Climate Change and The Rise of Adult Male Dropouts*

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Abstract

Prime-age male labor force participation has trended downward since the 1970s. I develop and test a simple demand-supply theory in which rising temperature warming shrinks the outdoor-job premium—by shifting firm labor demand and raising the value of time at home—thereby lowering participation. Measuring daily work-hour temperature across US commuting zones using weather-station data spanning five decades, I find that sustained exposure to extreme heat and cold reduces prime-age men's participation—especially among younger and non-college workers in nonmetropolitan areas—with little effect for women. The decline is stronger where outdoor jobs and housing amenities, such as air conditioning, are more prevalent. Overall, climate change is narrowing the rural male labor force while accelerating its selective aging and upskilling.

JEL Classification: J21, J22, Q54

Keywords: Climate change, Male labor force participation, Outdoor jobs

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1 Introduction

The Earth has become—and will continue to be—a hotter planet. Climatological evidence shows that the recent global temperature rise is unprecedented in two millennia (Esper, Torbenson and Büntgen (2024)), trending upward around the 1970s, and accelerating further after 2000 (IPCC (2021)). Economists have extensively studied climate impacts on economic growth (Dell, Jones and Olken (2012)) and industrial production (Zhang et al. (2018)). This evidence rests on the heat-induced decline of labor efficiency (Lai et al. (2023)), arising from the physiological limits of the human body (Hancock, Ross and Szalma (2007)). Given the secular transformation of workplace environments with of higher cost of physical fatigue (González-Alonso et al. (1999)) and mental discomfort (Venugopal, Latha and Kjellstrom (2023)), however, the decision to work—or not to work—remains an understudied margin to climate change.

This paper advances a hypothesis that modern climate change, especially, manifested in rising temperature after 2000, contributed to a secular decline in labor market participation rate (LFPR below) of prime-age males, as widely observed in developed countries[1]. I empirically feature the US—witnessing the severest LFPR drop in the OECD countries. Until 1970, a non-participation rate for US prime-age (aged 25-54) males had been limited to 2-4%, in 2019, however, the rate has risen to an alarming height of 12%[2], leading to rising income inequality, morbidity and poor subjective well-being (Krueger (2017)). Little consensus is formed except that conventional culprits of technological shock (Autor, Levy and Murnane (2003); Acemoglu and Restrepo (2020)), free trade (Autor, Dorn and Hanson (2013)) and liberalized welfare system (Autor and Duggan (2003)) cannot exclusively account for the long-standing puzzle of the declining male LFPR.

My inquiry starts from contrasting the long-run nationwide trend of hot days (with daily temperature above 75°F) experienced by the US resident and the LFPR of prime-age males during 1950-2019, as illustrated in Figure 1. During a half century in 1970-2019, I compute that average hot days per year experienced by a US resident increased by 29.5 days—almost a month per a year. In parallel, one can observe the consistent decline in LFPR after 1970.

[1] See e.g., Grigoli, Koczan and Topalova (2020) for cross-country male LFPR declines.

[2] From the US Bureau of Labor Statistics.

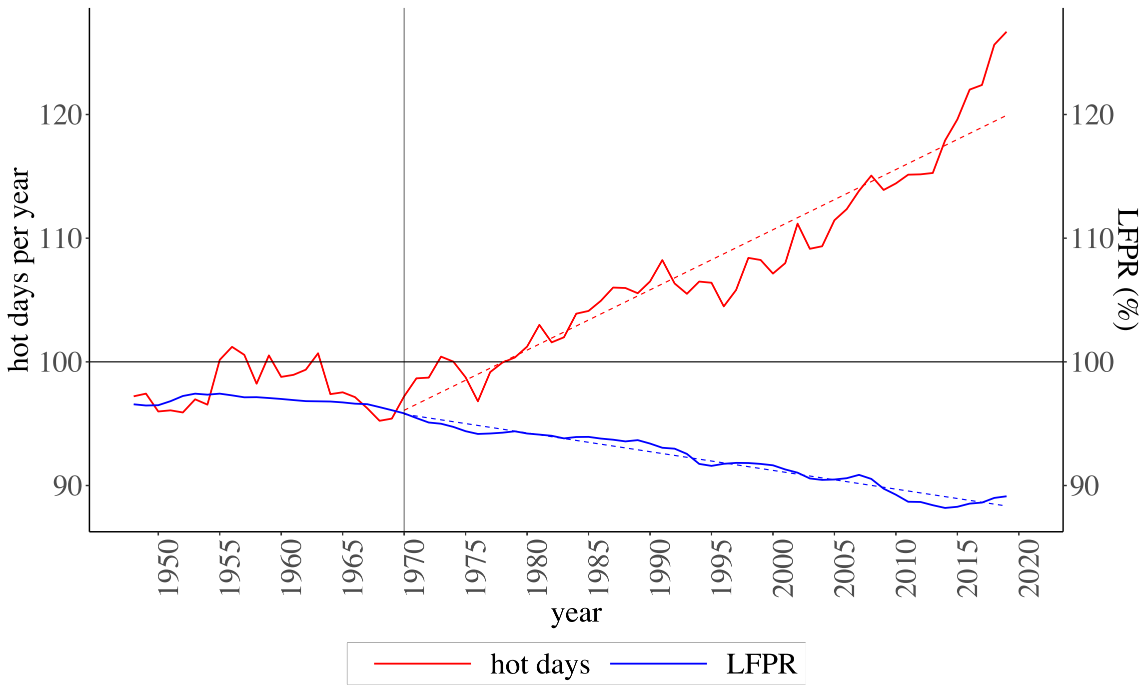


Figure 1: Nationwide Trend of Annual Hot Days and Labor Force Participation Rate (LFPR) of Prime-age Males (1950-2019, US)

Note: Nationwide hot days is a 5-year prior moving average of the nationwide average of exposure to hot days across counties in the continental United States. Daily maximum and minimum temperature station records from the National Oceanic and Atmospheric Administration (NOAA) are aggregated to the county level, weighted by annual county population from the historical decennial census (annual interpolation during 1940-1970) and Surveillance Epidemiology and End Results from the National Cancer Institute (1971-2019). A hot day has an average temperature of 75°F (23.9°C), and a daily weight attached to the maximum temperature is 0.75. Nationwide LFPR of prime-age (25-54) males is a headline figure from the US Bureau of Labor Statistics.

To bridge a seemingly independent coincidence with potentially myriad confounders, I highlight the under-recognized role of "outdoor jobs"— I document that consistently since 1970, one-third of all male occupations have involved regular outdoor work, typically in construction/mining, agriculture, transportation, and service sectors (e.g., lawn mower, gas station attendant, police officer), as identified by the O*NET Work Context Survey. Intriguingly, over 75% of the outdoor workers are men, and over 80% of them do not have a college degree. I find that an increasingly share of non-college graduates are employed in outdoor jobs, presumably "locked out" of indoor jobs in the wave of labor market polarization—middle-income indoor jobs in manufacturing plants or business offices have evaporated over time (Autor, Katz and Kearney (2006); Autor and Dorn (2013)). Notably, outdoor jobs remain prominent in disadvantaged, low-wage regions, where alternative, low-skill indoor service jobs (e.g., restaurant waiter, supermarket cashier, office clerk) are poorly supplied.

Imagine an adult male working outdoors under increasingly frequent exposure to hot days.

Engaged in manual labor while standing, walking, and sweating, he would experience physical fatigue and mental discomfort, putting him at higher risk for heat stroke, operational errors, and subsequent occupational injuries (Dillender (2019); Park, Pankratz and Behrer (2021)). Exposure to hot days would reduce labor efficiency (Lai et al. (2023)), lower workplace morale, increase adaptation costs (e.g., air control, health insurance) and presumably shrink labor demand of outdoor jobs. Experiencing more extreme hot days would therefore presumably suppress both the supply and demand of outdoor jobs. In parallel, as climate change emerged as a threat to outdoor activities, ongoing technological developments since the 1960s drastically enriched the value of indoor leisure—residential air conditioning (Biddle (2008)) and cable TV subscriptions (Waldman, Nicholson and Adilov (2006)) penetrated the home, and the relative cost of working outdoors vs. staying at home should have expanded. With all these forces combined, climate change would push the outdoor workers out of the labor force, even if he is unlikely to be aware of climate change.

To test the above hypothesis, I construct a balanced panel of regional exposure to climate change associated with LFPR across 722 US commuting zones during 1980-2019. The continental US contains a wide variety of climatic zones, providing an ideal testing ground for the climate-labor nexus. I construct a nearly half-century series of daily working hour temperature (8am-6pm) and additional climatological variables (e.g., humidity, precipitation, snowfall) of commuting zones from raw records of nearly 15,000 US weather stations. Connected with the prime-age male LFPR calculated from the microdata, this near-exogenous treatment allows for a natural experiment under two-way fixed effects (Dell, Jones and Olken (2014)). Although climate shocks are presumably near-random, I control for potentially confounding sociodemographic variables and industry structure.

The baseline results suggest that increased 5-year average exposure to 10 hot days (above 75°F) and cold days (below 35°F) per year significantly harms prime-age male LFPR by 0.3-0.4 percentage points, and consequently, increases the share of dropouts.[3] The response is systematically stronger for less educated males, on humid hot days and on business days, in areas dependent on outdoor jobs, especially in unpopulated rural areas. I find that the decline in the LFPR is closely associated with the loss of salaried jobs, especially, outdoor jobs and indoor jobs without air conditioning, which are prevalent across sectors, but most pronounced in construction/mining, low-tech manufacturing, and warehousing. I also find a small but limited transition to indoor jobs, manifested by relative

[3]Throughout this paper, I define dropouts as prime-age males (25-54) who are either not employed, unemployed, or in school, and who did not work in the year prior to the survey.

job growth in retail (e.g., supermarkets) and personal services (e.g., restaurants, education/health).

I then provide some evidence for the motivation of climate-induced dropouts. First, the effect is systematically larger for younger males, who are privileged with relative physical strength required for outdoor jobs and less likely to have disabilities[4]. Second, the climate impact was seemingly fueled by the leisure value of staying at home, proxied by the prevalence of housing amenities (e.g., air conditioning and color TVs). Third, the effect is also magnified by their access to family wealth of the retired parental generation or working women. Guided by these findings, I conclude that climate-induced dropouts reflect an adaptation in lifestyle, particularly among younger males without college degrees.

The implied climate impact is substantial. The baseline climate impact during 2000-2019 reaches −0.436 percentage points, accounting for 15.1% of the nationwide decline in LFPR[5]. Taking into account the differential response across educational groups into account, 72% of the climate-induced dropouts were high school graduates and below, an increasing proportion of whom work outdoors. Revealingly, the regional heterogeneity model shows that the 20 largest urban cities, which cover 40% of the prime-age male population, account for only 4.0% of the climate-induced dropouts, suggesting that the majority were produced in rural areas that are overly dependent on outdoor jobs but offer few air-controlled indoor jobs as climate shelters. Once grounded in their advantage in outdoor work, men's historical bond with the labor market now falters under a changing climate.

Related Literature By linking climate change to regional labor markets, the paper builds on the intersection of labor economics and climate science. First and foremost, the paper provides a novel climate perspective on the longstanding literature on the labor force participation (LFP) of prime-age men[6], who have been historically responsible for outdoor jobs. The literature has largely attributed their declining labor supply to shrinking labor demand for unskilled labor (Juhn (1992); Acemoglu (2002); Card and DiNardo (2002)), in particular due to skill-biased technical change (Katz and Murphy (1992); Autor, Levy and Murnane (2003); Autor, Levy and Murnane (2003)); automation (Acemoglu and Restrepo (2020); Lerch (2020); Grigoli, Koczan and Topalova (2020));

[4]Using the Census and two-year pooled ACS, I found that 72% of dropouts reported no difficulties with daily activities, 75% of dropouts did not receive Social Security or SSI benefits. Furthermore, 59% of males who reported difficulties were not dropouts. These findings suggest that disability is not a prerequisite for dropping out.

[5]Using alternative richer models, the valuation is approximately 10-15%. See Section 7 in greater detail.

[6]See Abraham and Kearney (2020) and Binder and Bound (2019) for a comprehensive review.

free trade (Autor, Dorn and Hanson (2013)) and offshoring (Harrison and McMillan (2011); Ebenstein et al. (2014))[7], which I argue jointly displaced low-skilled men in indoor manufacturing plants or business offices to outdoor jobs. This paper introduces another global and secular fundamental driver—climate change—that has manifested itself differently in the US regional labor markets, but has received little attention in the study of LFP.

On the labor supply side, Parsons (1980) and Autor and Duggan (2003) highlight the role of the relaxation of Social Security Disability Insurance (SSDI) benefits. My paper shows that climate change increases SSDI receipts to support dropouts, while highlighting the role of access to their family income. Focusing on young men, Aguiar et al. (2021) assess the effect of the development of video games in suppressing their labor supply in the new century, while I highlight the role of home air conditioning and cable television in the last century. The paper provides a coherent picture of how physiological functions of the human body—triggered by climate change in conjunction with workplace design and residential environments—are intimately linked to LFP.

Second, this paper complements the burgeoning body of environmental research that finds declining labor productivity and employment. Using an employer-side survey, Somanathan et al. (2021) (India) and Zhang et al. (2018) (China), Cachon, Gallino and Olivares (2012) (the US) showed that higher temperatures hurt labor productivity[8]. Because they use establishment-level data, all of these papers are inherently silent on LFP, which is readily measured by a population survey. In addition, most of the studies focus on indoor production facilities, while my work documents and assesses the role of outdoor jobs, which I show are prevalent in almost all sectors.[9]

In an alternative cross-regional approach similar to mine, recent climate papers report negative impacts on a variety of economic outcomes, such as GDP (Dell, Jones and Olken (2012)), income (Deryugina and Hsiang (2014)), labor shares (Qiu and Yoshida (2024)), and migration (Peri and Sasahara (2019); Colmer (2021)). Related to the spirit of climate-induced dropouts as climate adaptation, Graff Zivin and Neidell (2014) use time-use diaries (American Time Use Survey) to document that daily extreme weather shocks change daily time allocation by reducing hours of

[7]While these forces are typically measured by industry, and translated into shift-share shocks at the regional level, climate shocks can be mapped directly to each location without shift-share—a payoff for identification in my paper.

[8]Burke et al. (2023) shows that heat shocks hurt productivity of high-wage outdoor workers (i.e., professional tennis players). Falla et al. (2021) reviews experimental works of the effect of cold exposure on cognitive performance in healthy adults.

[9]A series of controlled laboratory studies show that extreme temperature hurts the productivity of office work (Seppanen, Fisk and Lei (2006)) and academic performance of kids (Wargocki and Wyon (2007)).

work and outdoor leisure. To the best of my knowledge, my paper is the first to bridge long-run climate exposure and LFP, which has traditionally been studied in labor economics.

The paper is organized as follows. Section 2 describes the data and variables used in my analysis. Section 3 introduces the empirical model. Section 4 presents the main results. Section 5 reveals the mechanism behind these results. Section 6 discusses alternative interpretations of the results. Section 7 quantitatively assesses the nationwide climate impact, its regressive nature, and policy implications. Section 8 concludes.

2 Data

To empirically identify climate impacts, I construct a panel data combining climate exposure and labor market attachment from 1980-2019[10]. As a regional labor market unit, I use a commuting zone (or CZ) as a combination of several neighboring counties (Tolbert and Sizer (1996)). Given the importance of cross-county commuting (Monte, Redding and Rossi-Hansberg (2018)), commuting zones are most likely to contain each worker's workplace and commuting routes to measure work-related exposure to climate change.

2.1 Climate Change

I construct daily weather at each CZ from raw weather station records from the Global Historical Climatology Network Daily (GHCN-daily) of the National Center for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA). GHCN-daily is an integrated database of daily climate summaries from land surface stations and contains the most complete collection of US daily climate summaries from the nineteenth century available under universal quality assurance controls. I use the weather variables of the daily maximum and minimum temperature, precipitation, snowfall. I complementarily use another set of station records from NCEI's Global Summary of the Day (GSoD) to obtain dew points to recover relative humidity. To construct climatological variables at the CZ level, I use an inverse distance-weighted method for station records[11] (e.g., Barreca et al. (2016) and many others): for each proxy, after restricting to

[10]Outcome years include 1980, 1990, 2000, 2010, 2019, excluding 2020 as the onset of the pandemic. Pre-period controls for each outcome period are 1970, 1980, 1990, 2000, 2010, respectively.

[11]Weather station records are more likely to be located in populated areas (see Figure A-1). In the context of my labor market study, however, selective agglomeration of weather-recording facilities is preferable because the study is interested in weather conditions that directly affect people's behaviors.

weather stations with complete records for a given year, the records from the three stations closest to each CZ population centroid[12] are averaged and weighted by the inverse of the squared distance from the centroid.

Climate at work To measure a temperature exposed to workers of each CZ i at day d, I construct a daily temperature $T_{i,d}$ as a weighted average of these two s.t. $T_{i,d} = \omega_{i,d} T_{i,d}^{max} + (1 - \omega_{i,d}) T_{i,d}^{min}$ where $\omega_{i,d} \in (0, 1)$ is a weight to the maximum. The majority of the literature conventionally uses the mean (i.e., $\omega_{i,d} = 0.5 \ \forall i, d$) of daily maximum and minimum temperatures[13]. In light of my focus on the labor market, this convention would be expectedly underestimates the actual temperature workers and commuters are exposed by including night time temperature.

To better proxy $\omega_{i,d}$, I use the alternative US Climate Normals dataset from NCEI, providing a within-day hourly temperature fluctuation from January 1 to December 31 averaged during 30 year period (1981-2010) across 412 weather stations[14]. I proceed in three steps. First, for a month m-by-week w, I match a nearest available station, provided in the Climate Normals, to the population centroid of each CZ i. Second, for each day d, I recover a $\omega_{i,d} \in (0, 1)$ to match a daily median temperature $T_{i,d}^{median}$ during business hours (8 am - 6 pm) s.t. $\omega_{i,d} = \dfrac{T_{i,d}^{median} - T_{i,d}^{min}}{T_{i,d}^{max} - T_{i,d}^{min}}$. Third, I compute $\omega_{i,d}$ for a day $d \in (m, w)$, averaged in month m-by-week w at CZ i[15].

The seasonal distribution of $\omega_{i,d}$ is substantial: The median is 0.8 in the summer versus 0.68 in the winter. Taking into account the hourly temperature fluctuations, I find that the median temperature during business hours was significantly higher by 6.9°F, and especially in the summer (Jul-Sep), by 9.0°F, compared to the conventional all hour daily average (see Figure A-3)[16]. Figure 2 on the left documents a dramatically rich variation in warming (measured by 5-year prior average of the annual number of hot days with 75°F and above) both between and within states, where

[12] Population centroids at CZ-level are constructed as population-weighted averages of county-level population centroid longitudes and latitudes available from the Census Bureau (see Figure A-2 for details).

[13] Alternatively, some of the literature uses either maximum temperature ($\omega = 1$, e.g., Graff Zivin and Neidell (2014); Baylis (2020)) or minimum temperature ($\omega = 0$, e.g., Cook and Heyes (2020)). Overall, the literature is highly context dependent on the weighting of maximum and minimum temperatures to calculate a daily temperature.

[14] Hourly temperature data is available from the National Weather Service (from NOAA). However, it is mostly limited in recent decades, and is not appropriate for the long-run scope of this study.

[15] Each month m is divided into 4 weeks: the first, second, third week consists of 8, 8, 7 days and the fourth week consists of $n - 23$ days, where n is the number of days in each month.

[16] In unreported results, applying the climate proxies with $\omega = 0.5$ significantly weakens the baseline estimates in Table 2, suggesting the importance of temperature construction in business hours.

some regions actually experienced cooling.

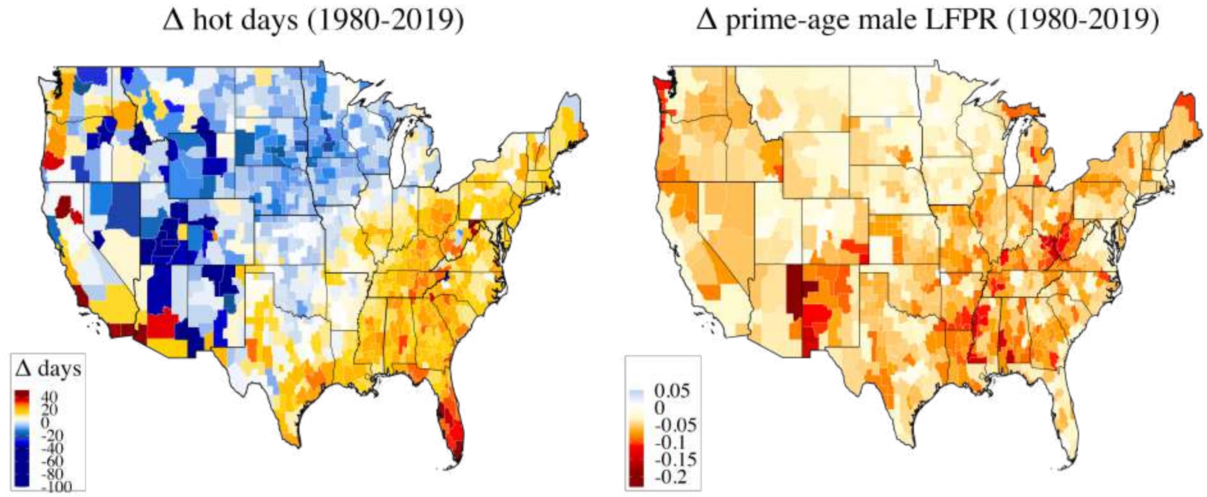


Figure 2: Descriptive Statistics: Temperature Warming and Declining Prime-age Male Labor Force Participation Rates (LFPRs) across US Commuting Zones

Note: The thresholds for hot days are set at 75°F of the median temperature during business hours (8am-6pm). I use an average number of hot days during 1976-1980 for 1980 and during 2015-2019 for 2019. LFPR is the share of the labor force in non-institutionalized prime-age (25-54) male population from the 1980 Census and the 2018-2019 pooled ACS.

2.2 Labor Force Participation—The Rise of Adult Male Dropouts

As a key outcome of the analysis, I construct the LFPR, which is a share of the labor force, either employed or unemployed, in the prime-age (ages 25-54[17]) male population. Using non-institutional samples in the US mainland and linking their place of residence to commuting zones (CZs), I compute CZ-level LFPR in years with a near-decade interval from the IPUMS of the Decennial Census (in 1980-2000, by decade) and the two-year pooled American Community Survey (ACS, in 2009-2010 and pre-pandemic 2018-2019)[18]—repeated cross-sectional representative surveys of 1-5 percent of the US population. The datasets are used consistently throughout the analyses to construct labor market attachment, sociodemographic characteristics, and other regional covariates. In 1970, over 90% of commuting zones had high LFPRs above 90 percent. By 2019, however, the US witnessed

[17]The age range precludes concerns about education choice and retirement through social security pension programs, although some adjustment by schooling is observed even for prime-age males (Table 3).

[18]To consistently measure the LFPR of prime-age males since 1980, a commuting zone is the finest publicly available geographic unit. Using David Dorn's crosswalks, the county groups (1980) from the 1980 Census and the Public Use Microdata Areas (1990-2019) from the 1990-2000 Census and the 2009-2010 and 2018-2019 pooled ACS are converted to CZs.

a significant decline in LFPR, albeit with large regional variation (see the right side of Figure 2).

Because the ACS randomly draws a monthly sample in the survey year and the Decennial Census collects data around April, when the weather is near its best in the continental US, the LFPR presumably represents the annual status of the economy's labor force, which is less likely to be affected by seasonal employment. However, in a snapshot of a cross-sectional survey, the measured non-participation rate is expected to contains temporary non-participants. To highlight relatively long-term non-participants, this paper defines "dropouts" as "non-labor force participants who are not in school at the time of the survey *and* have not worked in the year preceding the survey". The requirement of at least one year out of the labor force should exclude seasonal workers and a large fraction of "in and out" workers. For the period 1980-2019, I compute that 59-77% of the non-participants are dropouts, and 33-55% are dropouts with a non-working period of more than 5 years[19].

2.3 Outdoor Jobs—Who Works Outdoors?

To link climate change and the increase in dropouts, I explicitly document *who* works outdoors under regular exposure to temperature. To see this, I adopt a task-based approach (e.g., Autor, Levy and Murnane (2003)) to explore the occupational demands of work environments, using the Work Context survey of the US Department of Labor's O*NET (Occupational Information Network). In the category of "physical and social factors that affect the nature of the work", I use the question "How often does this job require working outdoors, exposed to all weather conditions?".[20] I compute a share of regular outdoor work for 873 ONET-SOC occupations linked to Census and ACS occupation codes. I define "outdoor jobs" as jobs requiring outdoor work at least weekly, and "outdoor workers" as workers engaged in outdoor jobs. The number of outdoor jobs/workers is calculated as the sum of sample weights interacted with the proportion of at least weekly outdoor work in each worker's occupational title.

