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Climate Change and Outdoor Jobs: The Rise of Adult Male Dropouts

Masahiro Yoshida

Waseda INstitute of Political EConomy
Waseda University
Tokyo, Japan

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Masahiro Yoshida†

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Abstract

Male labor force participation rates (LFPR) in developed economies have been declining since the 1970s. This paper argues that modern climate change has fueled dropouts of adult males by eroding the traditional advantage of working outdoors. Using exposure to climate change across US commuting zones constructed from granular daily weather records for nearly half a century, I find that extreme temperature days hurt the LFPR of prime-age males. In the new century, climate change accounts for approximately 10-15 percent of the nationwide decline in LFPR. I find that outdoor jobs—prevalent across sectors and prominent in disadvantaged regions—are likely hotbeds of dropout. Disability accounts for a substantial proportion of climate-induced dropouts, but the majority of these are likely due to preference; the decline in LFPR has been catalyzed by the spread of housing amenities (e.g., air conditioning and cable TV) and access to affluent family backgrounds. Overall, the results suggest that climate change exacerbates socioeconomic inequality.

JEL Classification: J21, J22, Q54

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

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†Department of Political Science and Economics, Waseda University, Tokyo
E-mail: m.yoshida@waseda.jp

1 Introduction

The Earth has become and will continue to be a hotter planet. Climatology found that the global temperature rise is unprecedented for two millennia since the late 19th century, trended up around the 1970s[1], and further accelerated after 2000—currently ends up being called as "global boiling" (Guterres, 2023)[2]. Economists and climate scientists have extensively studied climate impacts on ecosystems and agricultural production (Mendelsohn, Nordhaus and Shaw (1994); Deschênes and Greenstone (2007)), as well as countermeasures to reduce CO2 emissions (Nordhaus (2019)). However, little is known about how climate change has shaped human behavior in the labor market. The dearth of research is surprising, given the historical centrality of outdoor workplaces, especially for men privileged by their muscular strength, in securing food, building structures, transporting goods, and protecting the communities, which has traditionally been viewed as a socioeconomic duty of masculinity.

This paper advances a novel 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[3]. 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%[4], 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.

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[1] See e.g., Masson-Delmotte et al. (2021), Intergovernmental Panel on Climate Change (IPCC) and Esper, Torbenson and Büntgen (2024).

[2] In July 2023, the United Nations Secretary-General, António Guterres announced that "The era of global warming has ended. The era of global boiling has arrived."

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

[4] From the US Bureau of Labor Statistics.

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.

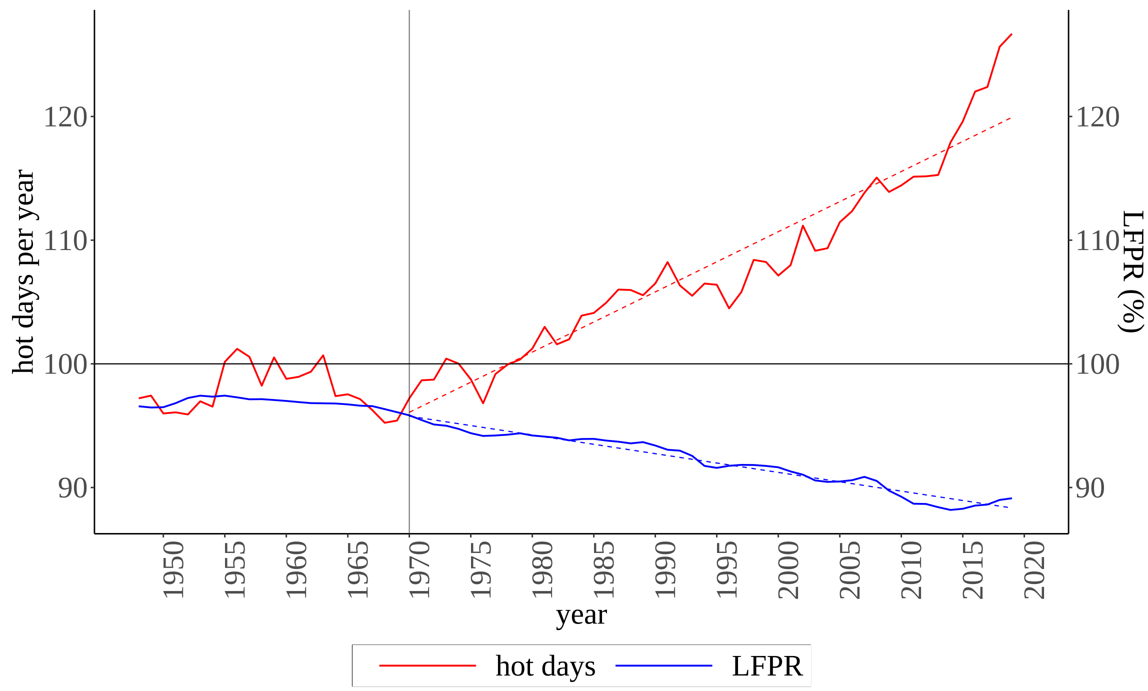

Figure 1: Nationwide Trend of Annual Hot Days and Labor Force Participation Rate (LFPR) of Prime-age Males (1950-2019, US)

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 jobs in indoor manufacturing plants or business offices have evaporated over time (Autor, Katz and Kearney (2006); Autor and Dorn (2013)). Notably, outdoor jobs remain prevalent in disadvantaged, low-wage regions, where alternative, low-skill indoor jobs (e.g., restaurant waiter, supermarket cashier, office clerk) are poorly filled.

