHI) and employment share of large establishments with over 1,000 employees. (Source: County Business Patterns)
- $\mathbf{D}_{k,\underline{I}}$ includes employment compositions by educational attainment: less than high school, high school, college graduates and above; the shares of junior (aged 16–35) and senior (aged 55 and above); and the shares of non-Hispanic White, immigrants (foreign-born, non-citizens), and males. (Source: Census and American Community Survey)
- $\mathbf{M}_{k,\underline{I}}$ includes per capita non-labor income, and the share of renters. (Source: Census and American Community Survey)

Temperature thresholds. For the analyses on robot stocks and investments, we conduct robustness checks with alternative temperature cutoffs defining hot and cold days. Table A-13 presents the robustness checks for the BEA data and Table A-14 for the IFR data. Reassuringly, the results are robust to alternative cutoff choices.

Table A-13: By Temperature Thresholds (industrial robots from the BEA)

	dependent variable: Robot/Capital (units: percentage points)					
	(1)	(2)	(3)	(4)	(5)	(6)
hot days≥70°F	4.765					
	(1.604)					
≥75°F		4.350				
		(1.491)				
≥77°F			3.996		4.063	3.930
			(1.614)		(1.516)	(1.550)
≥80°F				4.175		
				(1.792)		
cold days <50°F	4.296	3.370	2.984	2.808		
	(1.907)	(1.540)	(1.510)	(1.422)		
<45°F					3.807	
					(2.047)	
<40°F						4.572
						(2.985)
N	194	194	194	194	194	194
Adjusted R^2	0.967	0.966	0.966	0.966	0.966	0.966

Notes: Unit of analysis: outcome years (1980–2010 by decade) × industries. All models inherit the controls, sector trend, and two-way fixed effects in the specifications from Panel A of Table 5. The regressions are weighted by the industry-level GDP. Standard errors in parentheses are clustered at the sector level.

Table A-14: By Temperature Thresholds (industrial robots from the IFR)

	dependent variable: Robot / Capital (units: robot stocks per 100 million USD)					
	(1)	(2)	(3)	(4)	(5)	(6)
hot days≥70°F	4.761					
	(0.171)					
≥75°F		4.207				
		(0.525)				
≥77°F			3.345		2.457	1.438
			(0.786)		(0.662)	(0.803)
≥80°F				1.109		
				(1.255)		
cold days <50°F	4.618	4.006	3.287	1.343		
	(0.334)	(0.370)	(0.551)	(0.811)		
<45°F					2.580	
					(0.500)	
<40°F						1.568
						(0.672)
N	48	48	48	48	48	48
Adjusted R^2	0.991	0.990	0.990	0.990	0.990	0.990

Notes: Unit of analysis: outcome years (2005, 2010, 2015) × industries. All models inherit the controls, sector trend, and two-way fixed effects in specifications from Panel B of Table 5. The regressions are weighted by the industry-level GDP. Standard errors in parentheses are clustered at the sector level.

Climate effect on capital. Table A-15 replicates the analysis using other capital measures that include equipment, structures, and IPP capital. These results do not yield statistically significant estimates.

Table A-15: Climate Impact on Capital Deployment by Broad Categories

	Equip. /Capital	Structure /Capital	IPP /Capital	Equip. Inv. /Capital Inv.	Structure Inv. /Capital Inv.	IPP Inv. /Capital Inv.
	(units: percentage points)					
	(1)	(2)	(3)	(4)	(5)	(6)
10 hot days	5.679	−4.395	−1.283	10.787	−8.962	−1.825
	(4.469)	(4.880)	(1.906)	(6.814)	(3.680)	(5.031)
10 cold days	5.507	0.808	−6.315	14.814	−4.146	−10.668
	(2.212)	(1.381)	(1.396)	(3.752)	(2.718)	(2.675)
N	194	194	194	194	194	194
Adjusted R^2	0.945	0.966	0.955	0.903	0.915	0.935

Notes: Unit of analysis: outcome years (1980–2010 by decade) $\times$ industries. All models inherit the controls, sector trend and two-way fixed effects in the specifications from Panel A of Table 5. The regressions are weighted by the industry-level GDP. Standard errors in parentheses are clustered at the sector level.

Climate effect on digitalization. Table A-16 replaces BEA robots with ICT capital and software and similarly does not produce statistically significant estimates. In the National Income and Product Accounts (NIPA) from the BEA, ICT capital consists of PCs and mainframes, and software consists of prepackaged software, custom software, and own-account software.