To showcase prime examples of outdoor jobs, Table 1 documents a ranking of occupations (over 0.5 million jobs in 2019), in order of a highest proportion of daily outdoor work. Note that outdoor

[19] 5-year dropouts are detected from "Worked 6-10 years ago", "Worked more than 10 years ago", and "Never worked" in a "Year last worked" item (1980-1990 Census) and from "No, and did not work in past 5 years" in "Worked last year" item (2009-2010, 2018-2019 pooled ACS). A corresponding indicator is missing from the 2000 Census. My calculation is consistent with Coglianese (2018), who finds that about half of nonparticipating males are near-permanent dropouts.

[20] The answer is from 5 choices: *1. Never. 2. Once a year or more, but not every month. 3. Once a month or more, but not every week. 4. Once a week or more, but not every day. 5. Every day.*

Table 1: Occupation Rankings of Outdoor Exposure (2019)

Rank	Description	Sector of largest employment	Work outdoors everyday (share)	Work outdoor weekly (share)	Male share	Colleged worker share	Median annual earning (USD)	Total emp.
1	Construction Laborers	Construction	0.812	0.814	0.964	0.048	30,000	1,894,577
2	Driver/Sales Workers and Truck Drivers	Transportation	0.756	0.917	0.929	0.058	40,000	3,693,299
3	Police Officers and Detectives	Public	0.660	0.846	0.839	0.337	65,000	914,691
4	Agricultural workers, nec	Agriculture	0.659	0.835	0.753	0.058	21,000	775,745
5	Grounds Maintenance Workers	Agriculture	0.653	0.663	0.936	0.061	22,500	1,313,673
6	Laborers and Freight, Stock, and Material Movers, Hand	Retail/Wholesale	0.572	0.631	0.792	0.052	24,000	2,343,732
7	Industrial Truck and Tractor Operators	Manufacturing	0.566	0.601	0.918	0.029	31,000	634,115
8	First-Line Supervisors of Construction Trades and Extraction Workers	Construction	0.558	0.909	0.964	0.091	60,000	779,073
9	Carpenters	Construction	0.540	0.711	0.979	0.059	35,000	1,254,008
10	Maintenance and Repair Workers, General	Service	0.506	0.848	0.956	0.069	42,000	582,331

Note: Constructed in IPUMS of the 2018-2019 pooled American Community Survey. Occupational rankings are ordered by the proportion of workers who work outdoors everyday, imputed from the ONET Work Context Survey, and limited to occupations with more than 0.5 million jobs. Sectors consist of agriculture, mining, construction, manufacturing, transportation, retail/wholesale, services and public. Median annual earnings are in contemporaneous USD for non-missing samples.

workers conceptually overlap with "essential workers (key workers)" (ILO (2023)), who are required to commute outside the home and thus were subject to high mortality during pandemic lockdowns[21]. Notably, all of the top 10 occupations are predominantly held by men and non-college graduates across the primary, secondary and tertiary sectors.

Demography and sector To capture the demographic profiles and cross-sector presence of outdoor workers, Figure 3 illustrates the selection to and composition of outdoor workers by gender, education level, and sector. Panel (a1) shows that a remarkably consistent one-third of male employees work outdoors, compared to 10-15% of female counterparts. As shown in Panel (a2), 71-82%

[21] Using the Work Context Survey, Dingel and Neiman (2020) defined a job that can be done *at home*. Conceptually, jobs that can be done at home and outdoor jobs are mutually exclusive, but not exhaustive. Indoor jobs (e.g., restaurant server, high school teacher, yoga instructor, laboratory scientist) that are performed away from home are not included in either category.

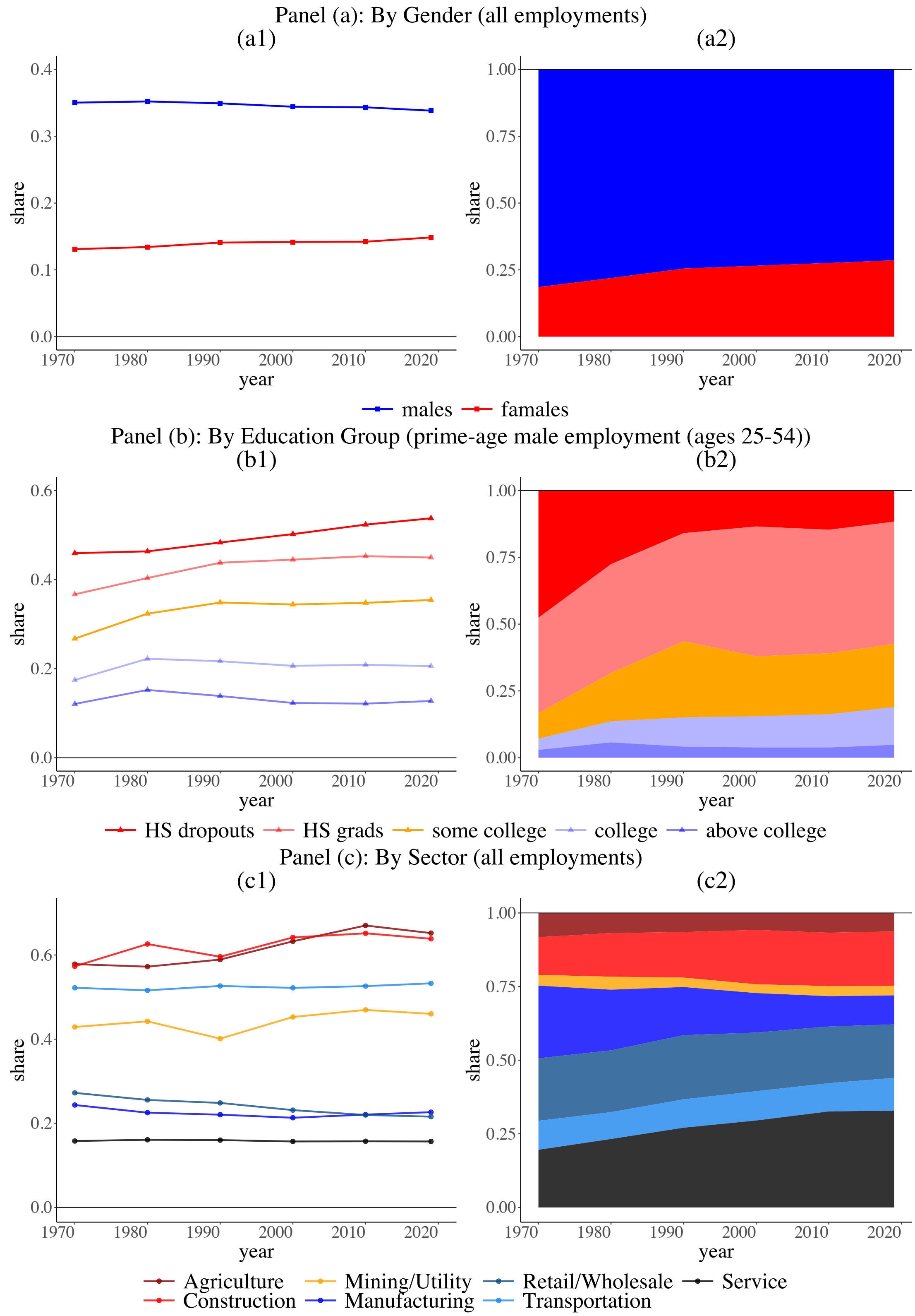


Figure 3: Socioeconomic Characters of Outdoor Workers (Selection and Composition)

Note: Calculated from IPUMS of the 1970-2000 Census by decades and pooled American Community Survey 2009-2010 (for 2010) and 2018-2019 (for 2019). Outdoor workers is the sum of a sample weight multiplied by a share of regular outdoor work at least weekly, derived from the Work Context Survey (see main text for details). Panel (a1/b1/c1): A proportion of outdoor workers employed at each category. Panel (a2/b2/c2): A compositional share of outdoor workers.

of outdoor jobs are held by men, indicating that outdoor jobs are "male occupations". Restricting to prime-age males in Panel (b)[22], I analogously document the selection into and composition of outdoor workers by their educational attainment. Revealingly, less-educated workers are increasingly more likely to work outdoors[23]. By 2019, over 40 percent of workers without a college degree work outdoors (Panel (b1)). Panel (b2) suggests that more than 80% of prime-age male outdoor workers consistently do not have a college degree. Given that the vast majority (88-94%) of labor market dropouts do not have college degrees, outdoor labor markets appear to be culprits in sourcing future dropouts.

Panel (c1) shows the proportion of outdoor workers within sectors. Approximately 60% of agriculture and construction workers, 50% of transportation and mining/utility workers, and 25% of manufacturing and retail workers and 20% of service workers regularly work outdoors. Panel (c2) shows the sectoral composition of outdoor workers, suggesting that outdoor work is widespread across all sectors. Agriculture and construction have consistently accounted for a quarter. Consistent with the sectoral transformation of the US economy, the share of manufacturing has been declining, while the presence of services (e.g., repair workers, lawn mowers, janitors) has been expanding. One natural explanation is that outdoor jobs are filling the void of lost indoor manufacturing jobs, conjuring up a well-rehearsed narrative of labor market polarization (Autor and Dorn (2013); Autor, Dorn and Hanson (2013); Ebenstein et al. (2014))—technological change, global trade, and offshoring have displaced middle-income indoor jobs in the tradable sector out to low-income outdoor jobs in non-tradable sector. This is also consistent with increasing self-selection into outdoor jobs among unskilled workers—who I view as economically "locked out" of indoor jobs.

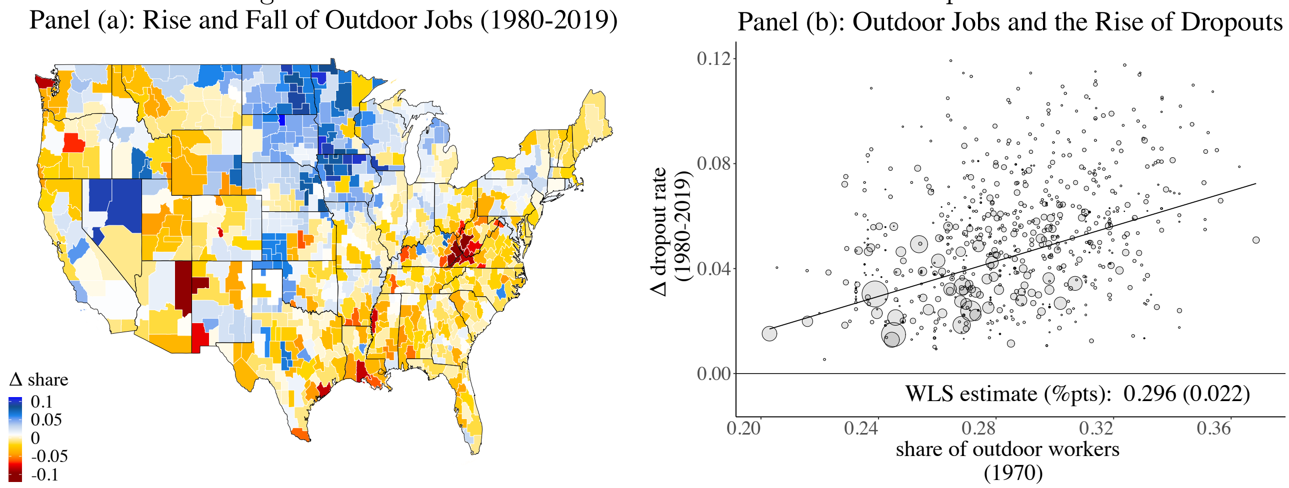
Geography At first glance, the remarkable stability of outdoor jobs nationwide seems puzzling, if outdoor workers are sources of increased dropouts. Perhaps surprisingly, I find that the share of outdoor workers are stable over time with a comparable magnitudes in the range of 32-42% across nine broad climate regions[24] in the US continent (Figure A-8).

[22] I calculate that prime-age (25-54) workers, a primary focus of this study, have consistently accounted for 70-80% of outdoor workers. See Figure A-8 for analogous statistics by age group.

[23] Intriguingly, despite an increasing share of outdoor work among less educated males, the overall employment share of outdoor workers is fairly stable. This seems to be explained by the higher educational attainment of the younger generations.

[24] Nine climate regions consist of the Northwest, West, Southwest, West North Central, East North Central, Central, South, Southeast and Northeast.

Figure 4: Outdoor Jobs and the Rise of Adult Male Dropouts



Note: Outdoor jobs are imputed as sample weights multiplied by the share of workers who work outdoors at least weekly, as identified by an O*NET Work Context Survey. Panel (a): The population share of outdoor jobs is computed in prime-age male samples in the 1980 Census and the 2018-2019 pooled ACS.

Panel (b): The population share of outdoor jobs and the dropout rate are computed in prime-age male samples in 1970, 1980 Census, and the 2018-2019 pooled ACS. The size of the bubble indicates the prime-age male population in 1970, which is used as the regression weight.

Looking at a more granular level, however, reveals a bleak picture of regional heterogeneity. Panel (a) of Figure 4 shows the rise and fall of outdoor jobs as a share of prime-age men across commuting zones from 1980 to 2019. While 320 zones (notably, relatively warm areas, e.g., Arizona, New Mexico, Louisiana, and Mississippi) experienced significant *shrinkage* of outdoor jobs, the other 392 zones (especially, relatively cold areas, e.g., Minnesota, Indiana, North Dakota, and South Dakota in the West North Central) experienced *growth* of outdoor jobs—offsetting each other to maintain the nationwide consistency of outdoor jobs. Contrasting the decline in outdoor jobs in Panel (a) with a regional decline in the LFPR in Figure 2 on the right, one would find a similar correspondence (compare red areas).

Panel (b) illustrates that regions with a higher historical presence of outdoor workers in 1970 had a larger increase in dropouts from 1980 to 2019, suggesting that dependence on outdoor jobs fueled dropping out behaviors (see Table 6 for a formal test). I also find that rural areas with lower population density are systematically more dependent on outdoor jobs (Figure A-7). This is aligned with the conventional theory of structural change; cities are often called "engines of growth," armed with manufacturing and service sectors, while non-cities remained dependent on primary sectors (e.g., agriculture, mining, construction). As a result, urban factories and offices provided an abundance of well-paid indoor jobs, while outdoor jobs were disproportionately available as "outside" options in rural areas, which were left out of material prosperity. This overreliance on outdoor jobs suggests that rural areas would be hit harder by climate change (see the discussion on spatial heterogeneity in on page 25).

3 Empirical Strategy

Using the newly created panel of regional labor markets, this section estimates the key climate impacts on LFPRs and related market outcomes. To identify the effect of climate change, I construct the following two-way fixed effect panel data model with binned specification for a demographic group g (e.g., a baseline sample g is prime-age (25-54) males) over CZ i and outcome year $t \in \{1980, 1990, 2000, 2010, 2019\}$.[25]

$$y^g_{i,t} = \sum_{b\in\{1,\cdots,6,8,\cdots,10\}} \beta^{g,b} \text{days}^b_{i,I_t} + \underbrace{\Lambda^g \mathbf{C}_{i,I_t}}_{\text{a vector of extra climate variables}} + \underbrace{\mathbf{\Psi}^g \mathbf{X}^g_{i,t-1}}_{\text{a vector of pre-period controls}} + \delta_i + \delta_t + \epsilon_{i,t} \tag{1}$$

where $y^g_{i,t}$ is an i's outcome (e.g., LFPR, employment rates) in group g in year t.days^b_{i,I_t} is a 5-year average of number of days with median daily business hour temperature, falling into 10 bins $\{(-\infty, 15), [15, 25), \cdots, [55, 65), [75, 85), [85, 95), [95, \infty)\}$°F ordered by $b \in \{1, \cdots 10\}$ during a treatment window $I_t = [t-5, t-1]$[26]. The model leverages the large spatial variations in decadal changes in the average number of days across temperature distributions. This low-frequency measurement of climate change (e.g., a five-year average) is in stark contrast to standard models in the climate literature, which estimate the impact of higher-frequency temperature shocks (e.g., monthly or daily) on economic or health and mortality outcomes.[27]

[25] To avoid the pandemic shock in 2020 and to ensure a 10 year interval, I replace $y^g_{i,2019}$ by a linear extrapolated value $(y^g_{i,2019} - y^g_{i,2010}) \times (10/9) + y^g_{i,2010}$.

[26] For example, for the outcome years of 2019 and 2010, the treatment windows are 2014-2018 and 2005-2009, respectively.

[27] Liu, Shamdasani and Taraz (2023) takes a similar long-run specification in the panel approach. The five-year mean exposure to extreme temperatures may not capture the acute effects of extreme weather events related to temperature, such as heat waves, heavy snowfall, hurricanes, and droughts. Thus, the main impacts of long-term warming and cooling could underestimate the overall climate impact.

As an annual sum of bins is constant, I omitted a seventh ($b = 7$) bin, $[65, 75)$°F (or [18.3, 23.9)°C)[28] as a benchmark. Since any region (or even a country) is small enough to influence the entire data-generating process of weather, I assume that a day's weather in any region is meteorologically random[29]. $\beta^{g,b}$ is an estimand of interest, interpreted as the replacement of 10 days falling in a bth bin with the benchmark bin $[65, 75)$°F .

In addition to the temperature variables, I add $\mathbf{C}_{i,I_t}$, other climatological variables except temperature (relative humidity, precipitation, snowfall) averaged over the treatment window I_t with corresponding coefficients $\boldsymbol{\beta'}^g$.

Given a demographic group g, $\mathbf{X}^g_{i,t_{-1}}$ is a vector of common covariates in the previous outcome year t_{-1} (e.g., if $t = 2019$, then $t_{-1} = 2010$. For convenience, if $t = 1980$, then set $t_{-1} = 1970$) with its coefficients $\boldsymbol{\Psi}^g$, consisting of 4 components at the year t_{-1} (see Appendix A2.1 for a detailed list). The first is a rich vector of the demographic composition of a group g (e.g., a share of education groups, racial and ethnic groups, 10-year age bins). The second is industry structure to reflect labor demand-side dynamics: employment share of manufacturing, agriculture, and construction; average establishment size and Herfindahl-Hirschman index, computed from the County Business Pattern (Eckert, Fort and Yang (2021)). This accounts for potentially confounding technological shocks (e.g., ICT shocks; industrial robots) and trade competition shocks in warming regions. The third is miscellaneous regional characteristics (e.g., a share of seniors aged 65 and over; population density). The fourth is health and wealth factors (e.g., share of the self-reported disabled; receipt of public income) to shift labor supply.

The inclusion of two-way fixed effects (δ_i and δ_t) essentially formulates a difference-in-difference model that generates the estimates from within-CZ variation net of common time shifts (e.g., business cycle, technology shocks, federal taxation regime) (Dell, Jones and Olken (2014)). Because weather variables are spatially correlated, a normally distributed error term $\epsilon_{i,t}$ is clustered at the CZ level, a spatial unit of analysis[30]. The model is weighted by the pre-period t_{-1}'s CZ share of the

[28] According to the National Institute for Occupational Safety and Health (NIOSH) guidelines (2016), 75°F is the threshold temperature for unacclimatized workers for moderate (77°F) to heavy (73.4°F) workloads. Chen and Yang (2019) used 21-24°C as baseline bin in China, very close to mine.

[29] I assume that climate change occurs on a planetary scale and is influenced by various global factors (e.g., greenhouse gas emissions, sulfur aerosols, the polar vortex, and variations in volcanic activity). Therefore, the annual distribution of weather cannot be influenced by regional economic activities that simultaneously affect the labor market attachment of prime-age males.

[30] Table A-10 shows robustness to alternative clustering units of neighboring CZs and states.

national prime-age male population, a denominator of an outcome variable. With this near-complete set of plausible random meteorological variables, socioeconomic covariates, and two-way fixed effects, $\beta^{g,b}$ capture the primary climate impacts of interest. Section 4.2 addresses concerns about the robustness of the estimates and Section 6 discusses their interpretations related to migration or labor demand responses.

4 Results

4.1 Baseline Estimates

Semi-parametric bin estimates Using LFPR as the outcome in the semi-parametric bin model, equation (1) ($y^g_{i,t} = \text{LFPR}^g_{i,t}$), Figure 5 illustrates estimates along a spectrum of temperature exposure.

The analysis shows a clear non-linearity of climate impacts along daily temperature. Replacing 10 normal days (i.e.; business days in two weeks for typical full-time workers) in a benchmark bin ([65-75)°F) with hot days above 75°F significantly lowers the LFPR of prime-age males by about -0.3 to $0.4\%pts$. Similarly, a 10-day shift to cold days below 35°F began to produce negative point estimates, but with wider 95% confidence intervals. This nonlinearity is canonically reported in the climate literature on agricultural productivity (Schlenker and Roberts (2009)), labor productivity (Somanathan et al. (2021)), mortality (Deschenes and Moretti (2009)), and GDP (Burke, Hsiang and Miguel (2015)) as well as in indoor laboratory studies (Seppanen, Fisk and Faulkner (2003)).

Two-tailed model estimates Given the inverted U nonlinearity, I use a more parsimonious model featuring with upper and lower tails of the weather distribution to further improve the precision of the estimates (a la Barreca et al. (2016); Somanathan et al. (2021)). Operationally, I replace the climate change terms in the main specification (1), $\sum_{b=1} \beta^{g,b}\text{days}^b_{i,I_t}$, by $\beta^{g,h}\text{hd}_{i,I_t} + \beta^{g,c}\text{cd}_{i,I_t}$, where $\text{hd}_{i,I_t}, \text{cd}_{i,I_t}$ are the average number of hot and cold days during a treatment window $I_t = [t-5, t-1]$, respectively.

A key modeling strategy of the two-tailed model is to identify the thresholds for hot days and cold days, which appears to be highly dependent on each context in terms of mortality, health, agricultural production, or GDP, and thus seem to have little consensus in the climate literature. Guided by the previous bin estimation, and informed by the NIOSH and OSHA guidelines, I set

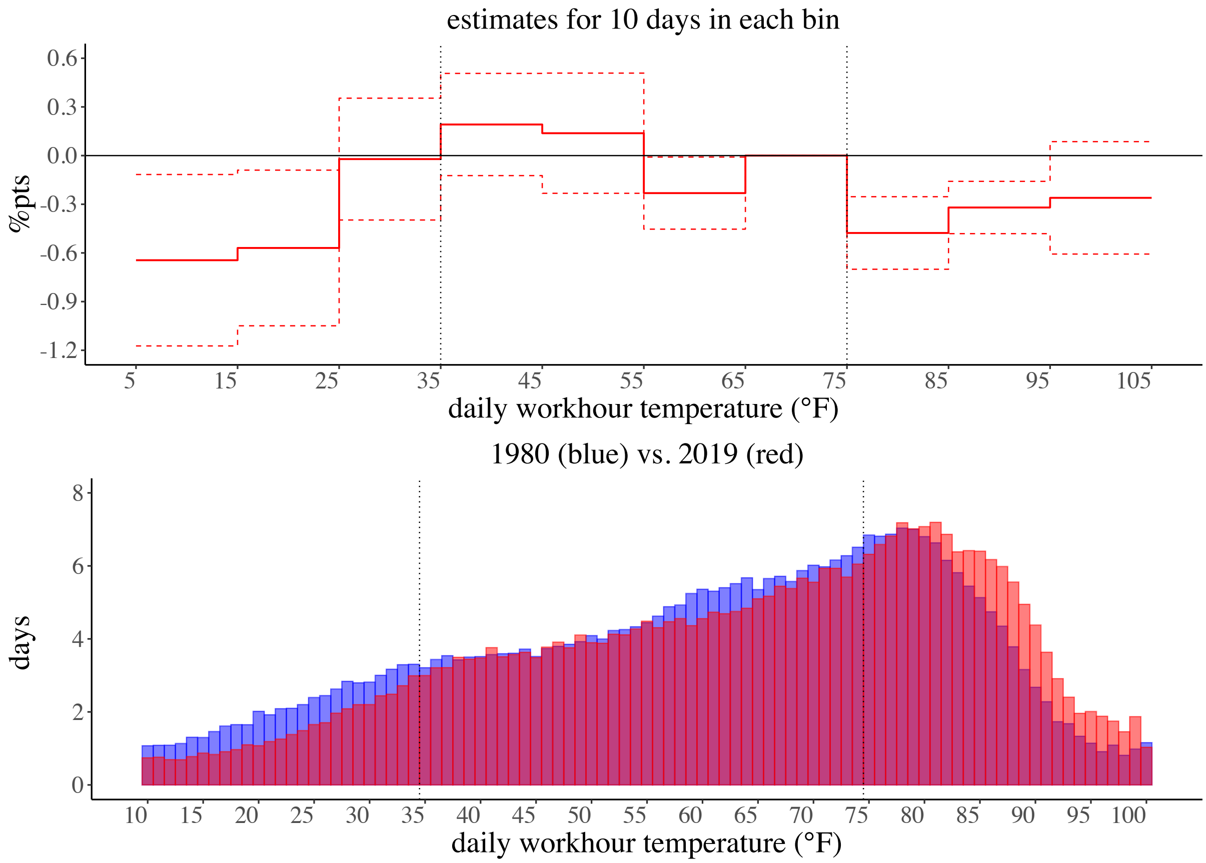


Figure 5: Climate Impact on Labor Force Participation Rate of Adult Males

Note: (top) Estimates of β^b in equation (1) are shown with 95% confidence intervals (red dashed lines). The baseline bin is a 65-75°F. (bottom) Nationwide temperature exposures normalized to 365 days, are distributed over 1°F bins (truncated at 10°F and 100°F) along the median workhour temperature during 1976-1980 and 2015-2019. The nationwide exposure is calculated as a weighted average of the regional exposure with the CZ prime-age male population in 1980 and 2019. Dotted lines are thresholds for hot ($\geq$75°F) days and cold days ($<$ 35°F) in the baseline model.

thresholds for hot days and cold days at 75°F[31] and 35°F (near freezing temperature) of the business hour median temperature, respectively. Therefore, $\beta^{g,h}$, $\beta^{g,c}$ captures the climate effect of interest for group g, capturing the effect of replacing 10 "normal days" with $[35, 75)$°F with 10 hot or cold days, respectively. Importantly, using alternative thresholds does not change the main analysis (see robustness check below in Section 4.2).