For those skeptical readers, 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)). To prevent injuries, outdoor workers 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). Exposure to hot days would reduce labor efficiency (see Lai et al. (2023) for a survey.), 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.

Intriguingly, 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. In addition, cohabitation with parents in the baby boomer generation (Fry, Passel and Cohn (2020)), as well as the increased labor supply of female spouses/partners (Stephens (2002)), provided informal social security for a dropout lifestyle. 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. In the age of "global boiling," the argument evokes the cautionary tale of "the frog in the boiled water"[5].

[5]"If you throw a frog in a pot of boiling water, it will hop right out. But if you put that frog in a pot of

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, unconditionally independent of technological/trade competition shocks or institutional changes (e.g., union rules), I control for potentially confounding industry structure and sociodemographic variables.

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.[6] The response is systematically stronger for less educated males, males under the age of 45, on humid hot days and on business days (weekdays except national holidays), 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 job growth in retail (e.g., supermarkets) and personal services (e.g., restaurants, education/health). Despite the significant employment loss from hot days (above 75°F), I find no effect of warming on total wages, but a more flexible model shows significant *increases* in total wages from scorching hot days (above 95°F), severely cold days (below 20°F), and mildly hot days (75-85°F)—suggesting that the supply

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tepid water and slowly warm it, the frog doesn't figure out what going on until it's too late." (Old proverb, in Meyer (2008)) This story warns that people may adapt immediately to an acute shock (i.e., a heat wave), but fall into catastrophe (i.e., labor market dropouts) under an incremental change (i.e., long-run global warming).

[6] 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.

of outdoor jobs shrinks to offset or even partially exceed the shrinking demand.

The analysis naturally raises a puzzling question about the motivation of climate-induced dropouts: whether adult men cannot work because of a disability or simply do not want to work. Alarmingly, I find that extreme temperature days generate self-reported disability and Social Security Disability Insurance (SSDI) recipients in physical and mental disorders. However, I find that climate change has produced even more non-disabled dropouts, suggesting that disability alone cannot account for the overall climate effect. Moreover, 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). Intriguingly, the effect is also magnified by their access to family wealth of the retired parental generation or working women. Putting pieces of evidence together, I conclude that climate-induced dropouts are not primarily a consequence of public health disasters, but should be understood as adaptation of their lifestyles.

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[7]. 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 alternative indoor jobs as climate shelters. Since pre-industrial times, adult males have been tied to the labor market by their advantage in outdoor jobs. In the age of climate change, however, the evidence casts a shadow on this classic narrative—outdoor jobs are likely to serve as a breeding ground for male dropouts, widening the nation's socioeconomic divide.

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

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

provides a novel climate perspective on the longstanding literature on the labor supply of prime-age men[8], 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)); free trade (Autor, Dorn and Hanson (2013)) and offshoring (Harrison and McMillan (2011); Ebenstein et al. (2014))[9], 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 virtually no attention in the study of labor supply.

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 labor supply.

Second, this paper complements the burgeoning body of environmental research that finds declining labor productivity and employment (see Lai et al. (2023) for a review). 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. Because they use establishment-level data, all of these papers are inherently

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

[9]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.

silent on labor supply, 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.[10]

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 work and outdoor leisure. To the best of my knowledge, my paper is the first to bridge climate change and labor supply, 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. The estimation model and results are presented in Section 3. Section 4 uncovers the mechanism behind the main results. Section 5 quantitatively assesses the nationwide climate impact, its regressive nature, and policy implications. Section 6 concludes.

2 Data

To empirically identify climate impacts, I construct a panel data combining climate exposure and labor market attachment from 1980-2019[11]. As a regional labor market unit, I use a commuting zone (or CZ) as a combination of several neighboring counties (Tolbert and Sizer (1996))[12]. 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.

[10] 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)).

[11] 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.

[12] To consistently measure the LFPR of prime-age males since 1980, a commuting zone is the finest publicly available geographic unit.

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 d's maximum and minimum temperature T_d^{max}, T_d^{min}, precipitation, snowfall. I complementarily use another set of station records from NOAA'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 (e.g., Barreca et al. (2016) and many others): for each proxy, after restricting to weather stations with complete records in a given year, records from the 3 stations closest to each CZ population centroid[13] are averaged weighted with an inverse of the square of the distance from the centroid.

Climate at work To measure a daily temperature, I construct a daily temperature T_d as a weighted average of these two s.t. $T_d = \omega T_d^{max} + (1-\omega)T_d^{min}$ where $\omega \in (0,1)$ is a weight to the maximum. The majority of the literature conventionally uses the mean ($\omega = 0.5$) of daily maximum and minimum temperatures[14]. However, I find that taking an arithmetic mean significantly underestimate the business hour temperature. I compute a month m by week w CZ i-specific $\omega_{m,w,i}$ to match the median temperature during business hours including commuting hours (8am-6pm), using the within-day hourly temperature variation averaged during 1980-2010 from the alternative Climate Normals dataset from NCEI. A seasonal distribution of $\omega_{m,w,i}$ is substantial: a median ω is 0.8 in the summer versus 0.68 in the winter

[13]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).