Table A-16: Climate Impact on Digitalization

	ICT /Capital	Software /Capital	ICT Inv. /Capital Inv.	Software Inv. /Capital Inv.
	(units: percentage points)			
	(1)	(2)	(3)	(4)
10 hot days	−0.055	−2.109	0.334	−3.133
	(0.134)	(1.779)	(0.565)	(4.995)
10 cold days	−0.094	−5.578	0.375	−10.400
	(0.205)	(2.188)	(0.482)	(4.148)
N	194	194	194	194
Adjusted R^2	0.896	0.840	0.790	0.838

Notes: Unit of analysis: outcome years (1980–2010 by decade) × industries. All models inherit the controls, sector trend and two-way fixed effects in the specifications from Panel A of Table 5. The regressions are weighted by the industry-level GDP. Standard errors in parentheses are clustered at the sector level.

Decomposition: labor income vs. GDP. In Table A-17, we decompose the labor share into its numerator and denominator and analyze each component separately. In the baseline specification, labor income shows a statistically significant decline, whereas GDP exhibits a negative but statistically insignificant effect. These results remain robust across alternative control specifications in columns 1–5.

Table A-17: Numerator vs. Denominator of the Labor Share

	(a) dependent variable: log(labor income) (units: percent change)				
	Baseline				
	(1)	(2)	(3)	(4)	(5)
10 hot days	−2.200	−2.422	−2.027	−2.548	−2.492
	(0.909)	(0.984)	(0.998)	(0.839)	(0.725)
10 cold days	−1.801	−1.599	−1.471	−2.476	−2.686
	(0.870)	(0.908)	(0.847)	(0.998)	(1.206)
N	92,803	93,445	90,330	90,311	90,311
Adjusted R^2	0.910	0.910	0.920	0.928	0.929
extra climate variables	✓	–	✓	✓	✓
industry concentration	–	–	✓	✓	✓
demography	–	–	–	✓	✓
labor market	–	–	–	–	✓
	(b) dependent variable: log(GDP net of proprietary income) (units: percent change)				
	Baseline				
	(1)	(2)	(3)	(4)	(5)
10 hot days	−0.577	−0.774	−0.617	−1.083	−1.076
	(1.011)	(1.103)	(0.948)	(0.791)	(0.704)
10 cold days	−0.423	−0.143	−0.263	−1.254	−1.354
	(1.191)	(1.175)	(1.076)	(1.227)	(1.414)
N	92,803	93,445	90,330	90,311	90,311
Adjusted R^2	0.897	0.896	0.906	0.914	0.915
extra climate variables	✓	–	✓	✓	✓
industry concentration	–	–	✓	✓	✓
demography	–	–	–	✓	✓
labor market	–	–	–	–	✓

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. All models inherit the county, state-year, industry-year fixed effects from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. Standard errors in parentheses are clustered at the state level.

III.1 Compositional Change

Testing the climate-induced concentration. Table A-18 examines the climate impacts on the employment share across establishment-size bins. In columns 1–7, we find that hot days reduce the employment share of relatively small establishments (with 20 employees or fewer), whereas cold days reduce the share of those with up to 100 employees. Conversely, cold days increase the share of large establishments (with more than 1,000 employees). Consequently, we find modest evidence that extreme temperatures have increased industry concentration, as reflected in the imputed Herfindahl–Hirschman Index (column 8). This pattern persists even when replacing county fixed effects with the more stringent county-industry fixed effects or stacking all years together.

Table A-18: Climate Change and Establishment Size Composition

	dependent variable: industry concentration (units: percentage points)							
	employment size							HH
	> 1000	500-1000	50-100	20-50	10-20	5-10	1-5	index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
10 hot days	−0.231	0.286	0.013	−0.081	−0.209	−0.191	−0.335	0.317
	(0.193)	(0.177)	(0.076)	(0.167)	(0.117)	(0.093)	(0.158)	(0.162)
10 cold days	1.402	0.319	−0.409	−0.400	−0.223	−0.136	−0.155	0.426
	(0.286)	(0.239)	(0.185)	(0.170)	(0.105)	(0.079)	(0.087)	(0.134)
N	89,985	89,985	89,985	89,985	89,985	89,985	89,985	91,656
Adjusted R^2	0.457	0.291	0.200	0.421	0.444	0.489	0.491	0.598

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. All models inherit the climate controls and county, state-year, industry-year fixed effects from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. Standard errors in parentheses are clustered at the state level.