[31] Because this cutoff is constructed based on the median temperature during the 8am to 6pm work period, the typical maximum temperature is 85-90°F. 75°F might seem moderate for office workers, but I emphasize that outdoor workers perform manual-intensive tasks for approximately 8 hours, which is a significantly longer climate exposure compared to periodic exposures (e.g., lunch break). See also footnote 28.

Table 2: Climate Change and Labor Force Participation Rates of Adult Males

	dependent variable: **Labor Force Participation Rate** (in % pts., prime-age individuals)					
	males					females
	(1)	(2)	(3)	(4)	(5)	(6)
10 hot days	-0.345^{***}	-0.333^{***}	-0.321^{***}	-0.320^{***}	-0.347^{***}	0.042
	(0.062)	(0.063)	(0.063)	(0.064)	(0.066)	(0.121)
10 cold days	-0.377^{**}	-0.437^{**}	-0.431^{**}	-0.409^{**}	-0.379^{**}	-0.277
	(0.176)	(0.174)	(0.190)	(0.186)	(0.170)	(0.269)
other climate variables	✓	✓	✓	✓	✓	✓
	pre-period covariates					
demography	✓	✓	✓	✓	✓	✓
industry structure	-	✓	✓	✓	✓	✓
market variable	-	-	✓	✓	✓	✓
health	-	-	-	✓	✓	✓
wealth	-	-	-	-	✓	✓
Adjusted R^2	0.866	0.869	0.870	0.874	0.876	0.922

Note: $N = 3,610$ (5 outcome years $\times$ 722 commuting zones). LFPR is calculated in non-institutionalized prime-age males (ages 25-54) in the continental United States in the years 1980-2000 by decades from the Census and in 2010, 2019 from the pooled 2009-2010 and 2018-2019 American Community Survey, respectively. Hot days and cold days are 5-year prior averages of the number of days during business hours (8am-6pm) with a median temperature above 75°F and below 35°F, respectively. Robust standard errors in parentheses are clustered by commuting zone. Models are weighted by the previous period commuting zone's share of the national prime-age population of males in columns 1-5 and females in column 6 (see main text for details). *** $p < 1\%$, ** $p < 5\%$.

Table 2 reports estimates from a parsimonious two-tailed model. In addition to two-way fixed effects, column 1 includes other climate variables (relative humidity, precipitation, snowfall) and demographic controls. Then I cumulatively add industrial structure in column 2, labor market status in column 3, health variables, in column 4, and wealth variables in column 5. A preferred baseline model in column 5 with a full battery of controls indicates that a decadal baseline shift of 10 more hot days and cold days hurts the LFPR by 0.347 *%pts* ($t = -5.3$) and 0.379 *%pts* ($t = -2.2$), respectively. Notably, the magnitudes and precision are fairly stable across the inclusion of previous period controls in all columns 1-5. This stability of estimates supports the identification assumption that climate change is plausibly random and unconditionally independent of other correlates of LFPR. Taking the sample group g as prime-age *females*, column 6 replicates the baseline model in column 5, and no significant impacts are observed. This corroborates my working hypothesis that outdoor exposure is critical for climate impacts and supports the observation that a much smaller percentage of women work outdoors (see Panel (a) in Figure 3).

4.2 Robustness Checks

Before uncovering the underlying economic mechanism behind the main results, this section establishes their robustness with respect to the following key specifications.

Temperature thresholds The baseline model uses 75°F (23.9°C) and 35°F (1.7 °C) as thresholds for hot and cold days. However, the sense of temperature would presumably differ across individuals, and the "normal" temperature of each region would be shaped by latitude or elevation. Alternatively, I examined the validity of reasonable cutoffs of 73, 75, 77, 80°F for hot days paired with 35, 30, 25, 15°F for cold days. Consistent with the inverted U-shaped estimates of temperature bins, all reasonable pairs show broadly stable negative climate effects (Table A-1).

Treatment windows In the baseline, I proxy a regional climate as a 5-year prior average of hot and cold days and additional climate variables (i.e., relative humidity, precipitation, and snowfall). Instead, I test the sensitivity in shorter or longer treatment windows of all climate variables, ranging from 1 year, 3 years, 10 years, controlling for other covariates. The point estimates become generally larger for longer exposures, consistent with proposed mechanism of cumulative labor costs (Table A-4).

State-year fixed effects and pre-trends Readers may worry that the baseline model fails to account for time-varying statewide institutions (e.g., welfare, health care. minimum wages, union right-to-work rules) that might covary with climate exposure. However, including state-year fixed effects seems challenging, because it largely eliminates the strong within-continent climate variation that is central to my identification strategy.[32] Reassuringly, although each state contains a limited number of 10-20 commuting zones, the estimates of hot days remain highly robust (-0.210 *%pts* for 10 hot days ($t = -3.0$)), suggesting that statewide institutions do not critically drive the results. In addition, the inclusion of the Census division, state or commuting zone level time trend largely maintains the estimates, ensuring that the pre-trend is not a confounder either (Table A-3).

[32] In more detailed analysis with over 3,000 US counties, Pierce and Schott (2020) point out this lack of statistical power under state-year fixed effects.

Long differences model The baseline model employs a two-way fixed effects panel regression to link the level of LFPR in the outcome years to the average exposure to hot and cold days during the preceding five years. An alternative modeling strategy is a long differences model that matches changes in LFPR with changes in climate exposure (e.g., Burke and Emerick (2016)). I performed cross-validation using a long differences model with a year fixed effect and stacked decades intervals ($\{[1980, 1990], \cdots, [2010, 2019]\}$) or two-decade intervals ($\{[1980, 2000]$ and $[2000, 2019]\}$). Despite having less dynamic variation than the baseline panel regression, the impacts of climate, especially, warming impacts, are largely sustained (Table A-4).

Labor market demand shocks Some readers may be reminded of the classical theories of labor demand shocks (computerization, industrial robots, and trade competition) that could potentially comove with the regional warming/cooling trend. To partially account for these industry-level dynamics, the baseline model includes previous period within-CZ sectoral composition and concentration (see Section 3). Nevertheless, to address this potential concerns, I performed a leave-one-out analysis by excluding areas that were particularly affected by each labor demand shock: "computerization shocks" (from Autor and Dorn (2013)), "China shocks" (from Autor, Dorn and Hanson (2013)), and "robot shocks" (from Acemoglu and Restrepo (2020)). I confirm that the areas experiencing these shocks are located differently from the warming areas (see Figure A-11). The leave-one-out estimates are fairly stable. This suggests that conventional labor demand shocks do not confound the estimates alongside climate shocks (Table A-5).

Agriculture Readers familiar with the earlier climate literature (e.g., Deschênes and Greenstone (2007); McLeman and Smit (2006)) would worry that my estimate depends on adverse productivity damages to the agriculture sector. Although this conventional theory is realistic for developing countries, I argue that it does not fit the US economy with its advanced industrial structure, where agriculture accounted for only 3.4 percent of prime-age male employment even in 1970. I also show below that the shrinkage of salaried jobs is primarily associated with non-agriculture sectors (Table 5), and, more directly, due to the loss of outdoor jobs within sectors (Table 6). I also rerun the analysis excluding the most agriculture-intensive regions, as measured by high shares of agriculture employment, but the estimates are unchanged. Thus, I judge that the result is unlikely to be mediated by agricultural productivity (Table A-6).

Weather conditions The baseline model characterizes climate change as a time-varying spatial distribution of daily temperature extremes. However, it is well known that subjective discomfort is jointly determined by humidity and temperature (Barreca (2012)). To capture their complementarity, I compute the discomfort index (DI) using a standard meteorological formula[33], where if a daily DI above 75 is considered to be uncomfortable for more than half of the people. For example, residents of humid New Orleans, Louisiana experience slightly fewer hot days but more uncomfortable days (DI $\geq$ 75) than residents of dry, Phoenix, Arizona[34]. Notably, replacing hot days by uncomfortable days yields equally significant but much larger estimates. Humidity is typically low on non-rainy days, but I find that non-rainy hot days hurt with more economic and statistical significance, presumably because workers are also disturbed by direct sunshine (Table A-7).

Seasons of extreme weathers The baseline model so far has estimated the impact of annual hot days and cold days within a year, covering both business days and holidays. Since outdoor workers, especially in full-time salaried workers, typically work on weekdays, one can predict that hot or cold business days will hurt more relative to holiday counterparts. To test this, I control for extreme temperature days, separately for business days (i.e., weekdays excluding national holidays) and holidays (i.e., Saturdays/Sundays and national holidays). Intriguingly, the climate effects are much stronger for business days (250 days per year) than for holidays (115 days per year), even though daily temperatures are of course perfectly correlated. Within a year, hot days in spring (Mar-May), summer (Jun-Aug) and cold days in winter (Jan, Feb, and Dec) are particularly harmful. In contrast, cold days in fall show and hot days in winter show slightly *positive* effects, suggesting that cooling after summer and warming in winter may refresh workers (Table A-8).

Immigrants In the US context, heat-sensitive sectors with manual tasks (e.g., agriculture, construction) may depend more on foreign labor (Peri and Sparber (2009)). If dropouts of native adults are fueled by regional availability of immigrants, the climate impact should be magnified in immigration-intensive areas[35]. To test this, I reran the analysis by dropping the relatively

[33]See equation (A2) for construction of the discomfort index.

[34]On average, New Orleans has 221 (vs. 249) hot days but 20.1 (vs. 23.2) uncomfortable days vs. Phoenix (in parentheses) from 2015-2019. This is due to a significant difference in annual average relative humidity; 60.8% in New Orleans vs. 25.6% in Phoenix.

[35]Since undocumented immigrants are less likely to respond to the Census and ACS, the observed share of immigrants is presumably an underestimate (Pew Research Center).

immigration-intensive CZs above the 25th, 33th, and 50th percentiles of the population share of prime-age male immigrants in 2019. Excluding immigration-intensive regions does not mitigate climate impacts, suggesting that the presence of immigrants does not drive the results (Table A-9).

4.3 Heterogeneity

Demographic sub-samples The previous section established the climate impact on the labor supply of adult males. Since the selection into outdoor jobs is systematically higher for the less educated (Figure 3, Panel (b1)), the negative impact on labor supply should be more pronounced for the less-educated workers. To test the regressive climate effects, I re-estimate the model within male subsamples of four educational groups $g \in \{\text{HS dropouts, HS graduates,}$ $\text{some college years, college graduates}\}$ with a reconstructed set of within-group controls $\mathbf{X}^g_{i,t_{-1}}$.

Table 3 reports systematically stronger effects of extreme temperature days, both in magnitude and precision, for less educated males. This is pronounced for the effects of hot days. The damage for high school graduates (-0.370) is 3 times larger than for college graduates (-0.125). Notably, the effect is by far the largest for high school dropouts (-0.482). For cold days, high school graduates and less show slightly greater harm (-0.465) than the higher educated ($-0.229, -0.243$), but its regressivity is milder compared to hot days.

In general, this regressivity is consistent with the theory that the less skilled are more likely to choose outdoor jobs, and thus be vulnerable to climate change. However, a significant harm remains even for college graduates, suggesting that college degrees are not all-powerful in protecting workers from climate exposure. One interpretation is that some college graduates choose outdoor jobs (e.g., police officers; taxi drivers) or ostensibly indoor jobs with frequent social interactions with customers and frontline workers (e.g., real estate agents; commodity buyers; construction supervisors).

In contrast to the well-established age-mortality link under temperature shocks (e.g., Deschenes and Moretti (2009), among others), the climate effects for older men are theoretically ambiguous, and thus, an empirical question. On the one hand, older workers are more vulnerable to heat and thus more likely to exit the labor force. On the other hand, younger workers are assigned more manual labor-intensive tasks outdoors and are thus more likely to opt for unpaid family work, schooling, or playing TV games at home. To see this empirically, I construct male subsamples g from 5 age bins,$\{[18, 24], [25, 34], [35, 44], [45, 54], [55, \infty]\}$, with their age-specific controls $\mathbf{X}^g_{i,t_{-1}}$. The climate effects of both hot and cold days are sharper for relatively younger males, especially

Table 3: Climate Impacts across Education Attainment and Age Groups

Panel A: Education Attainments

dependent variable: LFPR (in % pts; prime-age males)

	HS dropouts	**HS grads**	**HS grads and less** (1) + (2)	**Some college**	**College grads**
	(1)	(2)	(3)	(4)	(5)
10 hot days	-0.482^{***}	-0.337^{***}	-0.370^{***}	-0.164^{***}	-0.125^{***}
	(0.164)	(0.089)	(0.090)	(0.059)	(0.048)
10 cold days	-0.330	-0.150	-0.465^{*}	-0.229^{*}	-0.243^{**}
	(0.346)	(0.254)	(0.242)	(0.123)	(0.107)
within-group controls	✓	✓	✓	✓	✓
Adjusted R^2	0.844	0.888	0.882	0.800	0.724

Panel B: Age Groups

dependent variable: LFPR (in % pts; males)

	18-24	**25-34**	**35-44**	**45-54**	**55 and above**
	(1)	(2)	(3)	(4)	(5)
10 hot days	-0.406^{***}	-0.289^{***}	-0.290^{***}	-0.219^{***}	-0.003
	(0.144)	(0.103)	(0.063)	(0.068)	(0.086)
10 cold days	-0.510^{**}	-0.524^{***}	-0.493^{***}	-0.330^{**}	0.337^{*}
	(0.229)	(0.196)	(0.189)	(0.161)	(0.192)
within-group controls	✓	✓	✓	✓	✓
Adjusted R^2	0.843	0.800	0.849	0.892	0.943

Note: $N = 3,610$ (5 outcome years $\times$ 722 commuting zones). LFPR is calculated in non-institutionalized prime-age males (ages 25-54) by each subsample in the continental United States. All models inherit definitions of hot days and cold days, treatment windows (5-year averages), other climate, industry, and market variables, two-way fixed effects, regression weights, and clustering of standard errors in the baseline model, column 5 of Table 2. Demographic, health, and wealth controls are reconstructed within each subsample. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

for the young 25-34 and middle-aged 35-44.[36]Since the selection into outdoor jobs does not differ by each age group (32-36% in Figure A-8), the latter explanation seems more likely. The non-

[36]The response for the youngest males 18-25 is also striking, perhaps because climate change has induced an extension of schooling through college enrollment, consistent with the increase in prime-age full-time students in Table 3. Testing this scenario is intriguing, but given my focus on prime-age males, it will be left for future work.

participation of men in the early and mid-career period is alarming for their family formation and reproduction in the nation.

Urban vs. rural areas As discussed in Section 2.3, urban areas are systematically less dependent on outdoor jobs than rural areas. Guided by the economics of agglomeration, low-skilled service sectors that provide climate-proof indoor jobs (e.g., restaurant waiters and supermarket cashiers), are disproportionately concentrated in densely populated urban areas. Therefore, one might predict that the impact of climate change on labor supply would be less severe in urban areas.

To test this, I allow the model to estimate climate impacts that vary with pre-period regional population density. As expected, climate impacts on LFPR and dropouts are significantly attenuated in more densely populated cities ($| t |= 5$). Alternatively, when population density is replaced by the share of employment in the service sector, the estimates are again statistically significant ($| t |> 3$). The exercise reveals strong regional regressivity, suggesting that climate damage to the labor supply is exacerbated by overreliance on outdoor jobs and the lack of an indoor service safety net (Table A-11).

Adaptation With the prediction of accelerating temperature warming, adaptation by both employees and employers appears critical. For example, workers in the South might have already acclimatized to the local climate, or employers have taken some countermeasures against heat stress. To assess the state of adaptation, I test how much the estimate varies across climate regions or over time. I find significant, but small signs of adaptation for hot days, suggesting that extra hot days are less damaging in initially warm areas. I also find small intertemporal adaptation for hot days and cold days within regions (Table A-12). However, the magnitude of adaptation falls far short of the dramatic increase in recorded exposure to hot days in the new century, which will be quantified in Section 7.

5 Mechanism

5.1 Labor Market Attachment

To delve deeper into the source of the declining LFPR, this section examines modes of labor market attachment, highlighting the rise in climate-induced dropouts.

Table 4 classifies prime-age males into labor force, employed, unemployed, dropouts, and full-

Table 4: Climate Change and the Labor Market Attachment of Adult Males

	Labor force status (in % pts., share of prime-age males)						
	Laborforce (Baseline) (2) + (5)	**Employ-ment** (3)+(4)	**Salaried emp.**	**Self-employed**	**Unemploy-ments**	**Dropouts**	**Full-time students**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
10 hot days	-0.347^{***}	-0.390^{***}	-0.450^{***}	0.060	0.043	0.124^{***}	0.042^{***}
	(0.066)	(0.084)	(0.096)	(0.050)	(0.050)	(0.042)	(0.013)
10 cold days	-0.379^{**}	-0.661^{***}	-0.942^{***}	0.280^{***}	0.283^{***}	0.150^{*}	0.043
	(0.170)	(0.224)	(0.268)	(0.103)	(0.102)	(0.079)	(0.027)
Adjusted R^2	0.876	0.850	0.837	0.858	0.835	0.905	0.697

Note: $N = 3,610$ (5 outcome years $\times$ 722 commuting zones). Each outcome is computed in non-institutional prime-age (age 25-54) males in the continental US. All models inherit definitions of hot days and cold days, treatment windows (5-year average), full controls with two-way fixed effects, regression weights, and clustering of standard errors in the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

time students. For reference, column 1 repeats the baseline in column 5 of Table 2. Compared to the LFPR, the employment-to-population ratio in column 2 shows a slightly larger warming effect of $-0.390\%pts$, while the cooling effect is even larger at $-0.661\%pts$. Splitting employment to a salaried- and self-employment, column 3 shows that both hot and cold days hurt salaried employment even more, $-0.450\%pts$ and $-0.942\%pts$. In contrast, column 4 reports the null effect of hot days on self-employment, and even positive effects for cold days. Interpretatively, self-employment (including gig-type work such as ride-sharing drivers and IT freelancers), especially at home, allows for elastic labor supply with a flexible work schedule that makes workers resilient to climate exposure[37]. Column 5 examines an unemployment-population ratio and reports only significantly positive cooling effects. In parallel with the declining LFPR, column 6 examines a sensitivity of rising dropouts by $0.124\%pts$, which serves as the primary evidence of climate-induced dropouts. In a notable contrast to the increase in dropouts, column 7 reports an increase in full-time students, possibly at community colleges. Given our focus on adult males aged 25 and older, this may seem counterintuitive, but it makes sense if a campus building provides climate shelter and a degree or certificate is a passport to an indoor job after graduation.

[37] This is consistent with the recent spread of alternative work arrangements in the US labor market (see Katz and Krueger (2019)).

5.2 Sector-level Analysis

The previous section showed that the decline in the LFPR is tightly linked to the contraction of salaried employment. To identify the source of the employment contraction, I further decompose it by sector. Specifically, I diagnose the sensitivity of the CZ-level sectoral employment-population ratio across ten private sectors (agriculture, construction/mining, two manufacturing and six services)[38]. Since each sector varies greatly in its composition of employment and establishments, I recontrolled for previous period demographics of prime-age male salaried employees and industry structure at the sector-CZ level to reflect sector-specific dynamics of labor supply and demand of employment.

Panel A of Table 5 reports sensitivities of regional employment-population ratios, juxtaposed with each sectoral characteristics in Panel B. In agriculture and construction/mining (in columns 1-2), as expected from the highest (more than two-thirds) share of outdoor workers, hot days significantly reduce salaried employments.[39] In particular, job losses from both hot and cold days in construction/mining are most economically and statistically significant (-0.267 for hot days and -0.668 for cold days). Combining its large share of employment in the economy (11.9%), lowest share of college graduates (11.4%), and physically demanding work schedule, construction/mining appears to be a primary culprit for climate-induced dropouts. Engaged in risky tasks, workers in these sectors are often required to wear protective equipment (e.g., helmets, gloves, masks, and poorly ventilated clothing), which makes them resistant to cold but vulnerable to heat (OSHA guideline).

Since typical manufacturing industries operate indoors, one would expect that climate damages should depend on the quality of climate control. In low-tech manufacturing (e.g., chemicals, petroleum/coal, plastics and glass), column 3 shows a significantly large job losses on hot days (-0.302), though not on cold days, perhaps due to incomplete air control with furnaces or fires. On the other hand, column 4 covers high-tech manufacturing (e.g., machinery, automobiles, and instruments) and reports no effects from warming, and significant job gains from cooling ($+0.842$), presumably due to stringent year-round air quality controls.

Column 5 reports that retail/wholesale industries exhibit mild job *growth* ($+0.089$) from hot

[38]To identify the sector of employment contraction, the analysis is limited to employment counted as human bodies. Exploration of the intensive margin adjustment of weeks and hours deserves attention, but is relegated to future work.

[39]Cold days do not affect employment in agriculture, presumably because agriculture is off-season in winter.

Table 5: Climate Change and Sectoral Employment

	Primary		Manufacturing		Service					
	Agri-culture	**Construction /Mining**	**Low-tech**	**High-tech**	**Retail /Wholesale**	**Trans-portation (warehousing)**	**Trans-portation (driving)**	**Personal service**	**Business/ Engineering**	**Finance /Real estate**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Climate Change and Sectoral Employment — *dependent variables*: **employment-to-population ratio** (in %pts; prime-age males)										
10 hot days	-0.235^{**}	-0.267^{***}	-0.302^{**}	0.045	0.089^{*}	-0.076^{*}	0.051^{*}	0.161^{**}	−0.019	-0.137^{***}
	(0.110)	(0.096)	(0.123)	(0.184)	(0.049)	(0.043)	(0.030)	(0.065)	(0.074)	(0.046)
10 cold days	−0.072	-0.668^{***}	−0.040	0.842^{**}	-0.292^{***}	-0.220^{**}	−0.029	0.210	−0.144	-0.187^{*}
	(0.121)	(0.140)	(0.196)	(0.335)	(0.080)	(0.112)	(0.042)	(0.135)	(0.132)	(0.100)
CZ-sector level pre-period covariates										
employee demographics	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
industry structure	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2,460	3,600	3,577	3,525	3,610	3,479	3,560	3,609	3,604	3,571
Adjusted R^2	0.925	0.820	0.855	0.913	0.774	0.791	0.751	0.890	0.909	0.937
Share of Nationwide Employment (2000)										
	1.4%	11.9%	9.5%	14.4%	19.2%	2.00%	4.1%	17.0%	14.5%	6.0%
Panel B: Sector Characteristics (share of employment in 2000)										
College grads	12.2%	11.4%	18.1%	19.8%	19.4%	23.2%	8.3%	45.0%	41.1%	48.3%
Climate exposure at workplaces										
Outdoor ($\geq$ weekly)	73.3%	67.8%	30.0%	22.4%	31.3%	44.8%	68.9%	25.9%	23.3%	19.2%
Indoor uncontrolled ($\geq$ weekly)	44.1%	47.5%	45.8%	45.1%	28.5%	40.4%	38.7%	22.3%	22.7%	15.6%
Indoor controlled (everyday)	27.3%	28.3%	57.9%	57.2%	65.0%	53.7%	32.9%	67.6%	69.5%	76.0%

Note: Low-tech manufacturing includes food, textiles, apparel, paper, leather, lumber, chemicals, petroleum, plastics, and glass. High-tech manufacturing includes metals, machinery, electronics, motors, and instruments. Transportation (driving) includes taxis, trucking, and buses (Ind1990 codes: 400-410), and transportation (warehousing) includes warehousing and storage (Ind1990 codes: 411, 420-432). Personal services includes hotels, beauty parlors, repair shops, entertainment, laundry, and education and health services (Ind1990 codes: 742-810, 812-840, 842-871).
(Panel A) $N = 3,610$ (5 outcome years × 722 commuting zones). The employment-population ratio is the share of prime-age (25-54) male salaried employment in each private sector across commuting zones in the continental US. Industry structure includes average establishment size and Herfindahl-Hirschman index constructed from County Business Patterns (CBP) at previous outcome years. Each model inherits definitions of hot days and cold days, treatment windows (5-year average), two-way fixed effects, non-demographic, non-industry covariates, regression weights, and clustering of standard errors in the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$. (Panel B) Computed as a share of prime-age male salaried employments in the 2000 Census. See Section 5 for definition of climate exposure.

days, suggesting that the workspaces are well cooled in the summer, and may protect employment. However, they show negative effects from cold days (-0.292). Given that shopping malls and warehouses typically have wider floors with higher ceilings, the workplace remains vulnerable to cold weather because air conditioning would become prohibitively expensive to heat a large space in the winter.[40]

The transportation sectors show bifurcated responses between warehousing and driving. Column 6 reports job loss in the warehouse industry from both hot days (-0.076) and cold days (-0.220), suggesting that logistics facilities are vulnerable to outside temperatures, plausibly with poor air control. Column 7, on the other hand, reports job gains in the driving industry (e.g., taxis, trucks, buses) from hot days ($+0.051$), suggesting that enclosed vehicles may at least partially shield drivers from heat, humidity, and direct sunlight in the summer.