[14]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.

(Figure 2; left). Consequently, a conventional daily mean with $\omega = 0.5$ ignores the strong seasonality of the within-day temperature cycle and thus substantially underestimates the actual temperature workers and commuters are exposed to during the day (Figure 2; right).

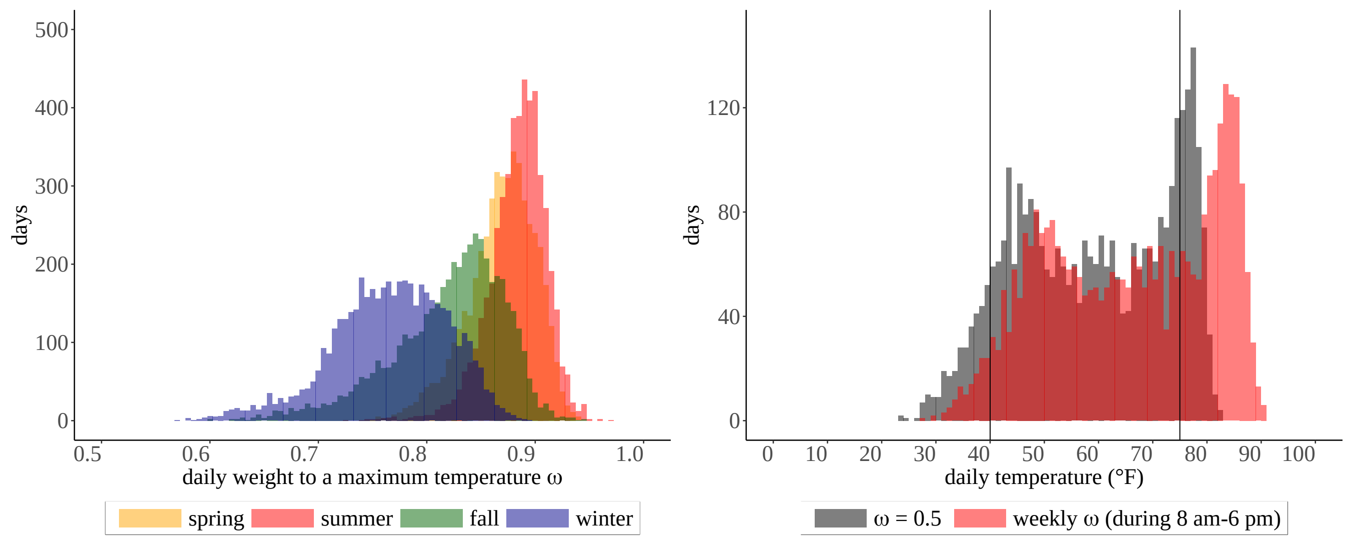


Figure 2: Distribution of Daily Temperature Weight on the Maximum across Seasons (left) and Annual Distribution of Temperature by Weight (right)

Note: (left) A unit of observation is $\omega_{m,w,i,t}$, computed in weekly averages among four weeks within each month, constructed from station records by Climate Normals, 1980-2010. Each year is divided into four quarters: Spring; Mar-May Summer; Jun-Aug Fall; Sep-Nov Winter; Dec, Jan, and Feb. (right) A unit of observation is a daily temperature within a year, averaged over 2011-2019, assigned to each bin. Gray bins show daily distributions with temperature computed with $\omega = 0.5$, as the arithmetic mean of the maximum and minimum temperature of the GHCN-daily. Red bins show those computed with month-by-week $\omega_{m,w,i,t}$, adjusted to fit the median temperature during 8 am-6 pm using Climate Normals (see main text for details).

Taking into account the hourly temperature fluctuations, I find that the median temperature during business hours (8am - 6pm) 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. Proxying climate change as a 5-year prior average of the annual number of hot and cold days, with median daily business hour temperature cutoffs of 75°F and 35°F, respectively, I document a dramatically rich variation of climate change, both between and within states, where some regions actually experienced cooling (see Figure A-3).

2.2 Labor Supply—The Rise of Adult Male Dropouts

As a key result 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[15]) 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 American Community Survey (ACS, in 2010 and 2019[16])—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, most of commuting zones had high LFPRs above 90 percent. By 2019, however, the US witnessed a significant decline in LFPR, albeit with large regional variation (Panel (a1) of Figure 5).

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. In order to highlight 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[17].

[15]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).

[16]To ensure sample size, I stack each ACS sample with a 2-year sample of 2009-2010 and 2018-2019.

[17]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 (2010-2019 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.