Controlling for establishment size composition. Table A-19 explicitly controls for the start-of-period employment share across bins. The climate estimates shrink modestly but remain largely stable.

Table A-19: Baseline Model Controlling for Establishment Size Composition

	Baseline (1)	(2)	(3)	(4)	(5)	(6)	(7)
	dependent variable: labor share (units: percentage points)						
10 hot days	−0.630	−0.581	−0.579	−0.582	−0.578	−0.576	−0.575
	(0.159)	(0.198)	(0.203)	(0.199)	(0.196)	(0.204)	(0.204)
10 cold days	−0.891	−0.838	−0.836	−0.848	−0.837	−0.831	−0.832
	(0.403)	(0.418)	(0.426)	(0.423)	(0.418)	(0.428)	(0.429)
HH index		−0.0005	−0.0005	−0.001	−0.001		−0.0004
		(0.0002)	(0.0003)	(0.0003)	(0.0003)		(0.0002)
emp. share (> 100)			0.039				
			(0.016)				
emp. share (> 500)				0.028			
				(0.013)			
emp. share (5-10)						0.090	0.062
						(0.037)	(0.037)
emp. share (10-20)						0.011	0.010
						(0.020)	(0.020)
emp. share (20-50)						0.039	0.038
						(0.020)	(0.020)
emp. share (50-100)						0.043	0.042
						(0.019)	(0.019)
emp. share (100-250)						0.070	0.069
						(0.026)	(0.026)
emp. share (250-500)						0.069	0.068
						(0.029)	(0.028)
emp. share (500-1000)						0.070	0.069
						(0.022)	(0.022)
emp. share (> 1000)					0.025	0.076	0.075
					(0.016)	(0.029)	(0.029)
N	92,803	90,330	90,330	90,330	90,330	90,330	90,330
Adjusted R^2	0.808	0.813	0.813	0.813	0.813	0.813	0.814

Notes: Unit of analysis: outcome years (2001, 2010, 2019) × counties × industries. All models inherit the climate controls and county, state-year, industry-year fixed effects from specification (1) in Table 2. The regressions are weighted by the denominator of the labor share, i.e., GDP net of proprietors' income. Standard errors in parentheses are clustered at the state level.

IV Back-of-the-Envelope Calculations

Between-county reallocation effects. Table A-20 examines whether climate change affects GDP shares (i.e., the denominators of our labor share proxies). We find little evidence of such effects.

Table A-20: Climate Impacts on GDP Shares

	dependent variable: GDP share (units: percentage points ($\times 10^{-4}$))			
	Baseline (1)	(2)	(3)	(4)
10 hot days	0.782	0.741	0.616	0.606
	(0.503)	(0.504)	(0.409)	(0.415)
10 cold days	0.472	0.446	0.423	0.402
	(0.858)	(0.829)	(0.861)	(0.837)
extra climate variables	✓	–	✓	–
county FE	Y	Y	-	-
state-year FE	Y	Y	Y	Y
NAICS-year FE	Y	Y	Y	Y
county-naics FE	-	-	Y	Y
N	92,803	93,445	92,803	93,445
Adjusted R^2	0.514	0.512	0.941	0.941

Notes: Unit of analysis: outcome years (2001, 2010, 2019) $\times$ counties $\times$ industries. All models inherit the climate controls from specification (1) in Table 2. The regressions are identically weighted. Standard errors in parentheses are clustered at the state level.

Second-order interaction between within- and between-county effects. Table A-21 examines whether climate change affects the second-order covariance term between the growth of GDP shares (i.e., the denominators of our labor share proxies) and the growth of labor shares. Using a first-difference model with reasonable combinations of fixed effects, we find significantly negative estimates for hot days, suggesting that the total climate impact may exceed the magnitude captured by our within-county estimates.

Table A-21: Climate Impacts on ΔGDP Shares × Δ Labor Shares

	dependent variable: Δ GDP share × Δ Labor share (units: percentage points × percentage points ($\times 10^{-4}$))			
	(1)	(2)	(3)	(4)
Δ 10 hot days	−7.029	−7.153	−6.653	−6.770
	(3.359)	(3.309)	(3.377)	(3.305)
Δ 10 cold days	0.225	0.247	0.038	0.024
	(4.626)	(4.469)	(4.839)	(4.628)
Δ extra climate variables	✓	–	✓	–
state-year FE	Y	Y	–	–
NAICS-year FE	Y	Y	–	–
state-NAICS-year FE	–	–	Y	Y
N	54,436	54,780	54,436	54,780
Adjusted R^2	0.007	0.007	0.014	0.014

Notes: Unit of analysis: outcome intervals (Δ2001-2010, Δ2010-2019) × counties × industries. All models inherit the first-differenced climate controls from specification (1) in Table 2. The regressions are identically weighted. Standard errors in parentheses are clustered at the state level.