The service sector also shows mixed results. In column 8, personal service (e.g., restaurants, hotels, education, health care) shows the largest job *growth* from both warming ($+0.161, t = 2.5$) and cooling ($+0.210, t = 1.6$) among all sectors,. Given its sizable share of employment (17.0%), personal service acts as a cooling shelter from climate change. The results are consistent with my earlier finding that climate damages are amplified in rural areas that lack personal services as an indoor safety net (see on page 25). In contrast, consistent with its high share of indoor workers under climate control (69.5%), column 9 finds that high-skilled service (business/engineering) show null effects of extreme temperature days. Combining a large employment share (14.5%) with a high share of college-educated workers (45.1%), this sector primarily protects college-educated males from climate change.

Column 10 shows significant job losses from both extreme temperature days (-0.137 for, hot days and -0.187 for cold days) in finance/real estate services. A presumable explanation would be that the industry includes temperature-exposed jobs (e.g., sales personnel or front-line customer service or alternatively, the demand for finance/real estate services is potentially weather-sensitive (Colacito, Hoffmann and Phan (2019))[41]. This sector appears to be partly responsible for the decline in the LFPR for the highly educated.

[40] In both homes and businesses, air conditioning costs (i.e., electricity consumption) are much more expensive in the winter than in the summer due to the wider range of temperature adjustment.

[41] Colacito, Hoffmann and Phan (2019) used a US state-level analysis to show that the GDP of the finance sector is most affected by summer temperatures across all sectors, even more so than in other sectors (e.g., construction, agriculture).

The overall analysis suggests that conventionally-considered heat-sensitive sectors (agriculture, construction/mining and a subset of manufacturing) are major sources of job loss, while transitions to indoor sectors (typically, services) are observed but limited. Because the data cannot speak to employment flows into and out of each sector nor to employment transitions across sectors, supposedly indoor service sectors may also have suffered from masked losses of outdoor jobs. Instead of using sectors as the unit of analysis, the next section directly tests the response of and influence from outdoor jobs under climate change.

5.3 Outdoor Jobs

Within-sector effects on outdoor jobs The previous section showed that shrinking salaried employment, especially in heat-sensitive sectors (e.g., construction), is a primary but not exclusive source of labor force contraction. Because supposedly indoor service sectors include jobs without air control (e.g., grocery store workers facing door openings; cooks using fire) or even outdoor jobs (e.g., lawn mowers, security guards), the previous broad industry analysis appears to be elusive in reflecting climate-related job losses.

To further highlight the role of outdoor jobs as a source of dropouts, I examine climate impacts on outdoor vs. indoor jobs *within* sectors, a previous unit of analysis in Table 5. Panel A of Table 6 examines the sensitivity of employments under three work environments—outdoor, indoor uncontrolled, and indoor controlled. Columns 1-3 report climate impacts on prime-age male salaried employment within sectors across CZs, separately by each climate exposure environment. Column 1 shows a significant loss of outdoor jobs in response to both hot and cold days (-0.045 and -0.045), providing a solid support that outdoor jobs are mostly likely sources of climate-induced dropouts within sectors. In the same vein, column 2 finds slightly milder job loss indoors without climate control from warming (-0.025) and cooling (-0.039), speculatively because indoor environments block sunshine and cold wind. Under indoor controlled environments, column 3 continues to report mildly significant job loss from hot days (-0.024).[42] Overall, outdoor jobs experienced much more severe and statistically significant losses, which corroborates the proposed mechanism in the paper.

[42] I offer two explanations for how climate change affects indoor workers under air conditioning. First, even indoor workers with supposedly perfect air control may be exposed to outdoor weather during work hours (e.g., door openings), on breaks or while commuting. Cachon, Gallino and Olivares (2012) demonstrate that even factories with supposedly perfect air control in the US automobile industry experienced productivity losses. Second, outdoor and indoor workers may be complements within establishments. Then, the exit of establishments (Ponticelli, Xu and Zeume (2023)) or the reallocation of labor (Acharya, Bhardwaj and Tomunen (2023)) would reduce the number of indoor workers (see the discussion on the labor demand channel in Section 6).

Amplified effects of temperature exposure If the number of outdoor jobs disproportionately shrinks with exposure to extreme temperature days, the climate impacts of interest should be amplified by the initial prevalence of outdoor jobs. To test this climate exposure mechanism, I enrich the baseline model by interacting the climate variables $\mathrm{hd}_{i,I_t}, \mathrm{cd}_{i,I_t}$ with a regional shifter $z^e_{i,t_{-1}}$, a share of employment (measured by weeks worked) under different climate exposures e at pre-period outcome years t_{-1} (recall that if $t = 1980$, then $t_{-1} = 1970$). Analogous to the procedure in Section 2.3, climate exposure $e \in \{\text{outdoor}, \text{indoor uncontrolled, indoor controlled}\}$is constructed from several questions from the Work Context Survey.[43] Arranging equation (1), I construct a difference-in-difference style formulation replacing $\beta^h \mathrm{hd}_{i,I_t} + \beta^c \mathrm{cd}_{i,I_t}$ by $\beta^h \mathrm{hd}_{i,I_t} + \beta^c \mathrm{cd}_{i,I_t} + \gamma^{e,h} \mathrm{hd}_{i,I_t} z^e_{i,t_{-1}} + \gamma^{e,c} \mathrm{cd}_{i,I_t} z^e_{i,t_{-1}} + \mu z^e_{i,t_{-1}}$, where $\gamma^{e,h}, \gamma^{e,c}$ captures modifier effects under climate exposure e to hot days and cold days, respectively.

Table 6 reports climate effects $\gamma^{e,h}, \gamma^{e,c}$, interacted with a set of temperature exposures $z^e_{i,t_{-1}}$, measured by a share of employment in environment e. Column 1 shows significantly negative interaction estimates (-1.394) from hot days for the pre-period share of outdoor jobs, indicating that regions initially dependent on outdoor jobs experienced larger subsequent declines in LFPR. This interpretively shows that if all jobs were outdoor jobs, 10 more hot days in the 5-year average would hurt the LFPR by an additional $1.4\%pts$.

Similarly, columns 2-3 interact a variant of workplace climate exposure. Column 2 uses the proportion of imperfectly controlled environments (e.g., old warehouses; factories with furnaces; restaurant kitchens), showing comparable harm to outdoor workplaces (column 1)—plausibly because heat and humidity are easily retained indoors. On the other hand, the interaction with the previous period shares of workers employed in daily-air-controlled jobs (e.g., cashiers, waiters, office clerks, engineers) is significantly positive in column 3. A sharp contrast between column 2 (imperfect control) and column 3 (perfect control) confirms the role of workplace air conditioning in maintaining their work efficiency.

[43] The question includes "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 *indoors in environmentally controlled* conditions?".

Table 6: The Effect on and Influence from Outdoor vs. Indoor Jobs

	Panel A: Within-Sector Impacts on Outdoor Jobs *dependent variable*: **Employment-to-Population Ratio** (in %pts.; prime-age males) units of analysis: CZs × sectors × years				**Panel B: The Effects from the Prevalence of Outdoor Jobs** *dependent variable*: **LFPR** (in %pts.; prime-age males) units of analysis: CZs × years		
	share of employment by job types				pre-period share of employment		
	Outdoor jobs	**Indoor uncontrolled jobs**	**Indoor controlled jobs**		× **Outdoor jobs**	× **Indoor uncontrolled jobs**	×**Indoor controlled jobs**
	(1)	(2)	(3)		(1)	(2)	(3)
10 hot days	-0.045^{***}	-0.025^{*}	-0.024^{*}	10 hot days	-1.394^{***}	-1.615^{***}	0.847^{**}
	(0.015)	(0.014)	(0.012)	× pre-exposure	(0.461)	(0.451)	(0.369)
10 cold days	-0.045^{**}	-0.039^{**}	-0.038	10 cold days	-0.862	-1.876^{***}	2.563^{***}
	(0.018)	(0.018)	(0.023)	× pre-exposure	(0.788)	(0.720)	(0.623)
CZ × sector FEs	Yes	Yes	Yes	10 hot days	0.125	0.185	-0.815^{***}
					(0.172)	(0.160)	(0.223)
sector × year FEs	Yes	Yes	Yes	10 cold days	-0.076	0.247	-1.759^{***}
					(0.414)	(0.352)	(0.301)
Observations	34,623	34,623	34,623		3,610	3,610	3,610
Adjusted R^2	0.914	0.915	0.950		0.877	0.878	0.878

Note: The number of jobs in each occupational category is calculated as the sum of the sample weights interacted with the proportion of exposure at least weekly (or daily for indoor controlled workers) in each worker's occupational title, as measured by the O*NET Work Context Survey.
*** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.
Panel A: Unit of analysis: 5 outcome years × 722 commuting zones× 10 private sectors. Missing cells are dropped. Pre-period employee demographics for each occupational group is controlled at the CZ-sector level. Pre-period industrial composition (average size of establishment and Herfindahl-Hirschman index) is controlled at the CZ-sector level. A ratio of prime-age male salaried employment of each occupational category in each cell to the prime-age male population in CZ is computed across years. All models inherit definitions of hot days and cold days, treatment windows (5-year average), non-demography, non-industry controls, and clustering of standard errors in the baseline model, column 5 at Table 2. The regression weights are each cell's pre-period nationwide share of salaried employment.
Panel B: Unit of analysis: 5 outcome years × 722 commuting zones. All the models add interaction terms with pre-period temperature exposures to the baseline model, column 5 at Table 2.

5.4 The Home as a Cooling Lounge

5.4.1 Residential Amenities

The opportunity cost of working outside the home should be shaped not only by the discomfort of the ambient temperature, but also by the comfort of staying at home. To identify the sensitivity of labor supply interacted with the quality of leisure at home, I exploit the regional spread of residential amenities, especially, air conditioners and color televisions, since the late 1960s as a shifter to increase the opportunity cost of labor under climate change. In 1955, air conditioners were installed in office buildings, supermarkets and movie theaters, but less than 2% of homes had air conditioning (Biddle (2008)). Using the Census of Households, I calculate that the share of households with air conditioners surged from a minority of 37% in 1970 to a majority of 56% in 1980.

Although 97% of households owned a color television set in 1970, television viewing rapidly penetrated the American leisure time in the last century , adding 8 hours per week between 1965 and 2003 (Aguiar and Hurst (2007)). A trio of technology developments explains this trend. First, since the 1970s, cable TV subscriptions have spread rapidly to provide a battery of channels to suit the tastes of multi-generational family members, including adult programs (e.g., movies for HBO (1972), Showtime (1976), sports for ESPN (1979), music for MTV (1981)) and children's programs (e.g., Nickelodeon (1979); the Disney Channel (1983)). Second, a TV game technology (Odyssey (1972); Family Computer (1983); Play Station (1994)) have opened another non-real-time content of TV sets, especially for young males. In addition, in the 1980s, the VCR (video cassette recorder) rapidly diffused to the mass consumer markets. As television tastes for TVs vary among household members, it is increasingly common to have multiple TV sets in a household (Waldman, Nicholson and Adilov (2006))—while a teenage boy plays Super Mario upstairs, children enjoy Sesame Street in the children's room, parents watch football on the living room sofa.

To test the role of residential amenities as a shifter of climate impacts, I use a difference-in-difference formulation in equation (1), substituting the previous period's workplace climate exposure, $z^e_{i,t_{-1}}$, for the prevalence of residential amenities[44]. Because air conditioners and television sets became saturated in the U.S. after 2000, the analysis is limited to the 1970-2000 period with

[44] Barreca et al. (2016) use a similar identification strategy to document the benefit of air conditioners in reducing mortality on extremely hot days in the twentieth century.

richer spatial variation in adoption.[45] Since the Census of Households records the adoption of air conditioner in 1970 and 1980, I impute a CZ-level adoption rate of residential air conditioners for all CZs in 1990. Analogous to air conditioners, I compute the CZ-level number of televisions in 1960 and 1970 from the Census of Households to impute televisions in 1980 and 1990. The 1960 Census provides geographic identifiers for 214 CZs, which consistently cover 80% of the US population (see Figure A-10 for the spread of amenities).

Substitution effect from amenities Table 7 reports the interaction estimates with extreme temperature days for each residential amenity. To minimize potential threat from residential amenity confounders (e.g., statewide regulation of electricity supply, housing construction[46] and terrestrial TV broadcasting licenses), state-year fixed effects are imposed so that the estimates are interpretably free of statewide institutions. Column 1 shows the previous period (1970-1990) share of households with access to residential air conditioning and shows significantly negative estimates for hot days ($-0.277, t = -2.6$). Likewise, column 2 highlights a centralized air conditioning system that better accommodates the entire household, and shows more precise estimates ($-0.257, t = -3.3$). The negative estimates are consistent with the theory that residential air conditioning raises the opportunity cost of labor outside the home.[47]

This estimate is in stark contrast to the negative estimates paired with indoor *workplaces without* climate control in column 3 of Table 6, suggesting that air conditioning at home increases the opportunity cost of labor, but decreases it when installed in workplaces. Cold days show negative, but imprecise estimates in columns 1 and 2, presumably because air conditioning is a dominant climate control in summers but not in winters, relative to classical heating up technologies (e.g., gas heaters and stoves).[48]

Similarly, in column 3, I use previous period TV sets per capita and find a significant negative estimate from warming and cooling, suggesting that availability of TVs sets may have irresistibly

[45] In the Internet age after 2000, digital streaming televisions, as well as smartphones, tablets and personal computers became competitive with conventional TVs.

[46] Biddle (2008) showed that the diffusion of air conditioning is shaped not only by regional climate, but also by electricity price and housing stock supply in 1960-1980.

[47] The sign of estimates are ex ante ambiguous, because residential air conditioners could help increase labor efficiency, e.g., by improving sleep quality and resting on weekends. Minor et al. (2022) shows that global warming has hurt sleep quantity and quality, especially in developing countries.

[48] This is presumably because I use air conditioning data in the early periods of 1970 and 1980, when all air conditioners is used exclusively for cooling; air conditioners became compatible for heating around 1990.

Table 7: Quality of Life at Home and Pipelines to Wealth

	dependent variables: LFPR (in %pts; prime-age males)				
	Panel A: Richness of Residential Amenities				
	outcome years: 1980-2000			1980-2019	
	pre-period modifiers (share)				
	× Aircon share	**× Central system share**	**× TV Sets per house**	**× Room per house**	**× House value (log)**
	(1)	(2)	(3)	(4)	(5)
10 hot days × modifiers	-0.277^{**}	-0.257^{***}	-0.353^{***}	-0.114^{*}	-0.036^{***}
	(0.108)	(0.079)	(0.072)	(0.064)	(0.008)
10 cold days × modifiers	-0.123	-0.024	-0.351^{*}	-0.229^{**}	0.005
	(0.130)	(0.177)	(0.180)	(0.102)	(0.017)
10 hot days	-0.155	-0.185^{**}	0.174	0.402	0.068
	(0.102)	(0.093)	(0.141)	(0.371)	(0.082)
10 cold days	-0.411^{**}	-0.399^{**}	-0.352	1.281^{**}	-0.004
	(0.173)	(0.156)	(0.308)	(0.569)	(0.189)
czone FE	Yes	Yes	Yes	Yes	Yes
state × year FE	Yes	Yes	Yes	Yes	Yes
Observations	2,166	2,166	642	3,610	3,610
Adjusted R^2	0.963	0.963	0.976	0.919	0.919

	Panel B: Access to Financial Sources				
	outcome years: 1980-2019				
	pre-period modifiers (log of per-capita value in (1)-(4)/ share in (5))				
	× Total family income	**× Social security income of retired parents**	**× Labor income of spouses**	**× Personal non-labor income**	**× Farm share**
	(1)	(2)	(3)	(4)	(5)
10 hot days × modifiers	-0.043^{***}	-0.093^{**}	-0.063^{**}	-0.005	-1.677^{***}
	(0.010)	(0.038)	(0.027)	(0.050)	(0.624)
10 cold days × modifiers	0.003	-0.097	-0.008	-0.077	-1.787^{***}
	(0.018)	(0.064)	(0.049)	(0.074)	(0.545)
10 hot days	0.041	0.575^{*}	0.386	-0.176	-0.195^{***}
	(0.075)	(0.342)	(0.266)	(0.412)	(0.071)
10 cold days	0.007	0.858	0.129	0.649	0.039
	(0.173)	(0.568)	(0.458)	(0.620)	(0.149)
czone FE	Yes	Yes	Yes	Yes	Yes
state × year FE	Yes	Yes	Yes	Yes	Yes
Observations	3,610	3,610	3,610	3,610	3,610
Adjusted R^2	0.919	0.918	0.918	0.918	0.919

Note: $N = 2,166$ (3 years × 722 commuting zones) for columns 1-2 of Panel A, $N = 642$ (3 years × 214 commuting zones) for column 3 of Panel A, $N = 3,610$ (5 outcome years × 722 commuting zones) for columns 4-5 of Panel A and Panel B. All models inherit definitions of hot days and cold days, treatment windows (5-year average), full controls, regression weights, and clustering of standard errors from the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

attracted workers to stay home from labor.[49] The finding may partially explain a larger climate effect in rural areas, where urban leisure amenities (e.g., bars, theaters, stadiums, amusement parks, casinos) are scarce. This finding is also consistent with Aguiar et al. (2021), who highlight the role of video game technology in depressing the labor supply of young males in their early 20s and younger. Just as game technology trapped young males in the new century, my finding signals that increased access to television sets, fueled by cable television and classic video game technology, inhibited the labor supply of adult males in the last century.

Multiple television sets also indicate the availability of soundproofed rooms, that would easily accommodate adult males. The large, family-sized houses that were affordable during the 1950s baby boom should have created additional available rooms (e.g., empty children's room) in the homes of parents or relatives—potentially facilitating cohabitation to save on housing rent (Fry, Passel and Cohn (2020)) and begin a life as a dropout. Guided by this inference, I paired climate variables with the number of rooms per house through 2019 in column 4. Intriguingly, the estimates show adverse effects on both for hot and cold days, suggesting that extra rooms could become a den for idle men.

The comfort of living at home should be determined not only by the size of the house, but also by its quality. Column 5 examines the median regional housing value, which represents its market quality as well as its capacity. Intriguingly, the estimates are significantly negative for hot days, consistent with the idea that access to newly constructed or well-maintained houses will increase the recreational value of home. Although speculative, Panel A as a whole supports the theory that, under climate change, home assets provide a comfortable cooling lounge to keep adult males away from work.

5.4.2 Access to Wealth

Panel A of Table 7 shows that climate change, coupled with a richer housing environment, promotes labor force exit through the substitution effect. By contrast, climate-induced dropouts should be augmented through income effect, depending on the richness of their access to financial revenue.[50]

[49] Although not for prime-age adults, Waldman, Nicholson and Adilov (2006) show similar psychological effects of TV availability, documenting that the spread of cable TV subscriptions induced autism in children, compounded by precipitation.

[50] In the language of the classical labor supply model, assuming that leisure is a normal good, greater access to non-labor income reduces labor supply as an income effect.

Panel B examines the interaction of climate change and income effect, namely, how the access to a variety of assets impeded their labor supply under climate stress.[51]

Column 1 pairs previous period total family incomes from co-residence (labor and non-labor income of prime-age men's relatives living in the household) with extreme temperature days (-0.043). The model shows a significantly negative estimate for hot days, suggesting that deeper pockets of co-living relatives catalyzed non-participation under climate stress. However, access to family income does not necessarily require co-residence, but is accessible through remittances from parents and relatives who live separately. Column 2 presents a per capita Social Security income of the retired generation, proxied by over-62-year-old householders with at least one child (presumably, an adult)[52]. The model reports negative interactive effects for hot days ($-0.093, t = -2.4$) and cold days ($-0.097, t = -1.5$), suggesting that parental pensions earned through their prior labor history, may support their nonworking adult children. Column 3 examines prime-age married women's prior labor income as a potential source of within-couple transfers. The result shows negative interactions for hot days (-0.063), suggesting that husbands endowed with higher earning wives are more likely to leave the labor force[53].

These effects seem reasonable that about 90% of dropouts report no personal non-labor income (e.g., financial dividends or income from owned businesses and farms) to support themselves. As a placebo analysis, column 4 instead considers previous period personal non-labor incomes. As expected, no significant effects are observed, suggesting that climate-induced dropouts are not primarily "early retirees" supported by their own wealth, but rather "dependents" of parental generations or spouses.

Aside from financial wealth, Column 5 examines an availability of farm, characterized by a large land and sold produces in the market.[54] On farms, adult males could work unpaid farm-related jobs and have access to home-grown food. The estimates are significantly negative for both hot and cold days, raising the speculative scenario that farms pushed climate-stressed adult males out of

[51] To minimize the threat of potential confounding effects of wealth, state-year fixed effects are included as in Panel A.

[52] 62 is the minimum age for receiving Social Security benefits, which can include both retirement and disability benefits.

[53] This is consistent with the "added worker effect" (Stephens (2002)), which posits that worker displacement, typically occurring in recessions, induces spouses to enter the labor market.

[54] In the 1970 Census, a farm was either 1) a household on 10+ acres that yielded \$50+ in produce, or 2) a household on less than 10 acres that yielded \$250+ in produce. For the 1980-2000 Census and the 2009-2010 pooled ACS, a farm was any household on 1+ acres that yielded \$1000+ in produce in the previous year.

the market economy and into the "informal" sector. Taken together, the overall results in Panel B are well-aligned with the hypothesis that climate change, coupled with richer financial endowments, frees adult males from labor. Recall that the climate impact is consistently greater for younger men (Table 3), who have a lower disability rate[55] and are presumably more qualified for outdoor jobs than older counterparts. Combined with the findings in Table 7, I conclude that climate-induced dropouts should be understood as a lifestyle adaptation, especially among younger males without college degrees.

6 Discussions

6.1 Migration

It is well known that the US population has grown disproportionately in warm southern areas (e.g., Texas and Arizona) (see Molloy, Smith and Wozniak (2011)), possibly due to affordable housing. Although regional demographic composition is controlled for in each period, the results may be partially confounded by climate-induced migration (McLeman and Smit (2006)), as is common with the regional exposure approach. Given the secular decline in US internal mobility after 1980 (Olney and Thompson (2024)), and the decline in male LFPR declines in almost all commuting zones during 1980-2019, labor or nonlabor reallocation should not be an exclusive explanation, but, there are some speculative scenarios that deserve attention; if nonlabor (e.g., early retirees) move to warming areas (e.g., Florida) for residential amenities, the climate effect would be overestimated. Conversely, if workers systematically migrate to warming areas (e.g., California) for job availability, the same effect would be underestimated.

To address this concern, I first test whether regional climate change has affected the population size of prime-age males. However, no evidence is found that their population size is triggered by either warming or cooling (Table A-13). The null results persist when the population is split by college or non-college graduates or by including nine census division trends. I also find no evidence that extreme temperature days attract migration inflows, measured by recent (5 year) migrants to current residences or cross-state migrants. Rather, I find some evidence that hot and cold days inhibited in-migration (Table A-13). If extreme temperature days reduce in-migrants, out-migrants

[55]The DI receipt rate increases with age for both males and females (see, e.g., Autor and Duggan (2003)).

must respond by shrinking to maintain population size[56].