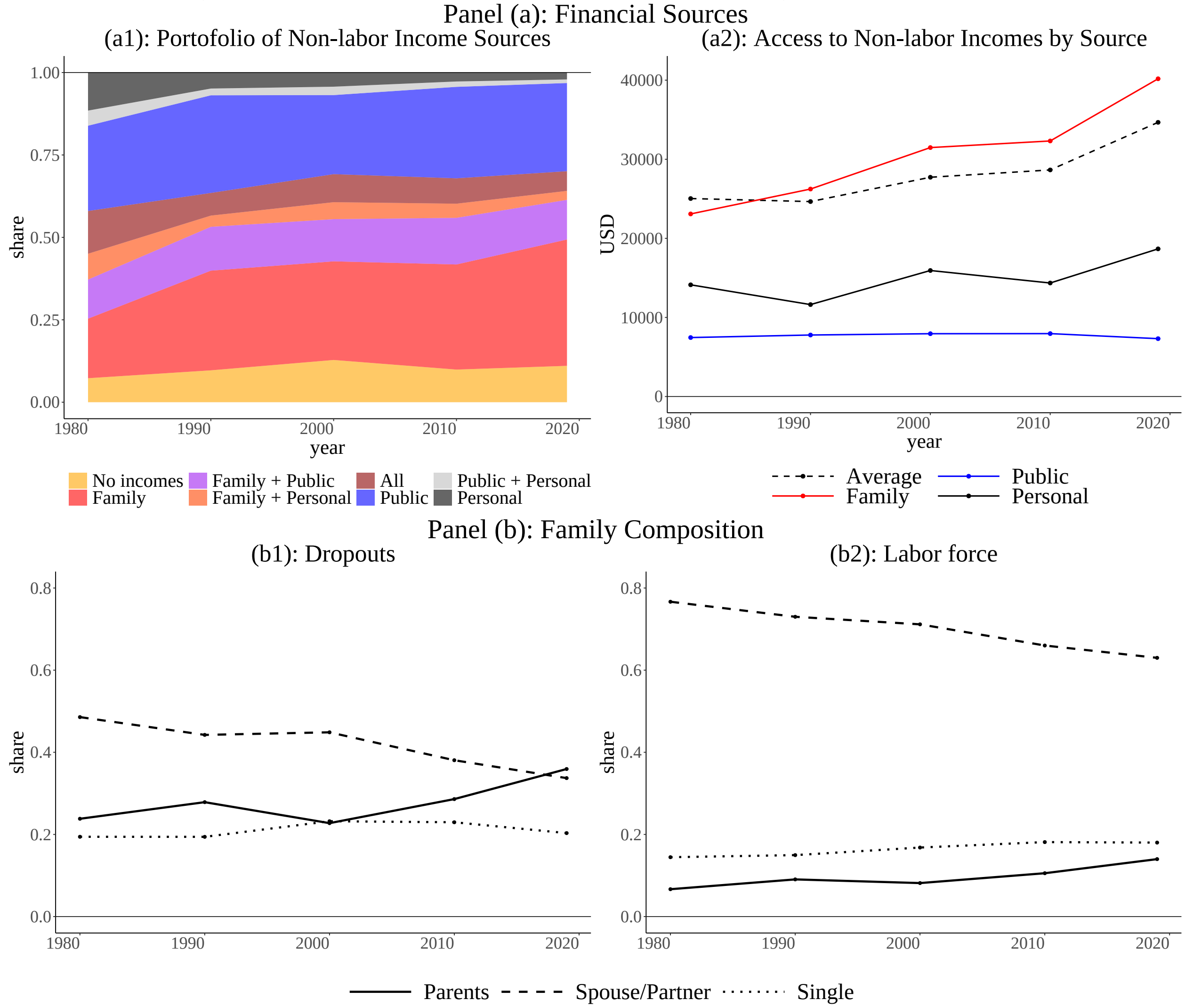
How do dropouts make ends meet? Given that dropouts by definition do not earn labor income, readers would naturally wonder how they sustain themselves, since securing a stable nonlabor income should be a first-order condition. Before studying the climate-dropouts nexus, I examine the socioeconomic characteristics of prime-age male dropouts, as shown in Figure 3.

Panel (a) reports their funding strategy for a dropout lifestyle. Panel (a1) shows the share of dropouts adopting each portfolio—a combination of public, family and personal finance. Revealingly, more than half to two-thirds of dropouts maintain access to family income, measured by labor and non-labor income of co-resident household members, including unmarried partners. A stable 30% of dropouts depend solely on public income. Since prime-age individuals are not eligible for Social Security retirement benefits after age 62, the public income provision is likely to be disability-related, namely, Social Security Disability Insurance (SSDI) and/or Supplementary Security Income benefits (discussed in detail in Section 4.3). Consistently 10 % of dropouts report no income, suggesting that they may be living off their saving or remittances from separated families. An overwhelming majority (nearly 90% after 1990) of dropouts report no personal income (e.g., financial dividends or business/farm income), implying that the majority of dropouts are unlikely to be "early retirees" of self-earned wealth.

Panel (a2), on the other hand, shows an intensive margin by financial source, that is, the average inflation-adjusted non-labor income conditional on receiving each source. During the period 1980-2019, public income continued to provide a minimum standard of living below USD 10,000. Relative to the other two sources, adult males had increasingly richer access to the wealth of co-residents, which broadly represents the average total income of dropouts (dashed line).