Robustness checks for the assessment. Figure A-9 presents robustness checks using alternative models to assess the macroeconomic impacts. Specifically, these models incorporate heterogeneity across periods and sectors to provide a more nuanced analysis. The first row of Figure A-9 replicates the assessment using the baseline estimates, β^h and β^c. The second row applies sector-specific estimates, β^h_K and β^c_K from Figure 3. The third row uses a model that allows for period-specific estimates, β^h_I and β^c_I from the regression:

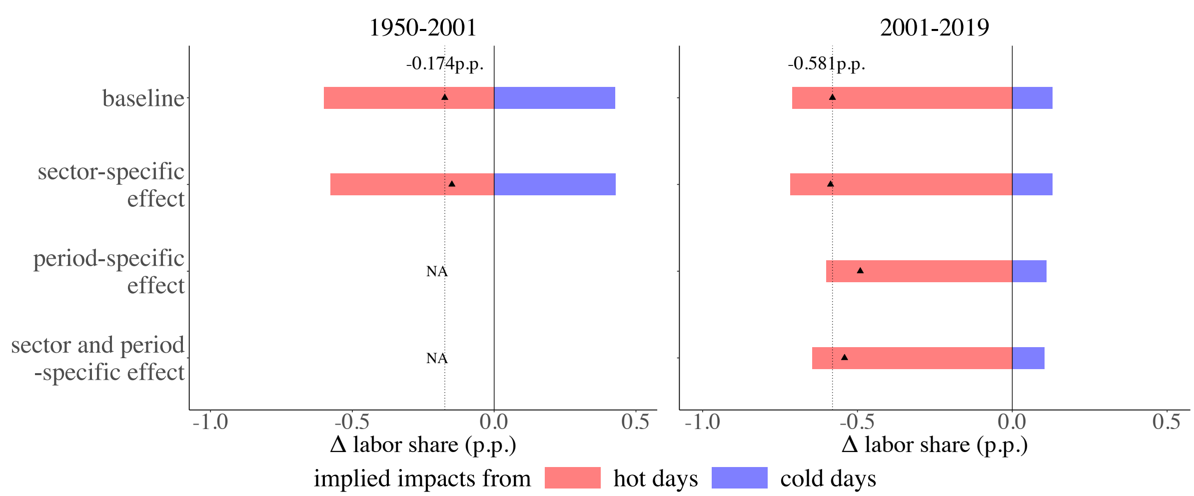
$$\text{LaborShare}_{l,k,\bar{I}} = \sum_I \mathbb{I}(I)\left(\beta^h_I \text{hd}_{l,I} + \beta^c_I \text{cd}_{l,I}\right) + \mathbf{\Lambda}\mathbf{C}_{l,I} + \delta_l + \delta_{s,I} + \delta_{k,I} + \varepsilon_{l,k,\bar{I}}. \tag{A1}$$

Finally, the fourth row uses a hybrid model that allows for sector-by-period specific estimates $\beta^h_{K,I}$ and $\beta^c_{K,I}$ from the following augmented regression:

$$\text{LaborShare}_{l,k,\bar{I}} = \sum_I \sum_K \mathbb{I}(I)\mathbb{I}(K)\left(\beta^h_{K,I} \text{hd}_{l,I} + \beta^c_{K,I} \text{cd}_{l,I}\right) + \mathbf{\Lambda}\mathbf{C}_{l,I} + \delta_l + \delta_{s,I} + \delta_{k,I} + \varepsilon_{l,k,\bar{I}}. \tag{A2}$$

Reassuringly, the macroeconomic implications derived from these alternative models remain consistent with the baseline results.