Although out-migration cannot be directly specified in the surveys, I find that extreme temperature days significantly increased the number of people living in the state of birth. Since in-migrants from other states did not increase in response to extreme temperatures, they are most likely born-and-raised native males who chose not to leave the state of birth after schooling, characterizing the systematic decline in US internal mobility in recent decades. Putting this together in perspective, extreme temperature days at least did not affect or rather helped maintain the prime-age male population. I therefore judge that the finding is not likely to be driven by climate-induced migration.

6.2 Labor Demand Channel

Standard theory suggests that the decline in salaried employment (shown in Table 4 and 5) suggest a contraction in not only labor supply but demand. Establishments would expectedly react to adjust the employment to avoid the heat shocks. This labor demand channel is exemplified by a series of recent works on declining labor productivity (Somanathan et al. (2021); Chen and Yang (2019); Kjellstrom et al. (2009)), the exit of small manufacturing plants (Ponticelli, Xu and Zeume (2023)), the reallocation of labor to non-warming areas in multi-county firms in Acharya, Bhardwaj and Tomunen (2023), or labor-saving technological change (Qiu and Yoshida (2024)).

Although the research design is not suitable for explicit decomposition of the channels, I examine the wage responses of salaried jobs, which would speak to the relative dominance of supply vs. demand forces; On one hand, increased labor costs (or discomfort) would raise survivors' wages from shrinking labor supply. On the other hand, decreased labor efficiency would suppress their wages from shrinking labor demand. The net impact is an empirical question.

To explore this, I use the flexible semi-parametric bin model in equation (1), by taking education groups-by-sector cells within CZs across years as a unit of analysis[57]. I find that scorching hot days

[56] If climate change inhibits both in-migration and out-migration, it amplifies the positive/negative neighborhood effects to prevent socioeconomic mobility. This prediction is intriguing, but is left for future work.

[57] This is to correct compositional changes within 10 private sectors (inherited from the classification of Table 5) in skill levels with five categories: high school dropouts, high school graduates, some college years, college graduates, above college. I take sector-state-year fixed effects to control for statewide institutional changes (e.g., minimum wage; right-to-work rules). Acemoglu and Restrepo (2020) use a similar strategy to estimate the impact of the introduction of industrial robots on wages.

(above 95°F), mildly hot days (75-85°F)[58], and severe cold days (<15°F) are associated with an *increase* in total wages, while cold days (25-35°F) are associated with a *decrease* in total wages, while other temperature bins show statistically insignificant effect on wages. According to the neoclassical view combined with the shrinkage of employment from days with extreme temperatures, the various signs of wage responses suggest that contractions in labor demand and supply counteract each other across temperature bins (see Figure A-12). This pattern remains consistent when using hourly wages and alternative units of analysis. The wage analysis provides suggestive evidence that climate change not only undermines labor demand, but also the supply, and consequently, pushes workers out of the labor force.

7 Assessment

7.1 Climate impacts

Building on the empirical models, this section quantitatively assesses the contribution of climate change to account for the nationwide decline in adult male LFPR. Having found that both warming and cooling reduce LFPR (Table 2), I interact the estimates with exposure to hot and cold days across regions, and aggregate them to compute the nationwide effect on LFPR. Specifically, an implied impact ΔLFPR_R^g for a demographic group g (prime-age males) in region R (a set of CZ i) from a year t_0 (e.g., 2000) to t_1 (e.g., 2019) is calculated as

$$\Delta\text{LFPR}_R^g = \sum_{i \in R} \omega_{R,t_0}^{g,i} \beta^{g,h} (\text{hd}_{i,I_{t_1}} - \text{hd}_{i,I_{t_0}}) + \sum_{i \in R} \omega_{R,t_0}^{g,i} \beta^{g,c} (\text{cd}_{i,I_{t_1}} - \text{cd}_{i,I_{t_0}}), \tag{2}$$

where $\omega_{R,t_0}^{g,i}$ is the population share of CZ i's group g within region R in the initial year t_0 and $\text{hd}_{i,I_t}, \text{cd}_{i,I_t}$ are the average number of hot days and cold days during each 5-year prior treatment window $I_t = [t-5, t-1]$. Given little evidence for climate-induced migration in my context (Section 6.1), two-way fixed-effect estimates of the formula (2) can be interpreted as within-CZ climate effects on the LFPR.

Because the temperature increase not only increases exposure to hot days, but also decreases exposure to cold days, the net regional impact would be an empirical question of the "horse race"

[58]The increase in wages within the 75-85°F bin coincides with the largest decrease in LFPR from hot days, as shown in Figure 5, suggesting the relat supply-side forces for suppressing LFPR.

between greater warming and milder cooling. Figure 6 illustrates regional exposure to climate change (Panel (a)) and its implied climate impacts (Panel (b)). Panel (a) splits climate change before and after 2000: (a1) 1970-2000 vs. (a2) 2000-2019. One can see a strong contrast in climate change. In 1970-2000, the warming is mainly manifested in a decrease of cold days; a population-weighted median CZ experienced 0.9 more hot days and 4.1 less cold days as a 5-year average. In contrast, in the new century period (2000-2019), when the United Nations announced the age of global *boiling* (Guterres, 2023), more hot days dominated fewer cold days (+15.5 vs. −0.2 days for a median CZ).

Combining the baseline estimates with regional climate exposure, the implied climate impacts are shown in Panel (b). Setting R as the entire 722 commuting zones, and plugging $I_{t_0} = [1966, 1970], I_{t_1} = [1995, 2000]$ into the formula (2), the total climate impact during the period 1970-2000 is a modest +0.158 $\%pts$—a consequence of the competing forces from fewer cold days (+0.241$\%pts$) and more hot days (−0.084$\%pts$). In contrast, in the new century, 2000-2019, the re-calculation with $I_{t_0} = [1996, 2000]$ and $I_{t_1} = [2015, 2019]$ yields a net climate impact of −0.436 $\%pts$, almost exclusively due to more hot days[59]. The back-of-the-envelope exercise suggests that climate change accounts for about 15.1% of the nationwide decline in the linear trend of the BLS headline prime-age male LFPR.[60]

By climate region and education group Because climate exposure varies dramatically across regions, and estimates vary widely across education groups (Table 3), the national assessment is likely to mask implied inequality between- and within-regions.

Panel (b1) illustrates the highly heterogeneous impacts across climatic regions. During 1970-2000, initially hot areas (South, Southeast, West) areas experienced a decrease in LFPR due to more hot days—initially sensitive areas to temperature warming in the last century. The effect of

[59]Because the estimate captures a decadal effect, the simulated impact of hot and cold days during 2010-2019 is discounted by a factor of 0.9 (see footnote 25). The calculation is robust to a number of alternative models of splitting by education group, interaction with population density, and dynamically variable effects (see Figure A-14). Estimates from alternative models suggest that the contribution of climate change is in the range of 11.2%-15.1% (baseline).

[60]I conservatively use −2.88$\%pts$ (linear trend) of the nationwide LFPR decline for prime-age males as the denominator instead of −2.51$\%pts$ (raw data) from the BLS headline records. Presumably due to oversampling of the non-labor force in the 2000 Census (see Lerch (2020) for this issue), the nationwide moments using the Census/ACS datasets are negatively smaller; the linear trend in LFPR over 2000-2019 is −2.18$\%pts$ and the within-CZ component of the decline in LFPR from 2000 to 2019 is −2.65$\%pts$, implying an even larger role for climate change than currently reported.

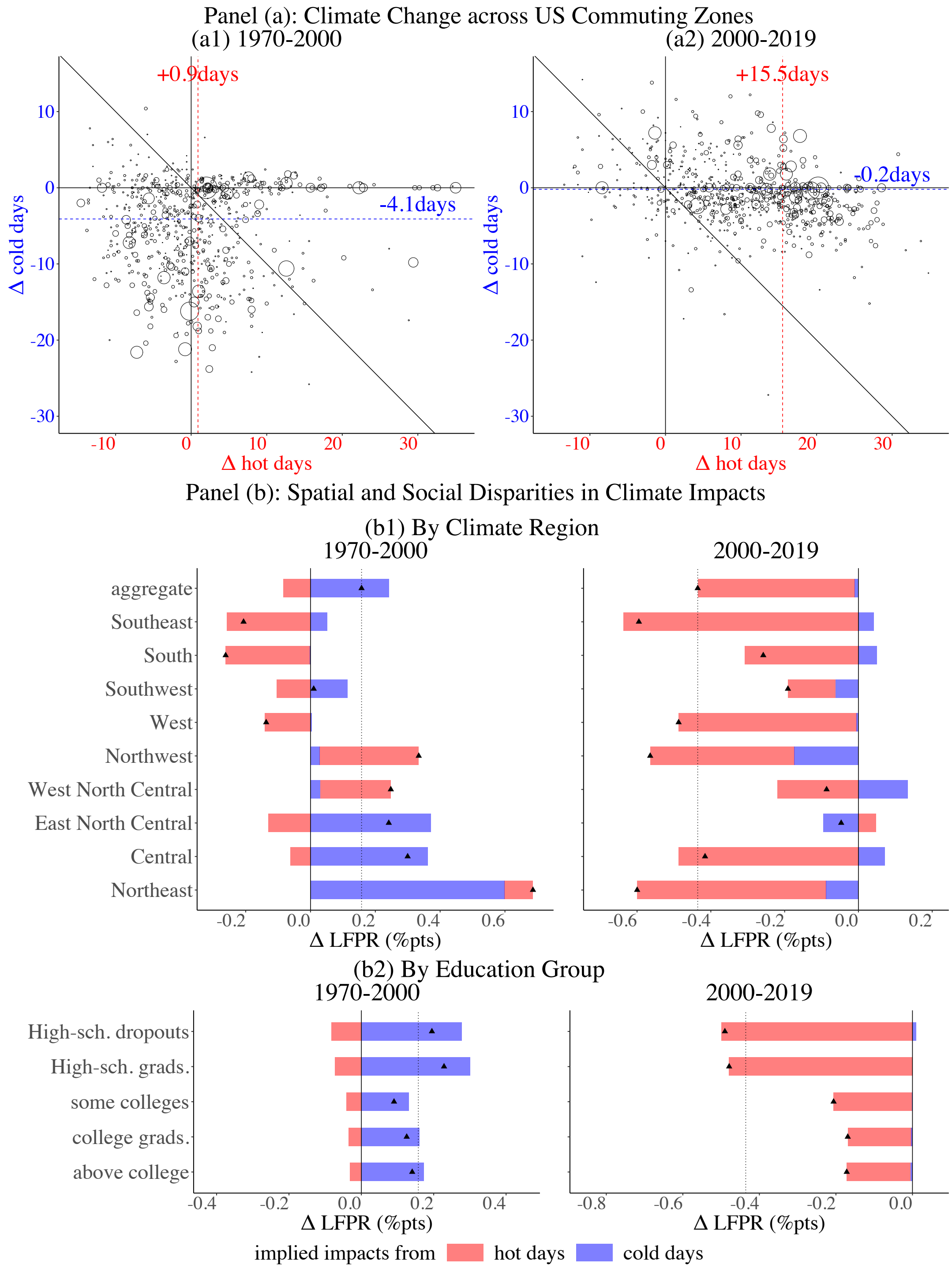


Figure 6: Implied Climate Impacts on the Labor Supply of Adult Males

Panel (a): Hot days and cold days are prior 5-year averages of the number of days with business hour (8am-6pm) median temperature above 75°F and below 35°F, respectively. Dashed lines are values of population-weighted median CZs. Panel (b1): Using formula (2), baseline estimates from column 5 of Table 2 are interacted with regional climate exposure to compute climate impacts at the CZ level. Climate impacts nationwide are then aggregated nationwide or by climate region with CZ-level prime-age male population weights at the start of each period (dashed lines). Panel (b2): Impacts by education group are computed analogously using education group-specific estimates in columns 3-5 of Table 3. Triangles indicate net climate impacts from exposure to hot and cold days.

temperature rise may be underestimated because of the strong interaction of high temperature and high humidity from the neighboring Gulf of Mexico[61]. On the other hand, initially cold regions (East North Central, Central, Northeast) experienced an increase in LFPR due to fewer cold days. Taken together, climate change during 1970-2000 produced a spatial LFPR disparity of up to about $0.9\%pts$ between the South and Southeast (most harmed by warming) and the Northeast (most benefited by milder cooling). Intriguingly, the implied disparity is consistent with a well-known regional divergence in male LFPR; the historically black South (e.g., Louisiana; Mississippi; Arkansas) and Southeast (e.g., Alabama; Georgia) experienced the steepest declines in male LFPR relative to other regions (Figure 2). Between 2000 and 2019, in contrast, all areas of the continental US experienced declines in LFPR, albeit to varying degrees. Notably, the Northeast, the largest beneficiary of milder cooling in the previous century, experienced the largest loss ($-0.600\ \%pts$) from severer warming. This loss is accompanied by the Southeast ($-0.595\ \%pts$), Northwest ($-0.564\ \%pts$), West ($-0.487\ \%pts$) and Central ($-0.416\ \%pts$). The East North Central ($-0.047\ \%pts$) and West North Central ($-0.086\ \%pts$) regions were less affected.

Panel (b2), in turn, shows the simulated damages across educational attainment. Using $\beta^{g,h}$, $\beta^{g,c}$ for three education groups g, borrowed from the sub-sample analysis (high-school graduates or less, some college, college graduate) in column 3-5 of Table 3, I recompute climate impacts separately by education group g. Plausibly reflecting the higher selection into outdoor jobs, high school graduates and dropouts experienced a significant reduction in the LFPR of $\%pts - 0.490$, $-0.479\%pts$, respectively, and men with some college experienced a reduction of $-0.206\%pts$. The effect for college graduates and above is also substantial, $-0.172\%pts$, $-0.169\%pts$, respectively, but about a third for high school graduates and below. By linking climate change and outdoor jobs, this exercise provides a unique explanation for the divergent LFPRs between college degree "haves" and "have nots" (see, e.g., Binder and Bound (2019)).

Performing the analogous exercise, I calculate the sociodemographic profile of climate-induced dropouts (Figure A-13). Using the education-specific estimates, the share of high school graduates and dropouts is an overwhelming 71.8%. Using the baseline model on climate impact of dropouts (column 6 in Table 4), I find that the dropouts are concentrated in the Northeast (31.2%), Southeast (21.8%), Central (16.1%) and West (15.0%). The 6 states account for nearly half, 49%: California

[61] Recall that using uncomfortable days measured by the interaction of temperature and humidity provides much larger estimates (see Table A-7).

(14.5%), New York (9.5%), Florida (7.6%), Pennsylvania (6.2%), Ohio (5.3%) and New Jersey (4.9%). Using a model that allows climate effects to vary with population density (see Urban vs. Rural Areas on page 25), I calculate that the 20 largest urban CZs, which account for nearly 40% of the nation's prime-age male population, produce only 4.0% of the climate-induced dropouts during 2000-2019. The smaller 632 CZs account for nearly 30% of the prime-age male population, but produce 58.9% of the climate-induced dropouts during 2000-2019. Based on the empirical findings so far, the aggregate exercise raises a warning sign that the less educated in disadvantaged rural areas are disproportionately harmed by climate change.

7.2 Policy Implication—Heat Regulation Law

Global temperatures are projected to rise in the coming decades of the 21st century (IPCC (2021)), and disadvantaged regions remain dependent on outdoor jobs through 2019[62]. This naturally raises a normative question of public intervention in the intensified heat damages. A common idea in the policy arena is a heat regulation law, which has been implemented in a handful of states, and is being discussed for implementation at the federal-level, mostly targeting workplaces outdoors[63]. A typical policy package includes a mix of primitive solutions: prohibiting work in extremely hot weather, flexible schedules, mandating personal heat-protective equipment (cooling vests or personal air fans), and frequent access to water, shade, and air conditioning.

The effect of the heat regulation law is prima facie ambiguous, depending on the relative dominance of labor demand and supply. Mandatory protection would be expected to serve to prevent further detachment of labor force, if the labor supply response is dominant. However, if labor demand response is dominant, the regulation would simply backfire, triggering unintended consequences of employment shrinkage—the mandated preventions would raise labor costs, and facilitate heat avoidance by firms, for example, through labor reallocation, exits of businesses, and adoption of automation, as discussed in Section 6.2. Because of the varying wage estimates across temperature bins (Figure A-12) and the implied counterbalance of shrinking regional labor demand and supply, the net benefit of the regulation appears to be purely an empirical question. Either ex-post regional

[62] Areas with lower average weekly wages and college-graduate rates had significantly higher shares of outdoor workers (Figure A-7)

[63] A small number of states (e.g., California, Colorado, Minnesota, Oregon, and Washington) have permanent occupational heat stress standards for the workplace. California has implemented the heat regulation law in both outdoor and indoor workplaces (Department of Industrial Relations (State of California)).

case studies or ex-ante net welfare evaluations are beyond the scope of this paper, and are left for future work.

8 Concluding Remark

Throughout human history, men have enjoyed a comparative advantage in working outdoors to make a living. This paper argues that modern climate change hurt their traditional advantage. Using a plausibly random variation in climate change across US commuting zones as a natural experiment, the paper shows that climate change has disrupted their attachment to the labor force, long considered as the normative responsibility of adult males. Ironically, the disengagement seems to be mediated by outdoor jobs——one of the most primitive jobs in economic history, but a remaining vocation for the unskilled men who were "locked out" of indoor jobs in the stream of technological revolution and globalization.

Directly exposed to planetary change in the last century, however, outdoor jobs have been, and will continue to be a hotbed of dropouts. In the new century, the damage from more hot days began to overwhelm the benefit from fewer cold days in every corner of the continent. Evidence of heat adaptation is limited. The harm is alarmingly uneven among adult males, both within and between regions—because outdoor jobs are primarily held by workers without college degrees, and because disadvantaged regions are critically dependent on outdoor jobs, accelerating climate change would exacerbate inequality nationwide.

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APPENDICES FOR ONLINE PUBLICATION

Climate Change and the Rise of Adult Male Dropouts

Masahiro Yoshida

July 15, 2025

A1 Data

A1.1 Climate

Weather stations Figure A-1 (left) plots availability of weather stations across different coverage of daily records of Global Historical Climatology Network daily (GHCN-daily) from Centers for Environmental Information (NCEI) by the National Oceanic and Atmospheric Administration (NOAA). Figure A-1 (right) visualizes a snapshot of geographic map of stations with complete records in 2019.

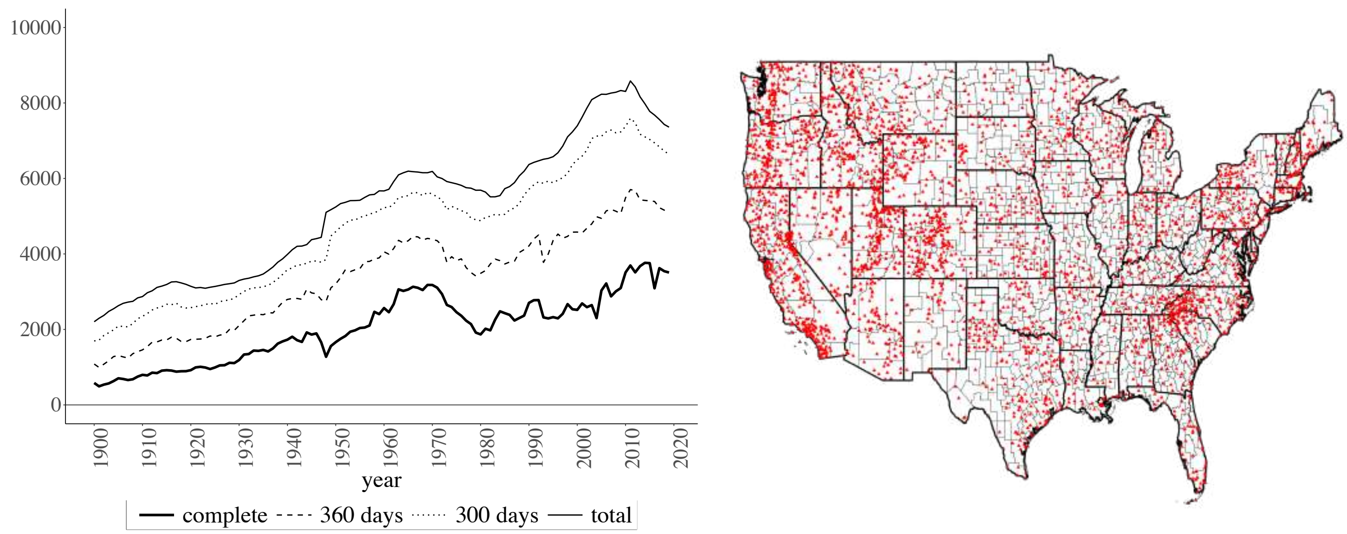


Figure A-1: Availability of US Weather Stations (left: trend in 1900-2019; right: distribution in 2019)

Note: (left) Weather stations are Global Historical Climatology Network Daily (GHCN-daily) from the NCEI. (right) Borders are commuting zones, and red dots indicate stations with full days available in 2019.

Population centroids To compute the daily temperature in the commuting zone (1990 version), I first construct its population centroids as a population-weighted average of the population centroids of the counties within each CZ, as determined by a county-CZ crosswalk from David Dorn. County-level population centroids in 2020 are available from the Census Bureau. The population weight is set as the county-level prime-age male population during 1969-2019, taken from the National Cancer Institute's Surveillance, Epidemiology, and End Results Program (SEER). Figure A-2 shows county-level population centroids (left) and imputed commuting zone centroids (right).

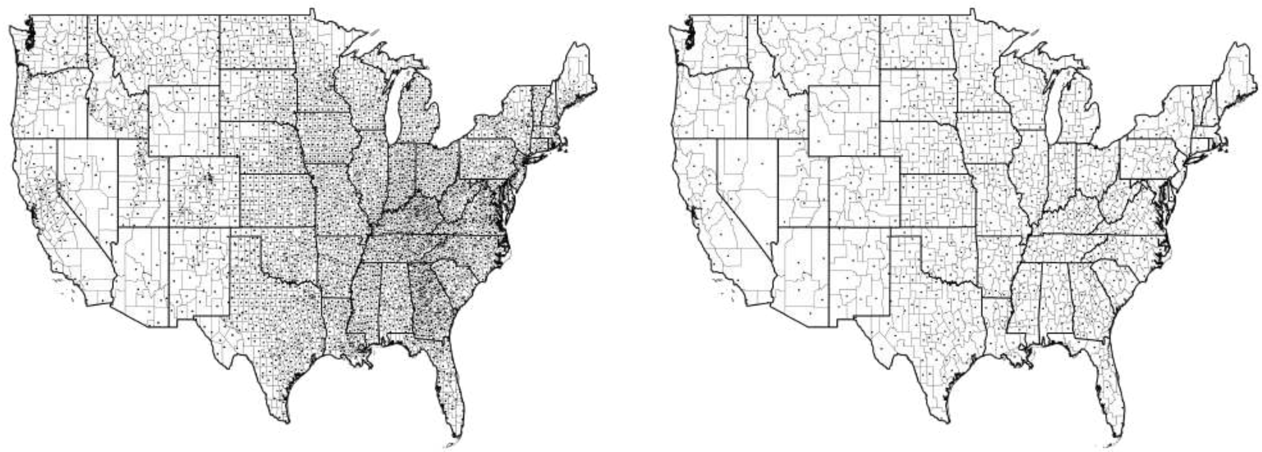


Figure A-2: County (left) vs. Commuting Zone (right) Level Population Centroids

Note: Boundaries are counties in 2020 and commuting zone (1990 version). County-level population centroids are from the Census Bureau.

Daily temperature weight To measure a temperature exposed to workers of each CZ i at day d, I construct a daily temperature $T_{i,d}$ as a weighted average of these two s.t. $T_{i,d} = \omega_{i,d} T_{i,d}^{max} + (1 - \omega_{i,d}) T_{i,d}^{min}$ where $\omega_{i,d} \in (0, 1)$ is a weight to the maximum. The U.S. Climate Normals provide information on within-day hourly temperature fluctuation from January 1 to December 31 averaged during 30 year period (1981-2010), computed from 412 weather stations in the US mainland. From the US Climate Normals, I assign an average of $\omega_{i,d}$ for a day $d \in (m, w)$ in month m-by-week w at CZ i, where $m \in \{1, \cdots, 12\}$ and $w \in \{1, \cdots, 4\}$.

In the left of Figure A-3, a unit of observation is $\omega_{i,d}$ at each station, computed in weekly averages among four weeks w within each month m, constructed from station records by Climate Normals, 1981-2010. In the right of Figure A-3, gray bins show daily distributions with temperature computed with $\omega_{i,d} = 0.5$ $(\forall i, d)$, as the arithmetic mean of the maximum and minimum temperature of the GHCN-daily.