To further capture the financial source of cohabiting families, Panel (b) plots the family composition of dropouts relative to the labor force for prime-age males. Notably, the share of dropouts living with a spouse/partner is much lower and also has been declining relative to the labor force, presumably reflecting their relative value in the marriage market (see Autor et al. (2019)). In contrast, especially under the severe global warming of 2000-2019, the share of dropouts living with their parents has increased by 13.2%pts compared to 5.8%pts in the

Figure 3: Socioeconomic Characters of Prime-age Male Dropouts



Note: Computed from IPUMS of the 1970-2000 Census by decades and the 2009-2010 (for 2010) and 2018-2019 (for 2019) American Community Survey overlays. Dropout is defined as a male not in the labor force (aged 25-54) who is not enrolled in school and did not work in the previous year of the survey.
Panel (a): Family income is the sum of the total income of the members of the household living together, including unmarried partners. Public income is the sum of social security income and welfare income. Personal income is self-earned non-labor income. "All" includes family, public, and personal income. Incomes are adjusted for inflation using the CPI in 2000. Panel (b): Living with parents and living with spouse/partner are not mutually exclusive. Single indicates a prime-age male living alone.

labor force. Their share among dropouts has consistently remained 2.5-3.5 times that of the labor force—reasonable if living with parents saves on housing rent and utilities, perhaps provides unpaid access to refrigerators and housekeeping (e.g., cleaning, laundry). In 2019, more dropouts are living with parents than with spouses/partners, suggesting the rise of "parasitic" singles.

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?".[18] 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 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[19]. 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 4 illustrates the selection to and composition of outdoor work-

[18]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.*

[19]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.

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	25,000	1,894,577
2	Driver/Sales Workers and Truck Drivers	Transportation	0.756	0.917	0.929	0.058	36,000	3,693,299
3	Police Officers and Detectives	Public	0.660	0.846	0.839	0.337	64,000	914,691
4	Agricultural workers, nec	Agriculture	0.659	0.835	0.753	0.058	20,000	775,745
5	Grounds Maintenance Workers	Agriculture	0.653	0.663	0.936	0.061	18,000	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	54,000	779,073
9	Carpenters	Construction	0.540	0.711	0.979	0.059	28,600	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 stacked 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.

ers 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% of outdoor jobs are held by men, indicating that outdoor jobs are "male occupations". Restricting to prime-age males in Panel (b)[20], 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[21]. By 2019, over 40 percent of workers without a college degree work outdoors (Panel (b1)). Panel (b2)

[20] 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.

[21] 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.