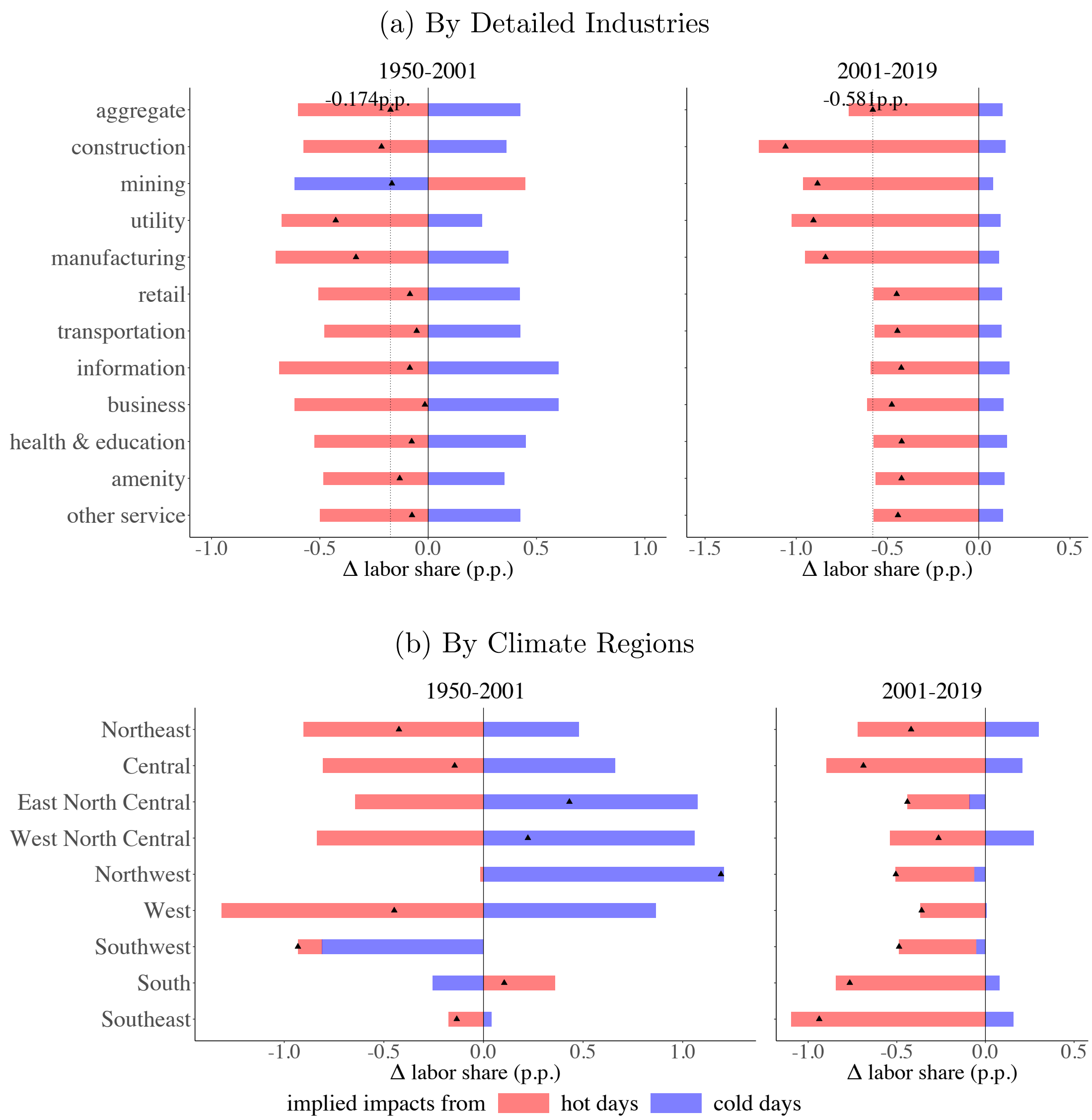
Figure A-9: Robustness Checks of Assessment across Modeling Choices



Notes: Black triangles mark the net effects of hot and cold days. The baseline results are calculated using the estimates from column 1 in Table 2. The sector-and-period-specific effects are based on the estimates from Equation (A2). In the third and fourth rows, the assessment is unavailable due to the absence of corresponding period-specific estimates for the years 1950–2001.

Implied impacts by industries and climate regions. Figure A-10 presents the implied impacts of climate change across 11 industries and 9 NOAA climate regions. These impacts are calculated using the sector-specific estimates from Panel (a) of Figure 3, providing a detailed breakdown of climate effects by industry and region.

Figure A-10: Implied Impacts of Climate Change on Labor Shares



Notes: Black triangles mark the net effects of hot and cold days. The implied impacts are calculated using the four broad sector-specific estimates from Equation (2). Panel (a): Dotted vertical lines represent the nationwide net climate impacts. Industries correspond to BEA-based NAICS classifications. Panel (b): Climate regions are defined according to NOAA classifications.