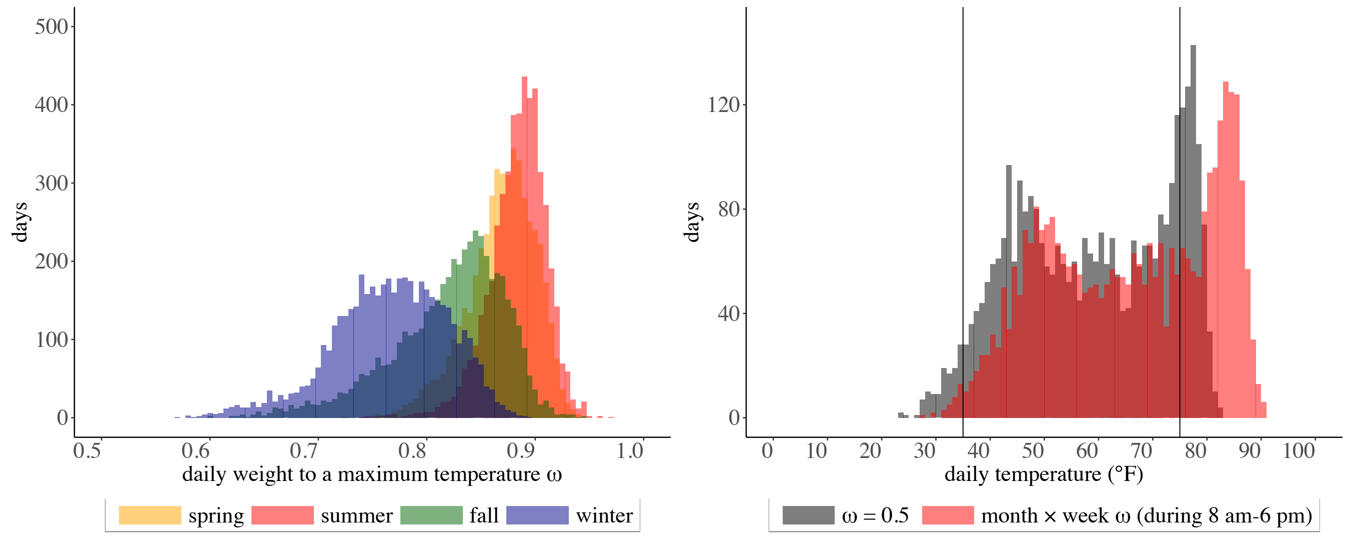


Figure A-3: Distribution of Daily Temperature Weight on the Maximum across Seasons (left; averaged over 1981-2010) and Annual Distribution of Temperature by Weight (right; 2011-2019)
Note: (left) Unit of observations: stations in the Climate Normals × 12 months× 4 weeks. For a day $d \in (m, w)$, averaged in month m-by-week w at CZ i, $\omega_{i,d}$ is constructed from the Climate Normals during 1981-2010. Spring; Mar-May Summer; Jun-Aug Fall; Sep-Nov Winter; Dec, Jan, and Feb. (right) A nationwide daily temperature during 2011-2019 is cumulatively allocated to each 1°F bin. Red bins show those computed with $\omega_{i,d}$ $d \in (m, w)$, averaged in month m-by-week w at CZ i, adjusted to fit the median temperature during 8 am-6 pm using the Climate Normals (see main text for details). Vertical lines are thresholds for cold days (35°F) and hot days (75°F) in the baseline.

Climate level and change

Figure A-4 shows the calculated levels and changes of hot days and cold days with temperature thresholds of 75°F and 35°F, respectively.

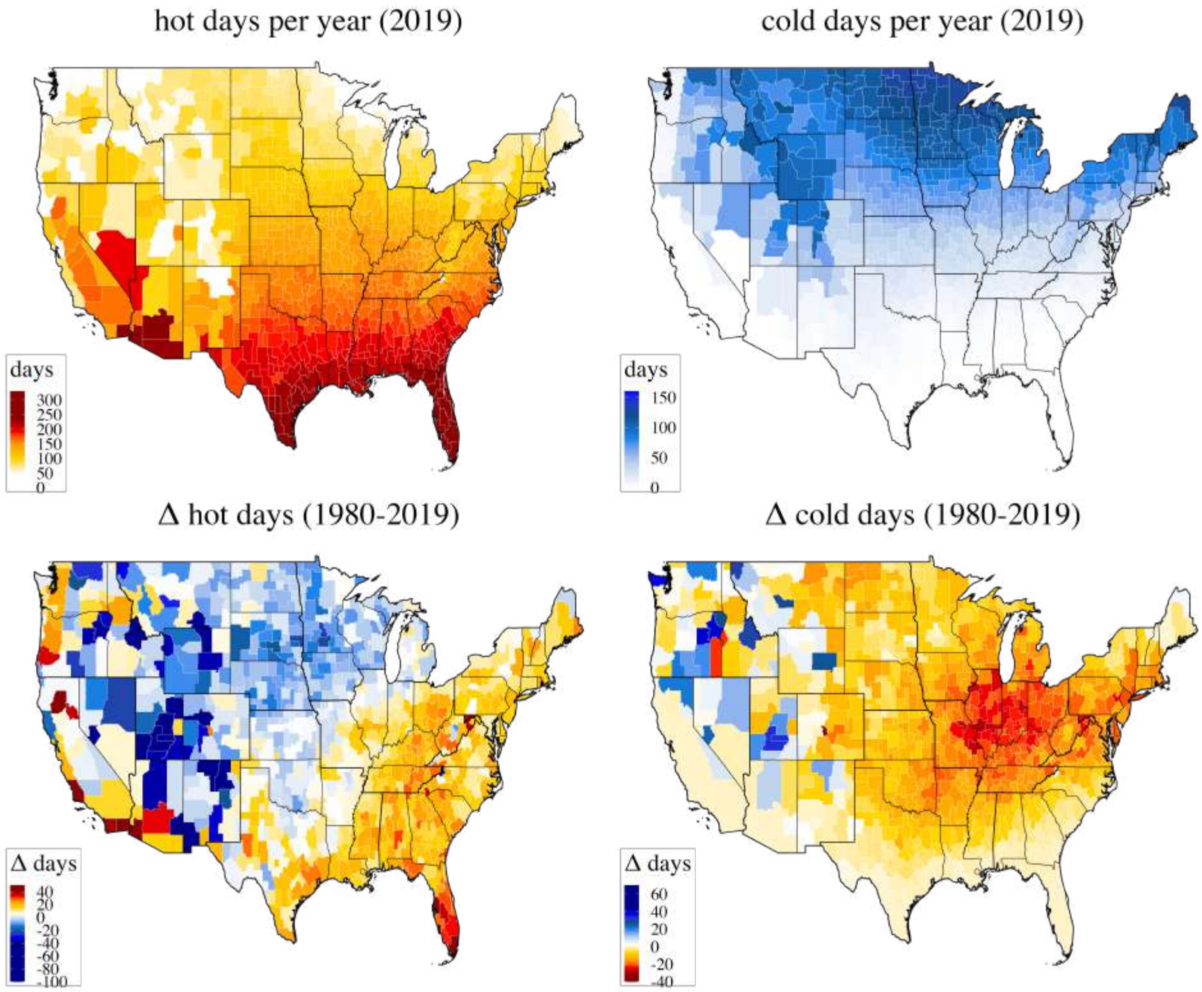


Figure A-4: Hot and Cold Days in US Commuting Zones

Note: The thresholds for hot days and cold days are set at 75°F and 35°F of the median temperature during business hours (8 am-6 pm). For the outcome years 2019 and 1980, I use an average number of hot and cold days during 2014-2018 and 1975-1979, respectively.

Precipitation and snowfall To compute daily precipitation and snowfall at each CZ, I apply a temperature calculation procedure to a set of weather stations that record precipitation and snowfall in GHCN-daily. Figure A-5 shows heat maps of the extensive margin and intensive margin of precipitation and snowfall over the CZs in the most recent treatment window, 2014-2018 for an outcome year, 2019.

Relative humidity and discomfort index I obtain dew points from weather station records from NCEI's Global Summary of the Day (GSoD). I use a standard meteorological formula from Glossary of Meteorology by the American Meteorological Society to compute a relative humidity and discomfort index. A relative humidity H_d of day d and a vapor pressure $v(T)$ as a function of

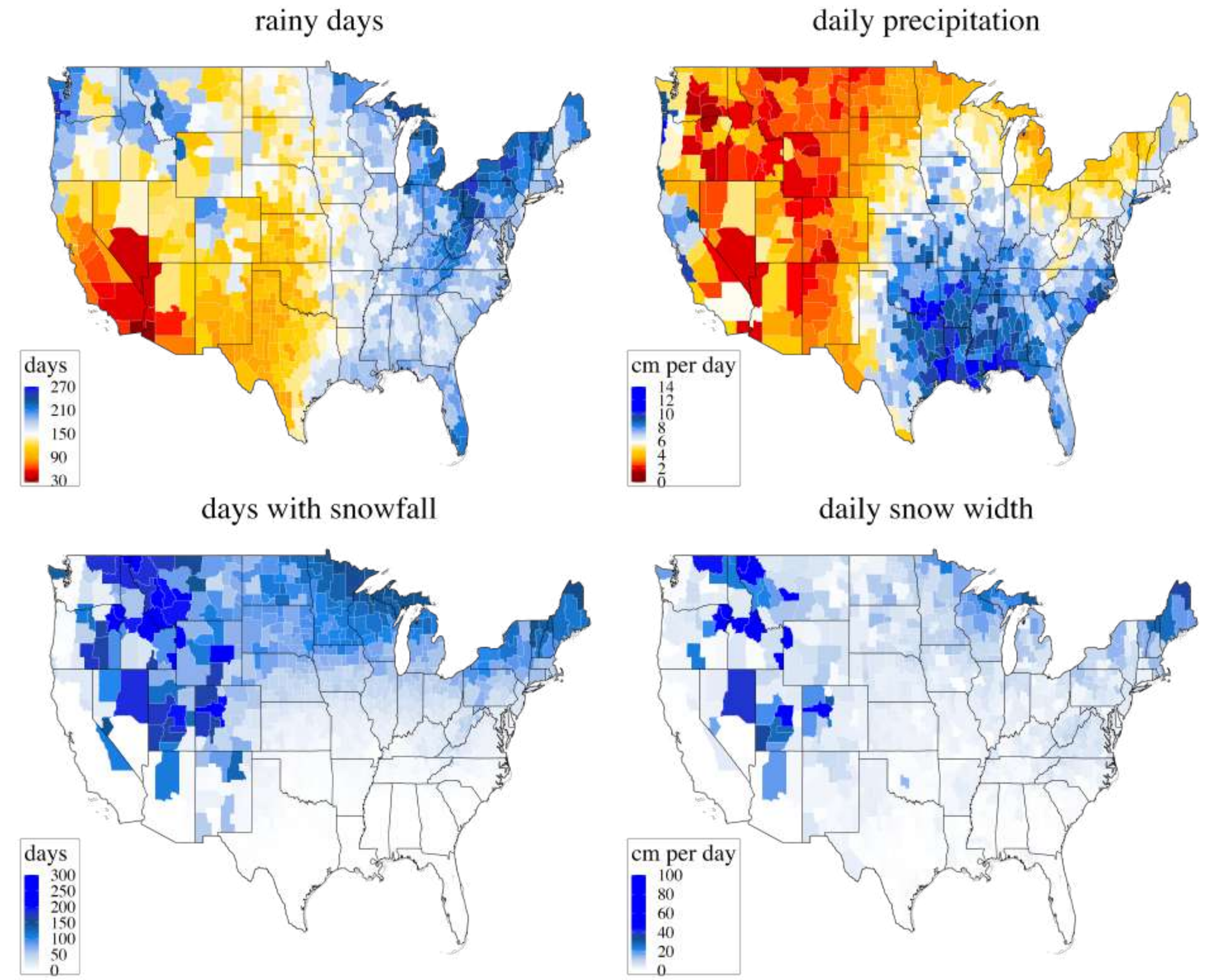


Figure A-5: Precipitation and Snowfall (exposed in an outcome year 2019)

Note: Precipitation and snowfall are constructed from GCHN-daily station records. The right column is an intensive margin, which is conditional on recording non-zero precipitation or snowfall. For the outcome year 2019, I use an average number of each proxy during 2014-2018.

temperature T is given by:

$$H_d \equiv \frac{v(T_{dew})}{v(T_d)},\ v(T) = 0.6112\exp(17.67T/(T+243.5))\times 10 \tag{A1}$$

where $v(T_{dew})$ is a saturation vapor pressure at the dew point T_{dew} and $v(T_d)$ is a day d's vapor pressure at a temperature T_d. Discomfort Index$_d$ is a function of a temperature T_d and a daily relative humidity H_d:

$$\text{Discomfort Index}_d = 0.81T + H_d(0.99T_d - 14.3) + 46.3. \tag{A2}$$

Figure A-6 shows heat maps of relative humidity and uncomfortable days with Discomfort Index is above 75.

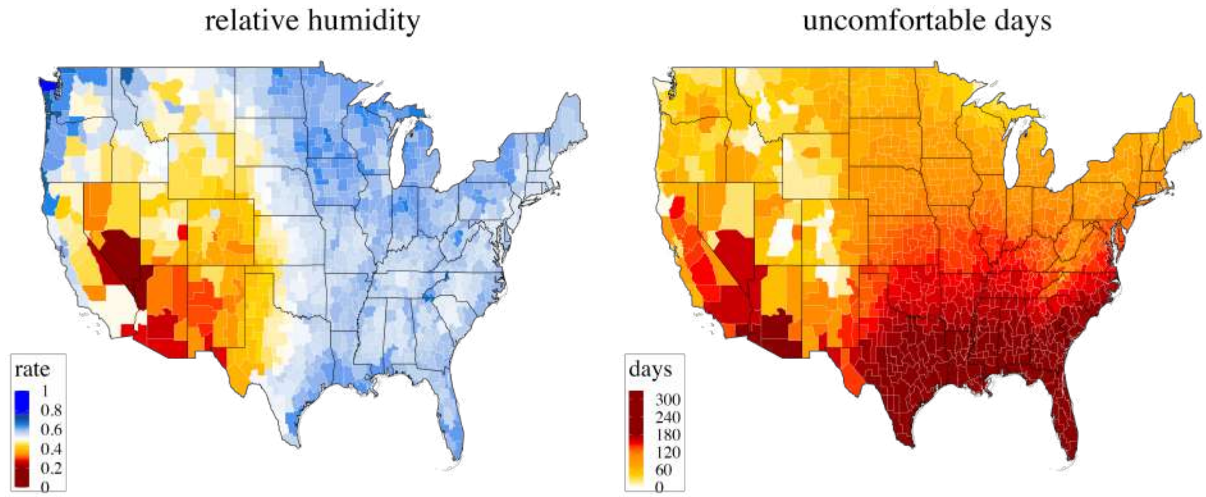


Figure A-6: Relative Humidity and Uncomfortable Days (exposed in an outcome year 2019)
Note: Relative humidity is calculated from station records using the Global Summary of the Day (GSoD). Uncomfortable days have discomfort indices above 75, computed from the formula (A2). For the outcome year 2019, I use an average number of each proxy during 2014-2018.

A1.2 Outdoor Jobs

Geography of outdoor jobs Panel (a) of Figure A-7 contrasts the prevalence of outdoor jobs in 1980 vs. 2019. Mountain regions in the Northwest Central and South experienced an increase in outdoor jobs, while other regions (e.g., Southeast, Southwest, Northeast) experienced a loss of outdoor jobs. Panel (b) relates the share of outdoor workers to population density in 1970 and 2019, indicating that metropolitan areas have been systematically less dependent on outdoor jobs. Panel (c) relates the prevalence of outdoor jobs as a share of the prime-age male population in 2019 to contemporaneous regional development, proxied by the median weekly wage of all workers and the share of non-college graduates.

Outdoor workers by age group and climate region Figure A-8 shows the selection into and composition of outdoor workers by age group and climate region. Panel (a1) shows the proportion of outdoor workers in the male population of each age group. Selection into outdoor work is stable for men in all age groups 25 and older. However, for men under the age of 25, the share of outdoor work shrinks over time, presumably due to higher educational enrollment (Panel (a1)). Male outdoor workers are consistently dominated by prime-age males, driven by the population aging, with the share of males aged 55 and over increasing after 2000 (Panel (a2)). Across all climate regions, the share of outdoor jobs is fairly stable, suggesting that shrinkage or growth of outdoor jobs occurs within climate regions (Panel (b1)).

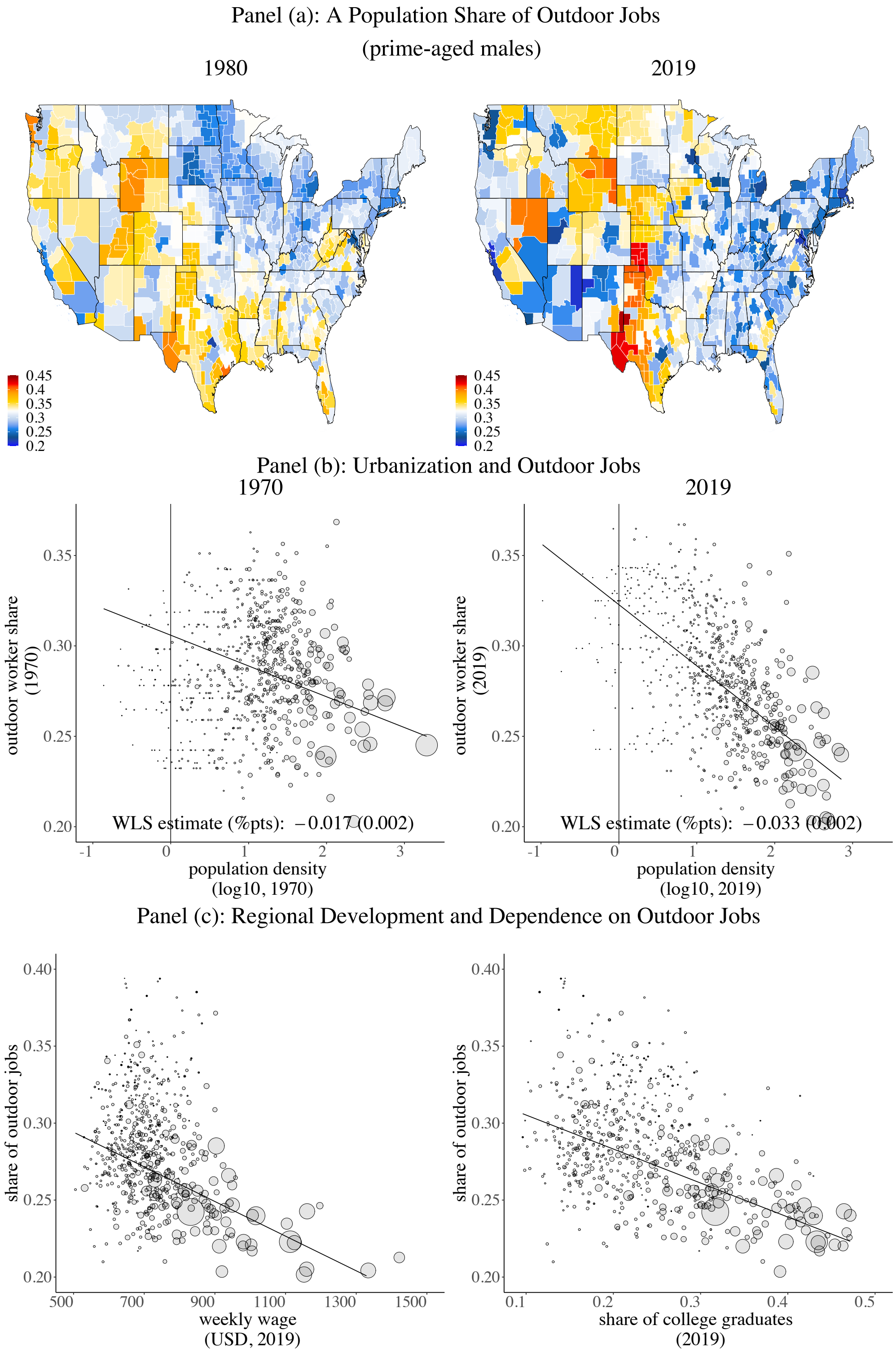


Figure A-7: Outdoor Jobs across Commuting Zones

Note: Computed from IPUMS of the 1970, 1980 Census and the 2018-2019 pooled ACS. Outdoor jobs are computed from sample weights of prime-age males multiplied by the share of those who regularly work outdoors weekly or more, as reported in the O*NET Work Context Survey (see main paper for details).

Panel (a/b/c): A share of outdoor workers in prime-age male population. Panel (b): Population density is calculated as a logged total population in square kilometers for each commuting zone. Panel (c): Weekly wages in prime-age male workers (left) and the share of non-college graduates in prime-age male population (right).

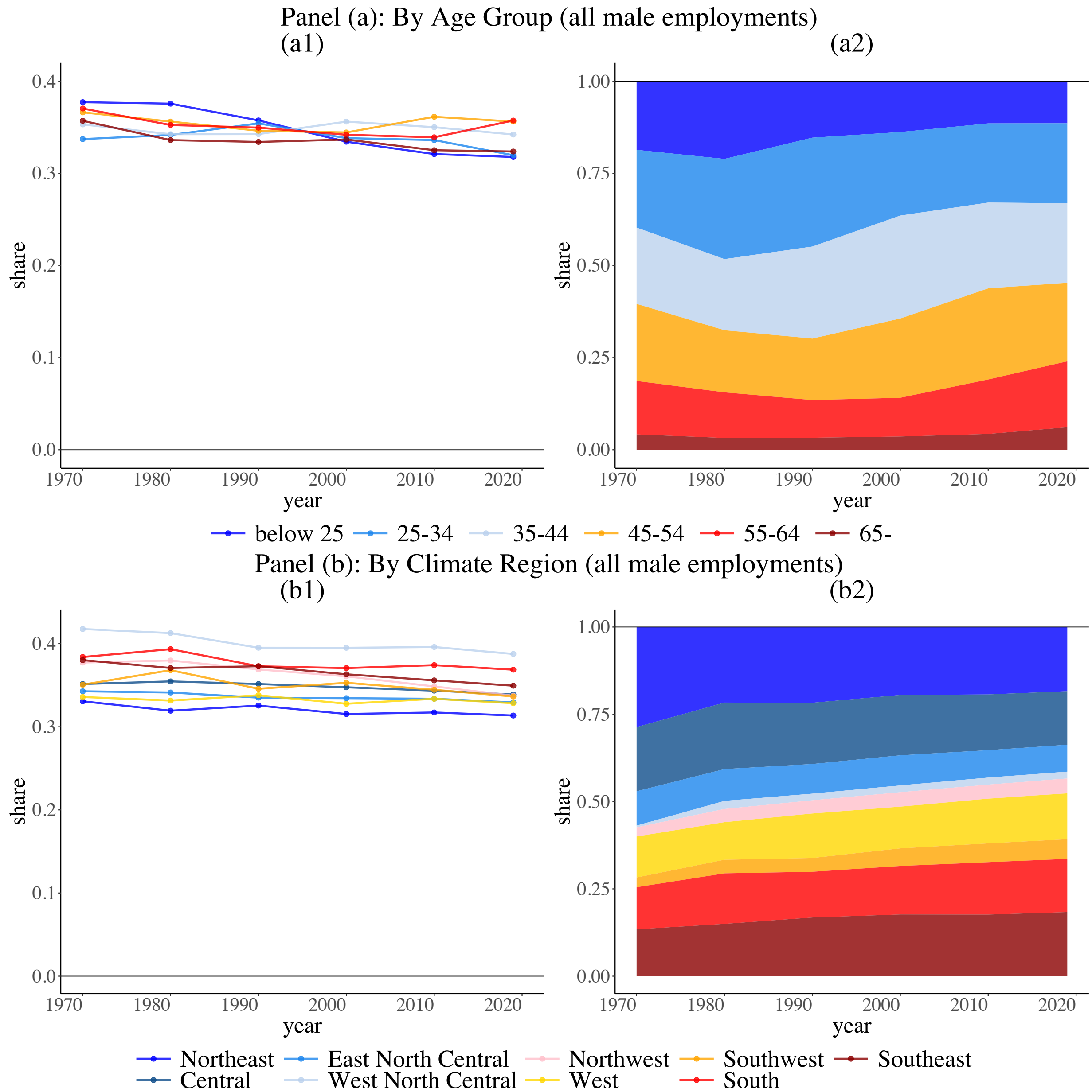


Figure A-8: Outdoor Workers by Age Group and Climate Region (Selection and Composition)

Note: Computed from IPUMS of 1970-2000 Census by decades and pooled American Community Survey 2009-2010 (for 2010) and 2018-2019 (for 2019). Outdoor workers are calculated by multiplying the sample weight by the proportion of those who regularly work outdoors at least weekly as reported in the O*NET Work Context Survey (see the main text for details). (Panel (a1)/(b1)) A proportion of outdoor workers employed at each category. (Panel (a2)/(b2)) A compositional share of male outdoor workers.