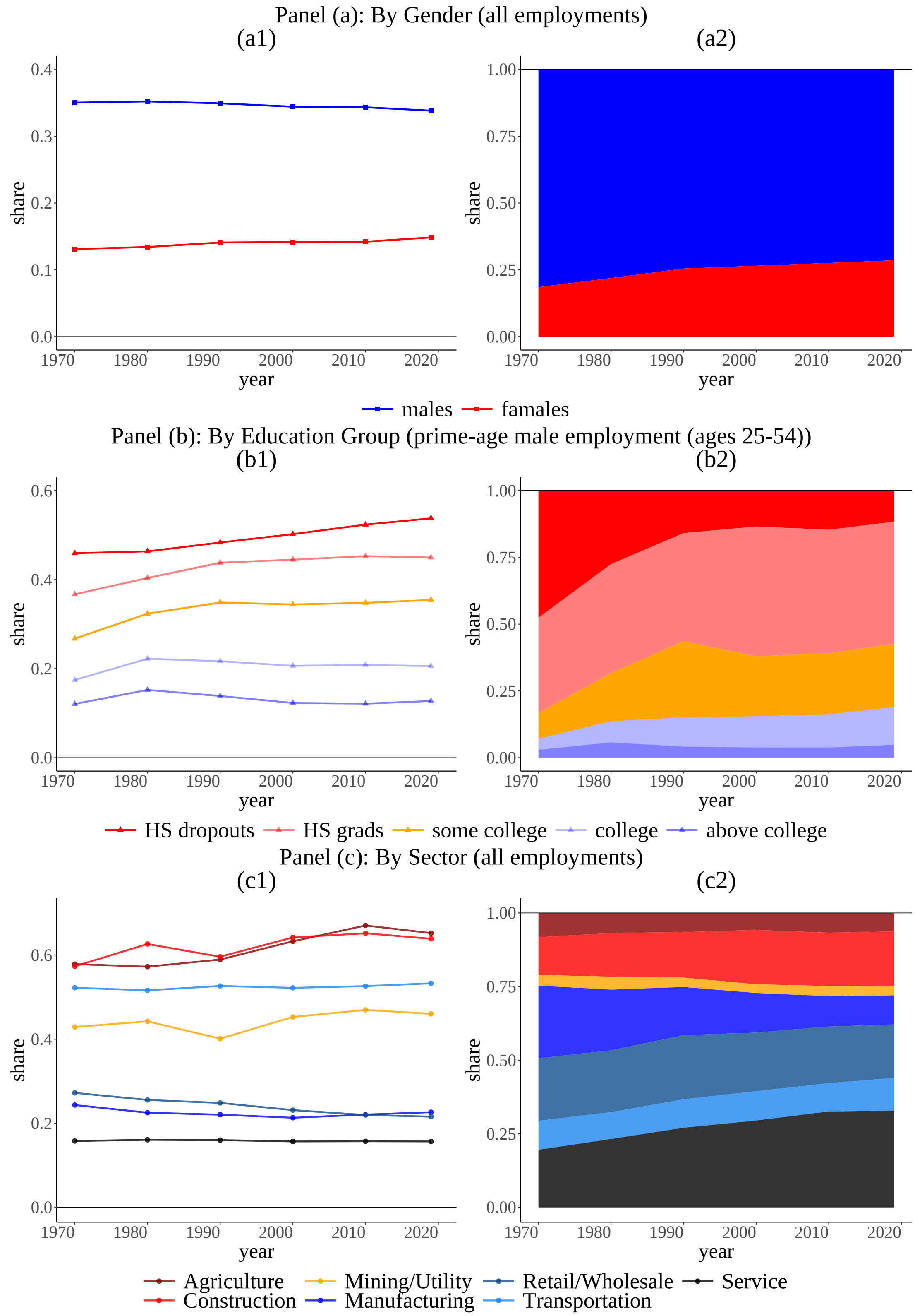


Figure 4: Socioeconomic Characters of Outdoor Workers (Selection and Composition)

Note: Calculated from IPUMS of the 1970-2000 Census by decades and stacked 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.

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.

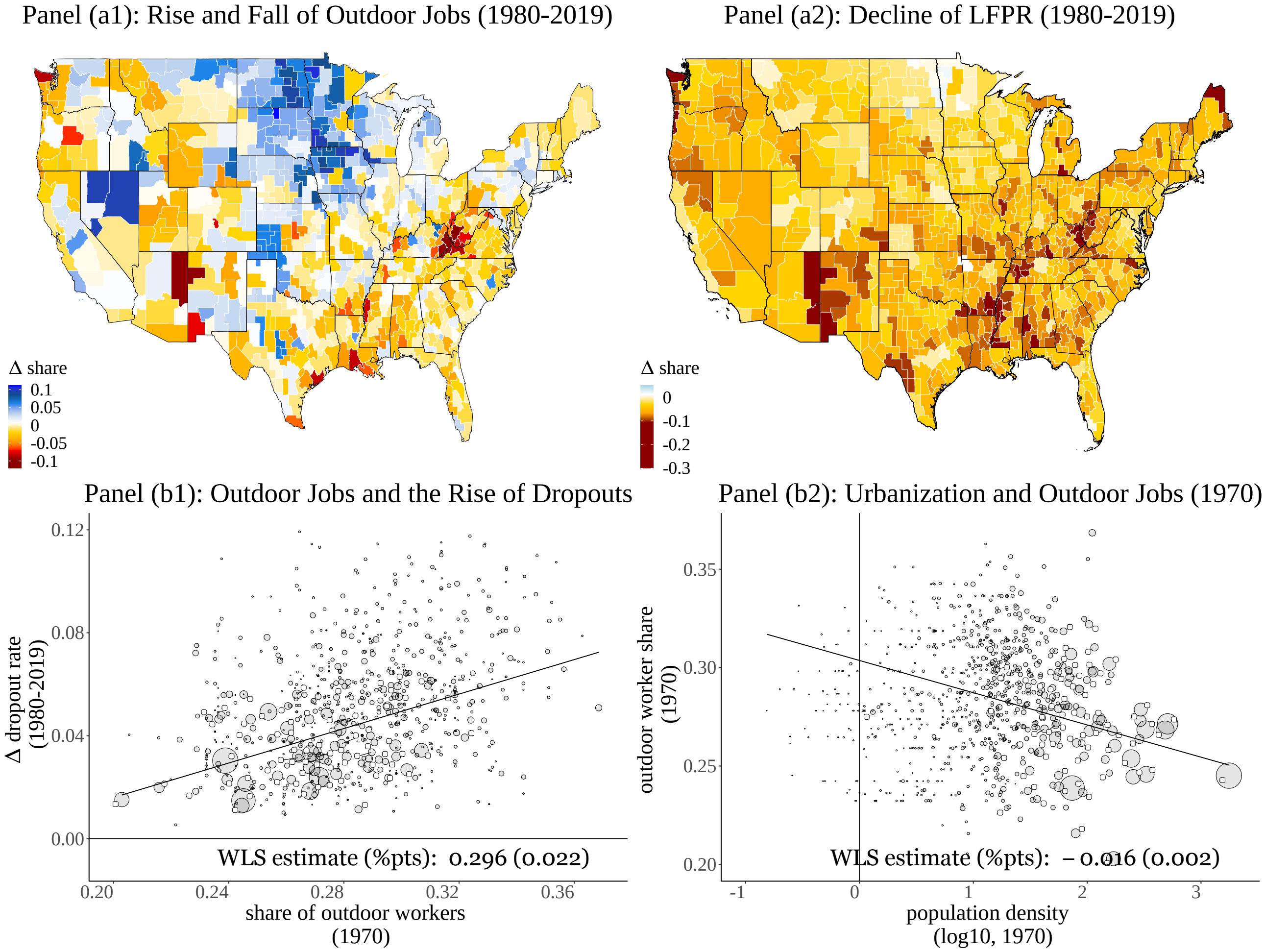
Panel (c1) shows the proportion of outdoor workers within sectors. Approximately 60% of agriculture and construction workers, 50% of transportation and mining/utility workers, and 25% of manufacturing and retail workers and 20% of service workers regularly work outdoors. Panel (c2) shows the sectoral 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[22] in the US continent (Figure A-8).