Indoor jobs in uncontrolled environments Figure A-9 illustrates the selection into and composition of indoor jobs without climate control by sector, in parallel to outdoor jobs as shown at Panel (c1/c2) of Figure 3. The left panel shows that 40% of prime-age male workers in manufacturing work indoors in uncontrolled environments, suggesting that manufacturing is also vulnerable to climate shocks. The right panel shows their sectoral composition similar to that of outdoor workers.

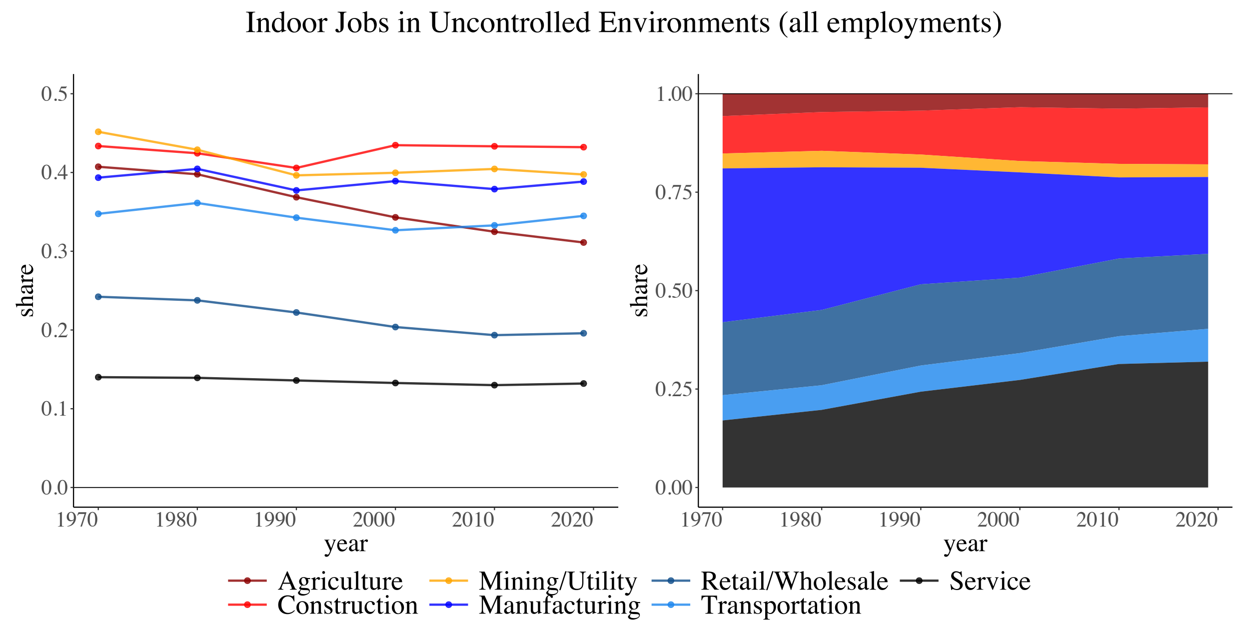


Figure A-9: Indoor Jobs in Uncontrolled Environments by Sector (Selection and Composition)

Note: Calculated from IPUMS of the 1970-2000 Census by decades and pooled American Community Survey 2009-2010 (for 2010) and 2018-2019 (for 2019). Indoor workers in an uncontrolled environment is the sum of a sample weight multiplied by a share of regular indoor work in an uncontrolled environment at least weekly, derived from the Work Context Survey (see main text for details). (left) A proportion of prime-age men working in uncontrolled environments by each sector. (right) A compositional share of prime-age male workers by sector.

A1.3 Residential Amenities

The Census Bureau's Census of Households asked each person about their ownership of household durable goods. Ownership of air conditioners in either 1 one-room unit, 2+ one-room units, and central systems is available in AIRCON in the 1960, 1970 Metro2, and 1980 samples. Following Barreca et al. (2016), I use linear extrapolation of 1970 and 1980 data of CZ-level proxies to obtain the proxies in 1990.

Similarly, television (TV) ownership was asked in the 1960 and 1970 Metro1 samples in either N/A, No TV, 1, and 2+. Responses with 2+ TVs are conservatively counted as a lower bound of 2. The 1960 Census covers a subset of counties, corresponding to 214 commuting zones, covering 80% of the prime-age male population. I then apply an analogous extrapolation method to the 1960 and 1970 data to obtain proxies for 1980 and 1990. In both cases, the extrapolated ratios are bounded by 100%. Figure A-10 illustrates the distribution of air conditioners and televisions per capita across commuting zones.

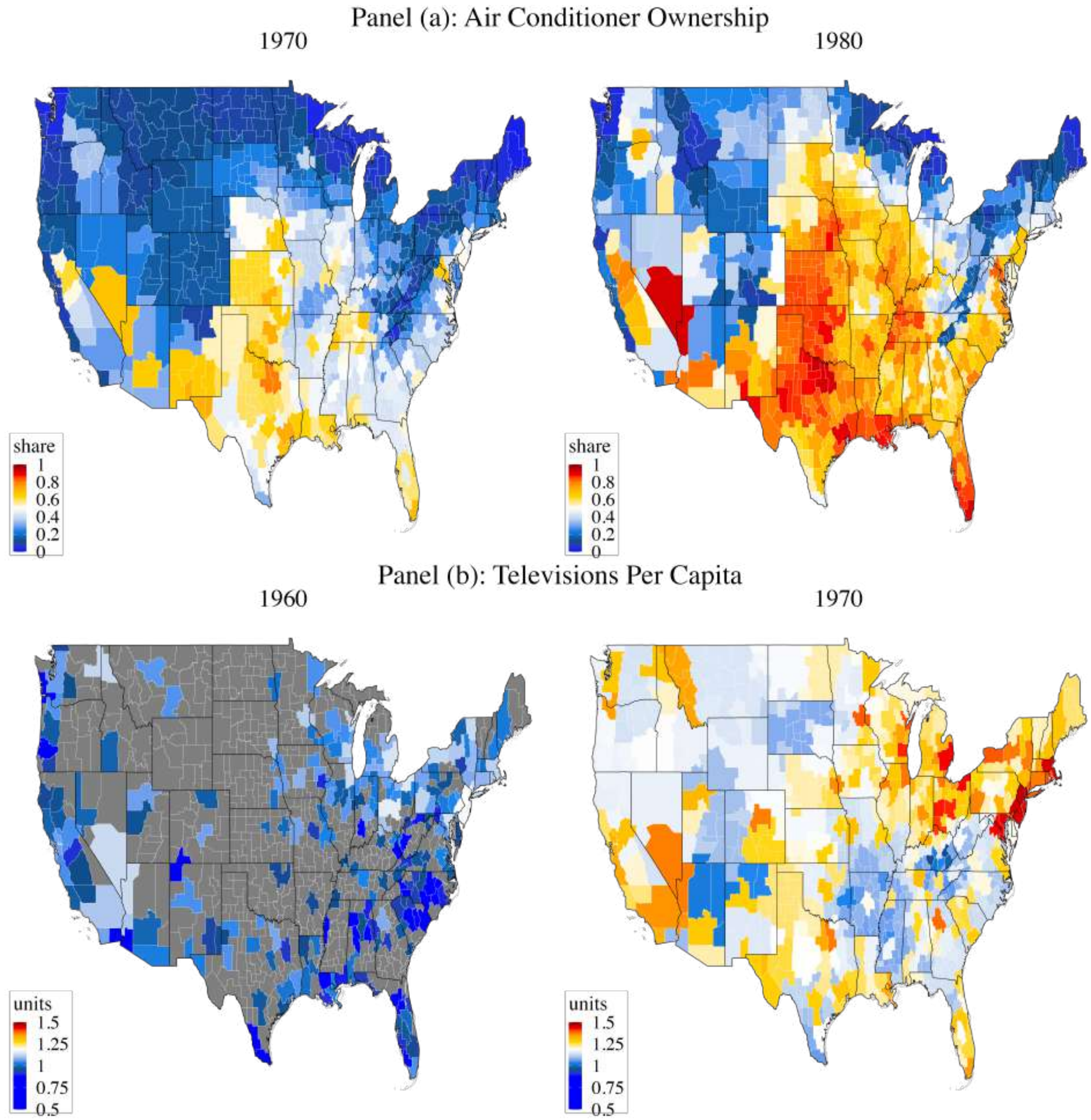


Figure A-10: Prevalence of Residential Amenities

Note: White borders indicate commuting zones. Panel (a) (Air conditioning): IPUMS of Census 1970, Metro2 and Census 1980. Panel (b) (television): IPUMS of 1960 Census and 1970 Census, Metro1. 1960 Census counties are translated to 214 commuting zones (non-gray areas), covering 80% of the prime-age male population. Gray commuting zones have no data in 1960.

A2 Analysis

A2.1 Covariates

In the baseline model (column 5 at Table 2), I include the following covariates.

- $\mathbf{C}_{i,I_t}$ (other climatological variables): average relative humidity, daily precipitation on rainy days, the number of non-rainy days, daily snowfall on days with snowfall, the number of days without snowfall, the number of days with snowfall ($\geq$10 cm) $\mathbf{C}_{i,I}$ are taken in 5-year average for each treatment window I_t.

A variable of $\mathbf{X}^g_{i,t_{-1}} = \{\mathbf{D}^g_{i,t_{-1}}, \mathbf{E}_{i,t_{-1}}, \mathbf{M}_{i,t_{-1}}, \mathbf{W}^g_{i,t_{-1}}\}$ is constructed on the previous outcome years t_{-1}.

- $\mathbf{D}^g_{i,t_{-1}}$(demography): a population share of each educational group (high school dropouts, high school graduates, some college, college graduates, above college); racial/ethnic groups (non-Hispanic whites, non-Hispanic blacks, non-Hispanic asians, Hispanics), immigrants, veterans, domestic interstate migrants (people who have crossed state borders within 5 years), 10-year age groups (age 35-44, age 45-54)

- $\mathbf{E}_{i,t_{-1}}$ (industry structure): share of employment in manufacturing, agriculture and construction; average size of establishment; Herfindahl-Hirschman index

- $\mathbf{M}_{i,t_{-1}}$(labor market variables): regional unemployment rate; a population share of elderly people (age 65 and over); a population share under poverty; population density (log)

- $\mathbf{W}^g_{i,t_{-1}}$(health and wealth variables): a population share of personal non-labor income receipt; public income receipt; home ownership

A2.2 Robustness Checks

To validate the paper's main findings of Table 2, this subsection presents a series of robustness checks.

Temperature thresholds Table A-1 evaluates the robustness of our results to alternative reasonable pairs of extreme temperature day thresholds. Columns 1-4 increase the thresholds for hot days from 73, 75, 77 to 80°F. Columns 7-9 lower the cold day thresholds from 35, 30, 25 to 15°F. I find that the negative climate effects remain statistically significant. Note that coincident with the increase in wages (Figure A-12), hot days between 75°F and 85°F hurt significantly (column 6).

Table A-1: Robustness through Temperature Thresholds

	dependent variable: **LFPR** (in %pts; prime-age males)								
		Baseline							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
10 hot days									
$\geq$ 73°F	-0.290^{***}								
	(0.084)								
$\geq$ 75°F		-0.347^{***}					-0.356^{***}	-0.355^{***}	-0.356^{***}
		(0.066)					(0.067)	(0.066)	(0.068)
$\geq$ 77°F			-0.233^{***}						
			(0.062)						
$\geq$ 80°F				-0.137^{**}	-0.304^{***}				
				(0.069)	(0.075)				
$\geq$ 75°F & $<$ 80°F					-0.680^{***}				
					(0.151)				
$\geq$ 85°F						-0.299^{***}			
						(0.082)			
$\geq$ 75°F & $<$ 85°F						-0.404^{***}			
						(0.094)			
10 cold days									
<35 °F	-0.381^{**}	-0.379^{**}	-0.395^{**}	-0.385^{**}	-0.378^{**}	-0.396^{**}			
	(0.171)	(0.170)	(0.172)	(0.172)	(0.171)	(0.166)			
<30 °F							-0.515^{***}		
							(0.188)		
<25 °F								-0.684^{***}	
								(0.169)	
<15 °F									-0.787^{***}
									(0.253)
Observations	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610	3,610
Adjusted R^2	0.875	0.876	0.874	0.874	0.877	0.876	0.876	0.877	0.876

Note: $N = 3,610$ (5 outcome years $\times$ 722 commuting zones). All models inherit treatment windows (5-year average of extreme temperature days), full controls, two-way fixed effects, regression weights, and clustering of standard errors from the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

Temperature windows Table A-2 examines the sensitivity of treatment windows I_t of extreme temperature days, hd_{i,I_t}, cd_{i,I_t} and other climate variables, $\mathbf{C}_{i,I_t}$. Longer treatment windows increase the magnitude of the climate effect with stable statistical significance. In particular, column 1 shows that a previous year's summer heat wave does not significantly affect the LFPR, suggesting that more than one year of exposure to hot days is required to adjust labor supply, consistent with a mechanism of cumulative labor cost.

Table A-2: Robustness by Treatment Windows

	dependent variable: LFPR (in %pts; prime-age males)			
	1 year	**3 years**	**5 years Baseline**	**10 years**
	(1)	(2)	(3)	(4)
10 hot days	-0.005	-0.194^{***}	-0.347^{***}	-0.526^{***}
	(0.070)	(0.059)	(0.066)	(0.136)
10 cold days	-0.242^{***}	-0.499^{***}	-0.379^{**}	-0.819^{***}
	(0.067)	(0.115)	(0.170)	(0.235)
Adjusted R^2	0.870	0.873	0.876	0.878

Note: $N = 3,610$ (5 outcome years $\times$ 722 commuting zones). All models inherit definitions of hot days and cold days except treatment windows, full controls, two-way fixed effects, regression weights, and clustering of standard errors in column 5, Table 2. *** $p < 1\%$; ** $p < 5\%$.

State-year fixed effects Table A-3 runs alternative model specifications around pre-trends and fixed effects. Including a linear time trend in Census divisions (New England, Middle Atlantic, South Atlantic, East North Central, East South Central, West North Central, West South Central, Mountain, and Pacific), states, and commuting zones does not affect the results (columns 1-3), suggesting that regional pretrends in labor supply and demand are not confounding factors. Including Census division-year or state-year fixed effects (columns 5-6), as expected, loses a substantial identification variation but largely preserves the effects of hot days.

Long differences model Table A-4 presents a long differences model estimates in column 2-6, as opposed to the baseline estimates in column 1. Columns 2-4 use a decadal interval ($\{[1980, 1990], \cdots, [2010, 2019]\}$). Column 2 uses the same set of pre-period covariates as column 1. Column 3 uses first-differencing only climate covariates, and column 4 uses first-differencing all covariates. Columns 5 and 6 take two-decade intervals ($\{[1980, 2000], [2000, 2019]\}$) with first-differenced climate variables and all co-

Table A-3: Robustness through Fixed Effects and Trends

	dependent variable: LFPR (in %pts; prime-age males)					
	Baseline	**+ division trend**	**+ state trend**	**+ czone trend**	**+ division $\times$ year FE**	**+ state $\times$ year FE**
	(1)	(2)	(3)	(4)	(5)	(6)
10 hot days	-0.347^{***}	-0.315^{***}	-0.321^{***}	-0.349^{***}	-0.244^{***}	-0.210^{***}
	(0.066)	(0.073)	(0.081)	(0.095)	(0.080)	(0.070)
10 cold days	-0.379^{**}	-0.339^{**}	-0.358^{*}	-0.222	-0.198	0.029
	(0.170)	(0.171)	(0.183)	(0.183)	(0.123)	(0.148)
czone FE	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.876	0.879	0.884	0.909	0.896	0.918

Note: $N = 3,610$ (5 outcome years $\times$ 722 commuting zones). All models inherit definitions of hot days and cold days, treatment windows (5-year average), full controls, two-way fixed effects, regression weights, and clustering of standard errors in the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

variates, respectively. The stability of the estimates suggests that the modeling strategy does not affect the climate impact.

Table A-4: Long Differences Models

	dependent variable: LFPR (in %pts; prime-age males)					
		long differences model				
	Baseline	**by decades**	**by decades**	**by decades**	**1980-2000 + 2000-2019**	**1980-2000 + 2000-2019**
	(1)	(2)	(3)	(4)	(5)	(6)
level (1) or change (2)-(6) in 10 hot days	-0.347^{***}	-0.272^{***}	-0.364^{***}	-0.315^{***}	-0.397^{***}	-0.451^{***}
	(0.066)	(0.091)	(0.082)	(0.080)	(0.116)	(0.103)
level (1) or change (2)-(6) in 10 cold days	-0.379^{**}	-0.389^{**}	-0.229	-0.253^{*}	-0.330^{*}	-0.632^{***}
	(0.170)	(0.162)	(0.145)	(0.152)	(0.191)	(0.198)
baseline covariates	Yes	Yes	-	-	-	-
			first-differenced covariates			
only other climate variables	-	-	Yes	-	Yes	-
all other covariates	-	-	-	Yes	-	Yes
Observations	3,610	2,888	2,888	2,888	1,444	1,444
Adjusted R^2	0.876	0.787	0.796	0.781	0.876	0.857

Note: Long differences models in column 2-4 stack 722 commuting zones $\times$ 4 intervals (of decades), while those in column 5-6 stack 722 commuting zones $\times$ 2 intervals (of two decades). Models inherit definitions of hot days and cold days and clustering of standard errors in the baseline model, column 5 of Table 2. Models include year fixed effects and are weighted by the start-of-interval commuting zone's share of the national prime-age population of males. See the definition of covariates in the main text. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

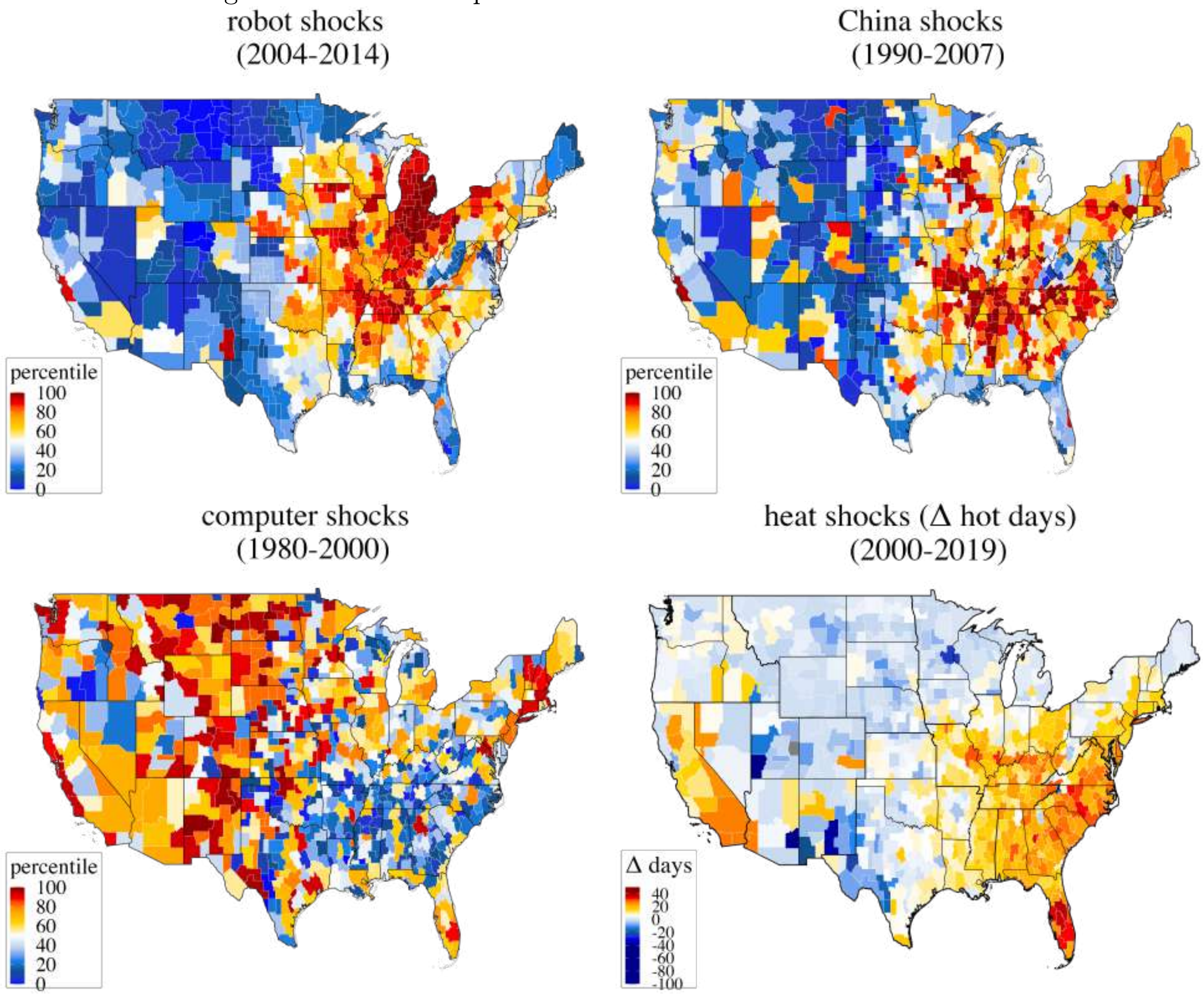
Labor demand shocks Table A-5 reports the estimates from subsamples excluding CZs that were severely affected by a particular labor demand shock. Computer shocks are changes in exposure to PCs per employee (*d_rpc*) in 1980-2000, borrowed from Autor and Dorn (2013). Robot shocks are changes in industrial robots per employee (*expof_us_adj04_14_*) in 2004-2014, constructed from Acemoglu and Restrepo (2020). China shocks are proxies for international trade competition with China (*d_tradeusch_pw*) in 1990-2007, constructed from Autor, Dorn and Hanson (2013). A set of CZs particularly affected by these shocks is specified by percentiles (25 pct. or 50 pct.) of CZ-level shocks. Excluding these areas does not weaken the robustness of the main estimates.

Table A-5: Leave-One-Out Analysis of Labor Demand Shocks

	dependent variable: **LFPR** (in %pts; prime-age males)						
		drop		drop		drop	
	Baseline	czones (< 25 pct.)	czones (< 50 pct.)	czones (< 25 pct.)	czones (< 50 pct.)	czones (< 25 pct.)	czones (< 50 pct.)
		hit by **computer shocks**		hit by **robot shocks**		hit by **China shocks**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
10 hot days	-0.347^{***}	-0.335^{***}	-0.315^{***}	-0.388^{***}	-0.400^{***}	-0.393^{***}	-0.345^{***}
	(0.066)	(0.072)	(0.087)	(0.071)	(0.097)	(0.064)	(0.080)
10 cold days	-0.379^{**}	-0.399^{**}	-0.409^{**}	-0.384^{*}	-0.386^{*}	-0.395^{**}	-0.336^{*}
	(0.170)	(0.170)	(0.180)	(0.197)	(0.210)	(0.178)	(0.195)
Observations	3,610	2,705	1,805	2,705	1,805	2,705	1,805
Adjusted R^2	0.876	0.875	0.878	0.879	0.888	0.877	0.883

Note: Unit of analysis: 5 outcome years × commuting zones of interest. All models inherit definitions of hot days and cold days, treatment windows (5-year average), full controls, two-way fixed effects, regression weights, and clustering of standard errors in the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

Figure A-11: Heat Map of Labor Demand Shocks vs. Heat Shocks



Note: Computer shocks are *d_rpc* from Autor and Dorn (2013). Robot shocks are *expof_us_adj04_14_* from Acemoglu and Restrepo (2020). China shocks are *d_tradeusch_pw* from Autor, Dorn and Hanson (2013). The shocks are normalized in percentile. The thresholds for hot days are set at 75°F of the median temperature during business hours (8 am-6 pm). I take a change of a five-year average number of hot and cold days from 2000 (during 1995-1999) to 2019 (during 2014-2018).

Agriculture Table A-6 tests whether the climate effect is driven by the agricultural sector. Columns 2-4 drop agriculture-intensive 112, 288, 505 commuting zones, measured by 1970 employment shares of agricultural workers above 15%, 10%, 5%, respectively. Despite the shrinking sample size, the estimates are quite stable.

Table A-6: Robustness to Exclusion of Agriculture

	dependent variable: **LFPR** (in %pts; prime-age males)			
	Baseline	drop agri-intensive czones ($> 15\%$)	drop agri-intensive czones ($> 10\%$)	drop agri-intensive czones ($> 5\%$)
	(1)	(2)	(3)	(4)
10 hot days	-0.347^{***}	-0.349^{***}	-0.312^{***}	-0.314^{***}
	(0.066)	(0.068)	(0.071)	(0.077)
10 cold days	-0.379^{**}	-0.419^{**}	-0.417^{**}	-0.398^{**}
	(0.170)	(0.171)	(0.189)	(0.187)
Observations	3,610	3,050	2,170	1,085
Adjusted R^2	0.876	0.879	0.885	0.896

Note: $N = 3,610$ (5 outcome years × 722 commuting zones) for column 1 and 5. Columns 2-4 respectively uses 610, 434, and 217 commuting zones. All models inherit definitions of hot days and cold days, treatment windows (5-year average), full controls, two-way fixed effects, regression weights, and clustering of standard errors in the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

Weather conditions Table A-7 explores the sensitivity to alternative climate proxies. Column 1 repeats a baseline (column 5, Table 2). Column 2 uses uncomfortable days with discomfort index above 75, as a function of relative humidity and temperature in the formula (A2), showing significantly larger effects. Column 3 narrows down to non-rainy uncomfortable days, yielding larger and more precise estimates. Similarly, column 4 splits the climate effect between rainy days and non-rainy days, and shows that the effect is larger on non-rainy days. Column 5 shows that a simpler proxy for the median daily temperature within a year has a negative effect on labor supply.

Table A-7: Robustness through Climate Proxies

	dependent variable: **LFPR** (in %pts; prime-age males)				
	Baseline				
	(1)	(2)	(3)	(4)	(5)
10 hot days	-0.347^{***}				
	(0.066)				
10 uncomfortable days		-3.828^{***}			
		(0.933)			
10 non-rainy uncomfortable days			-5.245^{***}		
			(0.850)		
10 cold days	-0.379^{**}	-0.408^{**}	-0.393^{**}		
	(0.170)	(0.172)	(0.162)		
10 non-rainy hot days				-0.465^{***}	
				(0.073)	
10 rainy hot days				0.041	
				(0.132)	
10 non-rainy cold days				-0.543^{***}	
				(0.170)	
10 rainy cold days				-0.085	
				(0.226)	
median temperature (°F)					-0.249^{***}
					(0.063)
Adjusted R^2	0.876	0.876	0.878	0.878	0.874

Note: $N = 3,610$ (5 outcome years $\times$ 722 commuting zones). Models inherit thresholds of hot days and cold days, treatment windows (5-year average), full controls, two-way fixed effects, regression weights, and clustering of standard errors in the baseline model, column 5 of Table 2. Uncomfortable days have discomfort index above 75, computed by the formula (A2). *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

Seasons Table A-8 examines the climate impact by seasons within the year. Columns 1 and 2 highlight the contrast in climate impact between business days and holidays. Columns 3 and 4 show intense warming impacts in summer quarters (Jun-Aug) and cooling impacts in winter quarters (Jan, Feb and Dec). By contrast, hot days in winter and cold days in fall show weak positive estimates $(0.693\,(t = 1.6), 0.823\,(t = 1.7)$, respectively in column 4).

Table A-8: Robustness through Seasons of Climate Change

	dependent variable: LFPR (units: %pts; prime-age males)			
	Baseline			
	(1)	(2)	(3)	(4)
10 hot business days	-0.563^{***} (0.101)			
10 cold business days	-0.626^{**} (0.246)			
10 hot holidays		-0.467^{**} (0.192)		
10 cold holidays		-0.304 (0.347)		
10 hot days in summer			-0.412^{***} (0.143)	-0.406^{***} (0.155)
10 hot days in non-summer			-0.249^{***} (0.093)	
10 hot days in winter				0.693 (0.438)
10 hot days in spring				-0.675^{***} (0.222)
10 hot days in fall				-0.222 (0.145)
10 cold days in winter			-0.701^{***} (0.184)	-0.713^{***} (0.193)
10 cold days in non-winter			0.606^{**} (0.253)	
10 cold days in spring				0.343 (0.291)
10 cold days in fall				0.823^{*} (0.473)
Observations	3,610	3,610	3,610	3,610
Adjusted R^2	0.877	0.873	0.878	0.880

Note: $N = 3,610$ (5 outcome years $\times$ 722 commuting zones). Business days are weekdays excluding national holidays, and holidays are Saturdays/Sundays and national holidays. Summer: Jun-Aug. Winter: Jan, Feb and Dec. Spring: Mar-May, Autumn: Sep-Nov. All models inherit definitions of hot days and cold days, treatment windows (5-year average), full controls, two-way fixed effects, regression weights, and clustering of standard errors in the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

Immigrants Table A-9 tests the robustness of subsample analysis by excluding immigration-intensive CZs. Column 1 repeats a baseline model. Columns 2-4 use a subset of 722 CZs, excluding those above the 25th, 33th, and 50th percentiles of the population share of prime-age male immigrants in 2019. The climate impact, especially, warming impacts, are broadly stable.

Table A-9: Robustness by Excluding Immigration-intensive CZs

	dependent variable: LFPR (in %pts; prime-age males)			
		exclude CZs with a popu. share of immigrants in 2019		
	baseline	$\geq$ 25 pct	$\geq$ 33 pct	$\geq$ 50 pct
	(1)	(2)	(3)	(4)
10 hot days	-0.347^{***}	-0.315^{***}	-0.352^{***}	-0.467^{***}
	(0.066)	(0.092)	(0.100)	(0.136)
10 cold days	-0.379^{**}	-0.278^{***}	-0.293^{**}	-0.189
	(0.170)	(0.105)	(0.122)	(0.165)
Observations	3,610	2,705	2,405	1,805
Adjusted R^2	0.876	0.901	0.900	0.900

Note: All models inherit definitions of hot days and cold days, treatment windows (5-year average), full controls, two-way fixed effects, regression weights, and clustering of standard errors in the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

Clustering units The baseline model uses a unit of analysis, commuting zone (CZ), as a unit of clustering errors. However, changes in temperature or other climate variables over the long term may be correlated across neighboring CZs. Columns 2-4 in Table A-10 show estimates under clustering neighboring CZs within a distance between population centroid of 10 km, 50 km and 100 km, respectively, and column 5 clusters errors by states. Relative to the baseline at column 1, the estimates are largely preserved.

Table A-10: Robustness by Clustering Units

	dependent variable: **LFPR** (in % pts; prime-aged males)				
	czone Baseline	**neighbors (< 10km)**	**neighbors (< 50km)**	**neighbors (< 100km)**	**state**
	(1)	(2)	(3)	(4)	(5)
10 hot days	-0.347^{***}	-0.347^{***}	-0.347^{***}	-0.347^{***}	-0.347^{***}
	(0.066)	(0.066)	(0.066)	(0.061)	(0.074)
10 cold days	-0.379^{**}	-0.379^{**}	-0.379^{*}	-0.379^{*}	-0.379^{*}
	(0.170)	(0.169)	(0.195)	(0.194)	(0.223)
Adjusted R^2	0.876	0.876	0.876	0.876	0.876

Note: $N = 3,610$ (5 outcome years $\times$ 722 commuting zones). All models inherit definitions of hot days and cold days, treatment windows (5-year average), full controls, two-way fixed effects, and regression weights in the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

A2.3 Regional Heterogeneity

Table A-11 examines how climate impacts vary by the level of economic development. Column 1 reports the positive estimates of the interaction terms of log-scaled population density in the pre-period outcome year t_{-1} and extreme temperature days, suggesting that more densely populated urban areas experienced less damage. Similarly, column 2 reports positive estimates paired with the share of employment in the service sector in the pre-period outcome year t_{-1}, as outdoor workers may shift to low-skilled indoor jobs in the service sector under climate stress. Consistently, columns 3-4 examine a dropout rate, and report expectedly negative estimates. Overall, Table A-11 supports that climate impacts are regressive for rural areas, where outdoor jobs are prevalent and alternative indoor jobs are poorly available.

Table A-11: Regional Heterogeneity: Urban vs. Rural Areas

	LFPR (in %pts; prime-age males)		**dropout rate**	
	(1)	(2)	(3)	(4)
10 hot days	-1.053^{***}	-0.683^{***}	0.514^{***}	0.334^{***}
	(0.167)	(0.129)	(0.091)	(0.088)
10 cold days	-1.150^{***}	-1.158^{***}	0.579^{***}	0.667^{***}
	(0.245)	(0.207)	(0.127)	(0.121)
10 hot days × *log*(pop density)	0.162^{***}		-0.089^{***}	
	(0.033)		(0.018)	
10 cold days × *log*(pop density)	0.172^{**}		-0.096^{***}	
	(0.163)		(0.115)	
10 hot days × share of employment in services		0.550^{***}		-0.345^{***}
		(0.165)		(0.161)
10 cold days × share of employment in services		1.295^{***}		-0.862^{***}
		(0.255)		(0.169)
Adjusted R^2	0.881	0.879	0.907	0.907

Note: $N = 3,610$ (5 outcome years × 722 commuting zones). *log*(pop density) and share of employment in services are taken at the pre-period outcome year. All models inherit definitions of hot days and cold days, treatment windows (5-year average), full controls, two-way fixed effects, regression weights, and clustering of standard errors in the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$.

A2.4 Adaptation

Table A-12 estimates heterogeneity across climate regions and periods. Column 1 interacts regional climate benchmarks (i.e., 5-year average hot and cold days in 1970) with subsequent warming/cooling, suggesting adaptation for hot days (+0.020) in initially hot areas. Column 2 interacts with a gap of hot and cold days in 1970. Consistently, initially warm regions adapted slightly for additional climate shocks. Column 3 allows a model to estimate the impact variant by decadal period lapse, showing within-CZ adaptation for both hot and cold days (+0.021 vs. + 0.061). Acclimation is larger for cold days, which makes sense because cold days have become fewer and milder in the continental US.

Table A-12: Heterogeneity by Time and Space

	dependent variable: **LFPR** (in %pts; prime-age males)		
	(1)	(2)	(3)
10 hot days	-0.597^{***}	-0.526^{***}	-0.351^{***}
	(0.154)	(0.123)	(0.074)
10 cold days	-0.166	-0.462^{**}	-0.391^{**}
	(0.247)	(0.196)	(0.168)
10 hot days × 1970 hot days	0.020^{*}		
	(0.010)		
10 cold days × 1970 cold days	-0.039		
	(0.028)		
10 hot days × 1970 hot days − cold days		0.018^{**}	
		(0.008)	
10 cold days × 1970 hot days − cold days		0.011	
		(0.015)	
10 hot days × periods			0.021^{***}
			(0.008)
10 cold days × periods			0.061^{***}
			(0.014)
Adjusted R^2	0.876	0.876	0.878

Note: $N = 3,610$ (5 outcome years × 722 commuting zones). All models inherit definitions of hot days and cold days, treatment windows (5-year average), full controls, two-way fixed effects, regression weights, and clustering of standard errors in the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

A3 Discussions

A3.1 Migration

Table A-13 examines the effect of climate change on inter-CZ migration. Panel A uses the baseline model to explore the sensitivity of the population size of prime-age males. Column 1 looks at the total population of prime-age males, and finds no significant responses. Column 2 finds null effects for the population of non-college graduates. Column 3 finds a slightly significant negative effect of cold days on the population of college graduates.

Columns 4 and 5 show shrinking inflows; column 4 shows that the share of interstate migrants (within the last 5 years for 1980-2000, and within 1 year for 2010 and 2019) shrinks significantly with extreme temperature days. Column 5 shows that the share of people who moved to their current residence within 5 years shrinks significantly with warming. In contrast, column 6 shows that the share of prime-age males residing in the state of birth increases with warming, suggesting shrinking outflows. Panel B replicates the analysis by including Census division trends.[64].

[64]Nine Census divisions consist of New Englands, Middle Atlantic, South Atlantic, East North Central, East South Central, West North Central, West South Central, Mountain, and Pacific.

Table A-13: Climate Change and Cross-regional Migration

	dependent variable: **Population Size (log-scaled)** (in percent; prime-age males)					
	Total	**Non-college grads**	**College grads**	**Moved-in between states**	**Moved-in in 5 yrs**	**Born at the state of residence**
			Panel A: Baseline			
	(1)	(2)	(3)	(4)	(5)	(6)
10 hot days	-0.902	-0.422	-0.830	-3.342^{**}	-2.576^{***}	1.750^{***}
	(0.610)	(0.581)	(0.765)	(1.644)	(0.993)	(0.608)
10 cold days	-1.031	-0.776	-1.588^{*}	-5.785^{***}	-1.264	0.825
	(0.708)	(0.709)	(0.956)	(2.101)	(0.918)	(0.975)
Adjusted R^2	0.999	0.999	0.997	0.987	0.997	0.997
			Panel B: Add Census division trends			
	(1)	(2)	(3)	(4)	(5)	(6)
10 hot days	-0.861	-0.414	-0.703	-2.970^{**}	-2.096^{**}	2.187^{***}
	(0.585)	(0.571)	(0.785)	(1.468)	(0.850)	(0.546)
10 cold days	-1.000	-0.864	-1.148	-5.507^{***}	-0.600	1.691^{*}
	(0.731)	(0.727)	(0.994)	(1.998)	(0.926)	(0.893)
Census division trends	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.999	0.999	0.998	0.987	0.997	0.997

Note: $N = 3,610$ (5 outcome years $\times$ 722 commuting zones). Due to a change in a survey question, the time frame for "moved-in between states" is within 5 years for the 1980-2000 Census and within 1 year for the 2009-2010, 2018-2019 pooled ACS. All models inherit definitions of hot days and cold days, treatment windows (5-year average), full controls, two-way fixed effects, regression weights, and clustering of standard errors in the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

A3.2 Labor Demand Channel

Wage analysis Panel A of Figure A-12 illustrates the semi-parametric bin (10°F) estimate of the climate impact on weekly wages across CZs-by-10 private sectors-by-5 education groups. Relative to the benchmark bin of $[65, 75)$°F, one can see the increase in weekly wages for very hot days ($[95, \infty)$°F), mildly hot days ($[75, 85)$°F), and very cold days (< 15°F), decrease in wages for cold days ($[25, 35)$°F), and insignificant effects on wages from other temperature bins. The pattern is sustained in Panel B-D, using hourly wage or alternative unit of analysis.

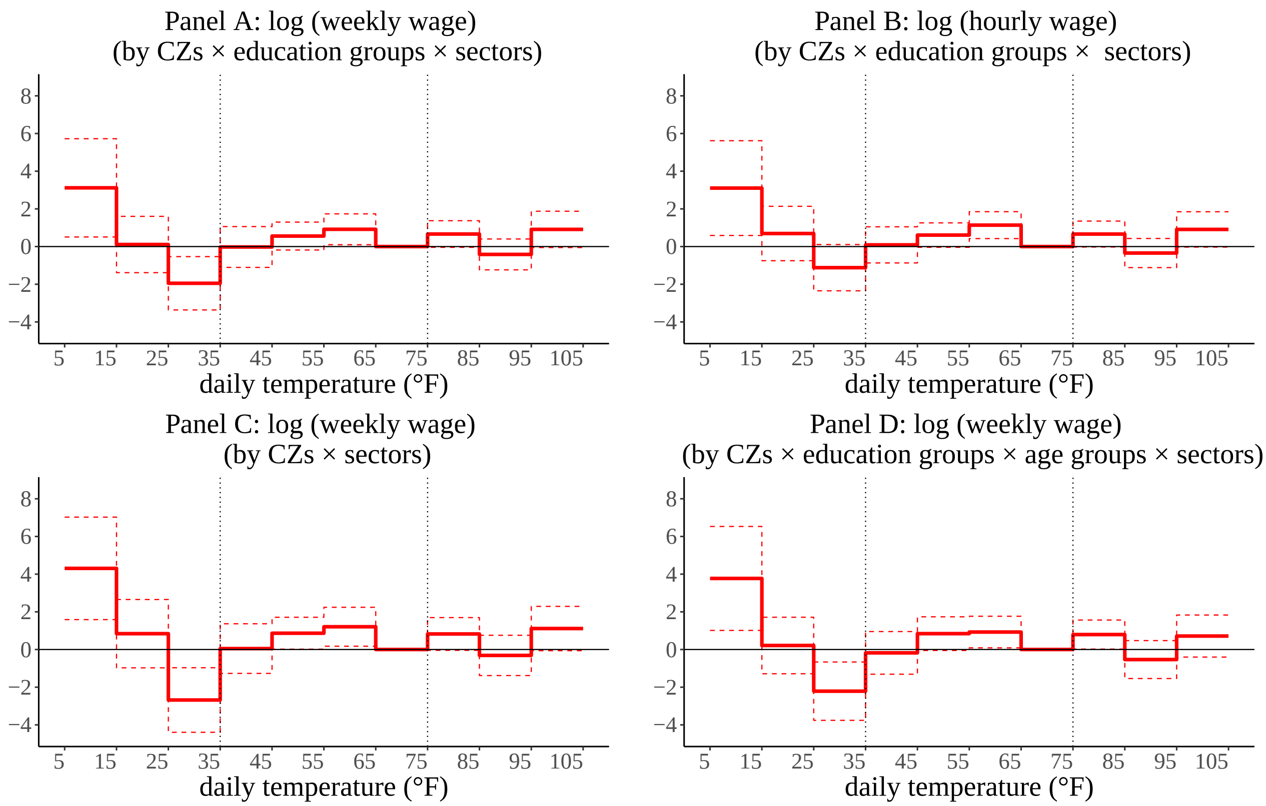


Figure A-12: Semi-parametric Climate Impacts on Wage within Sectors

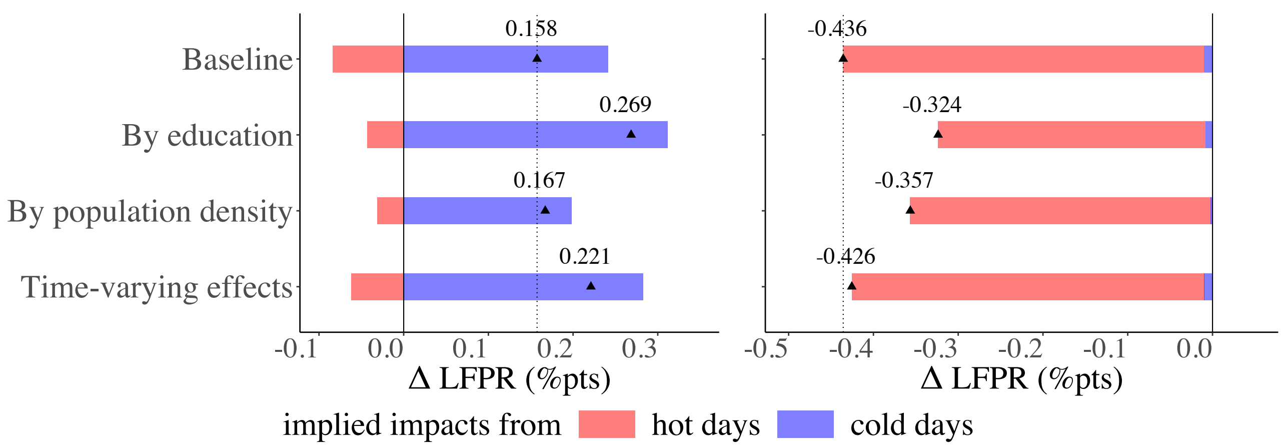
Note: Unit of analysis: 5 outcome years × cells. In each panel, cells are formed from 722 commuting zones, 5 education groups, 3 age groups and 10 private sectors (Table 5). Wages in each cell are calculated for prime-age male workers, excluding the self-employed. Bin estimates of log wages as the outcome variable relative to a baseline bin (65-75°F) are shown with 95% confidence intervals (red dashed lines). All models inherit treatment windows (5-year average), full controls, fixed effects at the level of cell and sector-state-year, regression weights, and clustering of standard errors.

A4 Assessment

Alternative models

For robustness, I use estimates from alternative models. The baseline model is column 5 in Table 2. In "By education", I use subsample models with coefficients specific to three education groups (HS graduate and less, some college, college graduate), used in columns 3-5 of Panel A of Table 3. "By population density" denotes a model that allows the climate effect to vary with population density (column 1, Table A-11). "Time-varying effects" suggests a model that estimates time-varying effects in outcome years $t \in \{1980, 1990, 2000\}$ vs. $\{2010, 2019\}$. Reassuringly, the overall valuation is unchanged across modeling specifications. Using each model in order, the climate effect explains 15.1%, 11.2%, 12.4%, 14.8% of the an overall decline in LFPR during 2000-2019, $-2.88\%pts$ (linear trend) from the BLS headline figure.

Table A-14: Robustness of Aggregate Impacts through Alternative Models



Note: Except for the explicit feature of the model, all models inherit the definitions of hot days and cold days, treatment windows (5-year average), full controls, two-way fixed effects, regression weights, and clustering of standard errors in column 5, Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

Composition of climate-induced dropouts

Figure A-13 illustrates the implied share of calculated climate-induced dropouts by climate region, commuting zone of different population size, and education group. Panel (a) uses the dropout estimates from column 6 of Table 4. Panel (b) uses the dropout estimates from column 3 of Table A-11. Panel (c) takes the nonparticipation estimates from the subsample analysis across education groups in columns 3-5 of Panel (a) of Table 3, assuming that the ratio of dropouts to nonparticipants is the same across education groups. Then, the nationwide number of climate-induced dropouts during 2000-2019 is aggregated from the interaction of CZ-level climate exposure, their respective estimates, and CZ-level prime-age male population in 2000.

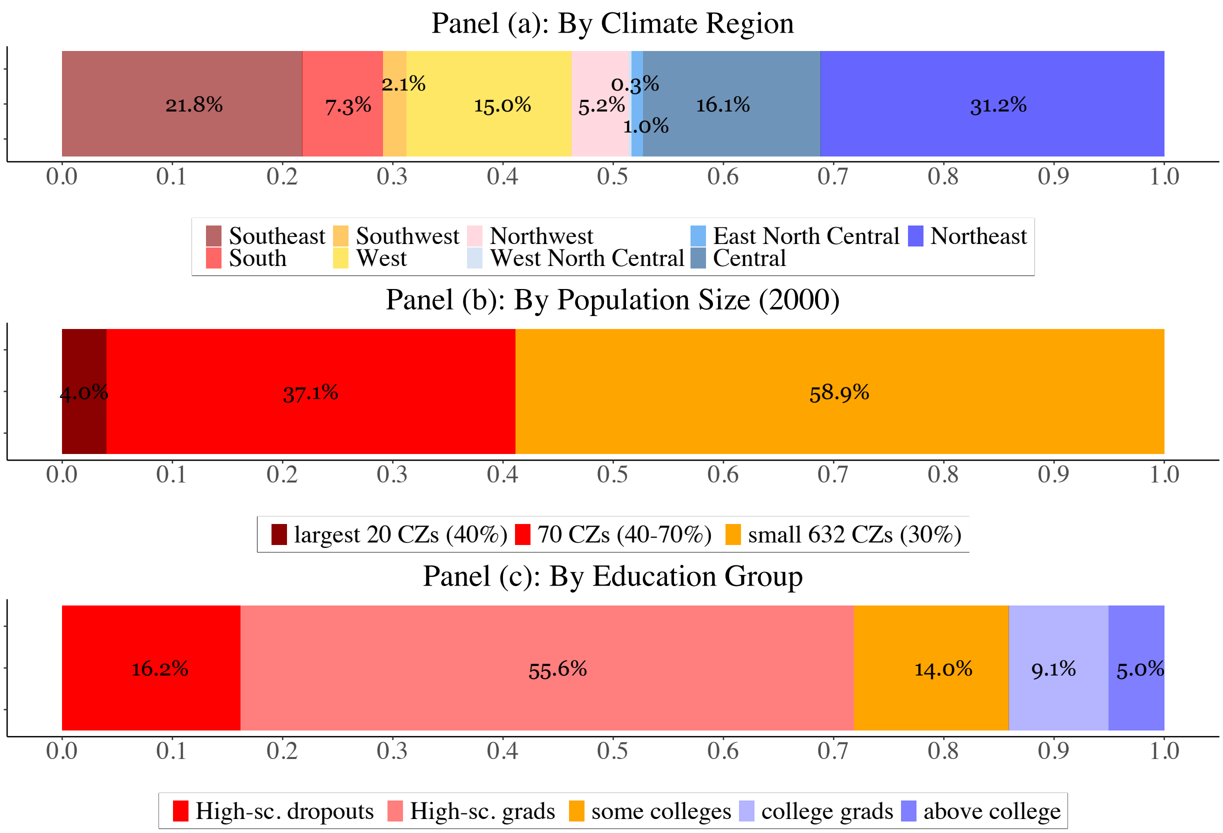


Figure A-13: Implied Composition of Climate-induced Dropouts during 2000-2019

Note: Climate regions are from NOAA. Population size is measured by non-institutionalized, prime-age males in 2000. The 20 largest CZs include Los Angeles, New York City, Chicago, Newark, Detroit, Philadelphia, San Francisco, Boston, Washington, DC, Houston, Atlanta, Seattle, Miami, Dallas, Bridgeport, Phoenix, Minneapolis, San Diego, Denver, and San Jose. See above for a simulation procedure.