Looking at a more granular level, however, reveals a bleak picture of regional heterogeneity. Panel (a1) of Figure 5 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

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

Figure 5: Outdoor Jobs and the Labor Supply of Adult Males



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 (a1/a2): The population share of outdoor jobs and the LFPR are computed in prime-age male samples in the 1980 Census and the 2018-2019 ACS. Panel (b1/b2): 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 ACS. Population density is the total population in square kilometers for each commuting zone. The size of the bubble indicates the prime-age male population in 1970, which is used as the regression weight.

outdoor jobs—offsetting each other to maintain the nationwide consistency of outdoor jobs. Contrasting the decline in outdoor jobs in Panel (a1) with a regional decline in the LFPR in Panel (a2), readers would find a strikingly similar correspondence (red areas).

A bubble plot in Panel (b1) confirms this visual impression: regions with a higher historical presence of outdoor workers in 1970 experienced a sharper subsequent increase in dropouts in 1980-2019, suggesting that outdoor jobs would be gateways to subsequent dropouts. Alarmingly, rural disadvantaged areas are historically intensive in outdoor jobs; Panel (b2) relates the historical share of outdoor workers in 1970 to population density, indicating that metropolitan area were initially less depended on outdoor jobs. In contrast, disadvantaged regions remain dependent on outdoor jobs through 2019—areas with lower average weekly wages had significantly higher shares of outdoor workers (Figure A-7).

This is non surprising from the conventional theory of structural change; while cities are often called "engines of growth," armed with manufacturing and service sectors, 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. In the event of adverse climate shocks, the over-reliance on outdoor jobs in rural areas would lead workers to drop out due to higher climate exposure and, importantly, by the lack of second-best indoor jobs.

3 Analysis

Using the newly created panel of regional labor markets, this section estimates the key climate impacts on LFPRs and related market outcomes.

3.1 Empirical Model

To identify the effect of climate change, I first construct the following binned specification for a demographic group g (e.g., a baseline sample g is prime-age (25-54) males) over CZ i and a 5-year treatment window of periods $I = [\underline{I}, \overline{I}] \in \{(1975, 1980], [1985, 1990], [1995, 2000], [2005, 2010], [2014, 2019]$:[23]

[23]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 $(y^g_{i,2019} - y^g_{i,2010}) \times (10/9) + y^g_{i,2010}$.

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

where $y^g_{i,\overline{I}}$ is a i's period-end outcome (e.g., LFPR, employment rates, wages) in group g and $days^b_I$ is a 5-year prior average during $t \in [\overline{I}-5, \overline{I}-1]$[24] 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 $b \in \{1, \cdots 10\}$. As an annual sum of bins is constant, I omitted a seventh ($b = 7$) bin, $[65, 75)$°F (or [18.3, 23.9)°C)[25] 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[26]. $\beta^{g,b}$ 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 $\mathbf{C}_{i,I}$, other climatological variables except temperature (relative humidity, precipitation, snowfall) averaged over the period I with corresponding coefficients $\boldsymbol{\beta'}^g$. Given a demographic group g, $\mathbf{X}^g_{i,\overline{I}_{-1}}$ is a vector of common covariates in the previous period outcome year $\overline{I}_{-1}$ (e.g., $\overline{I} = 2019$ (or 1980) and $\overline{I}_{-1} =$ 2010 (or 1970, respectively) with its coefficients $\mathbf{\Psi}^g$, consisting of 4 components such that $\mathbf{X}^g_{i,\overline{I}_{-1}} = \{\mathbf{D}^g_{i,\overline{I}_{-1}}, \mathbf{E}_{i,\overline{I}_{-1}}, \mathbf{M}_{i,\overline{I}_{-1}}, \mathbf{W}^g_{i,\overline{I}_{-1}}\}$, mostly calculated from the Census and ACS (see Appendix A2.1 for a detailed list). $\mathbf{D}^g_{i,\overline{I}_{-1}}$ contains 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) at the end of previous period $\overline{I}_{-1}$. To account for potentially confounding technological

[24]To take a precedent climate exposure prior to LFPR proxies, I take a 5-year prior average of days from one year prior to the outcome year. For example, for the years 2019 and 2010, the treatment years are 2014-2018 and 2005-2009, respectively.

[25]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.

[26]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.

shocks (e.g., ICT shocks; industrial robots) and trade competition shocks in warming regions, I include $\mathbf{E}_{i,\bar{I}_{-1}}$, previous period 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)). $\mathbf{M}_{i,\bar{I}_{-1}}$ comprises a previous period regional characteristics (e.g., a share of seniors aged 65 and over; population density). $\mathbf{W}^{g}_{i,\bar{I}_{-1}}$ is a 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 at the CZ level and δ_I at the period level) 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 $\epsilon_{i,\bar{I}}$ is clustered at the CZ level, a spatial unit of analysis. The model is weighted by the previous period CZ share of the national prime-age male population, a denominator of an outcome variable. Armed with this full battery of plausibly random meteorological variables, socioeconomic controls and two-way fixed effects, one would hardly expect other confounders to shape the labor market outcomes, and $\beta^{g,b}$should presumably be given a causal interpretation. Other concerns about the robustness of the results are discussed in Section 3.3.

3.2 Baseline Results

Semi-parametric bin estimates Using LFPR as the outcome in the semi-parametric bin model, equation (1) ($y^{g}_{i,\bar{I}} = \text{LFPR}^{g}_{i,\bar{I}}$), Figure 6 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

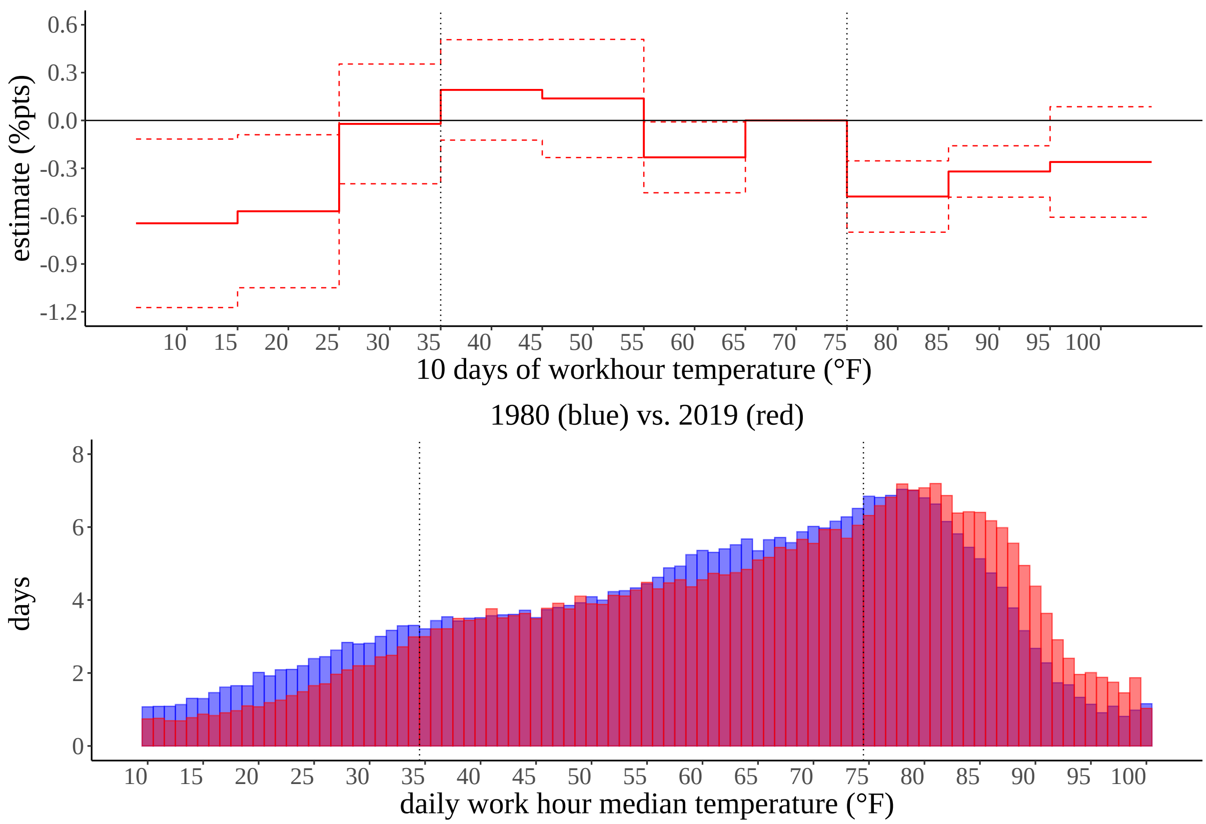


Figure 6: Climate Impact on Labor Force Participation Rate of Adult Males

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 work hour 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 at the end of each period. Dotted lines are thresholds for hot (≥75°F) days and cold days ($<$ 35°F) in the baseline model, column 5 at Table 2.

(Deschenes and Moretti (2009)), and GDP (Burke, Hsiang and Miguel (2015)) as well as in indoor laboratory studies (Seppanen, Fisk and Faulkner (2003)).

Baseline 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), $\sum_{b=1} \beta^{g,b} \text{days}^b_{i,I}$, by

$\beta^{g,h}\text{hd}_{i,I} + \beta^{g,c}\text{cd}_{i,I}$, where $\text{hd}_{i,I}, \text{cd}_{i,I}$ are the average number of hot and cold days, respectively, that region i was exposed to during period I.

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 thresholds for hot days and cold days at 75°F[27] 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 3.3).

Table 2 reports estimates from a parsimonious two-tailed model. In addition to two-way fixed effects, column 1 includes other climate variables $\mathbf{C}_{i,I}$ (relative humidity, precipitation, snowfall) and demographic controls $\mathbf{D}^{g}_{i,\bar{I}_{-1}}$. Then I cumulatively add industrial structure, $\mathbf{I}_{i,\bar{I}_{-1}}$ in column 2, labor market status, $\mathbf{M}_{i,\bar{I}_{-1}}$ in column 3, health variables in $\mathbf{W}^{g}_{i,\bar{I}_{-1}}$, in column 4, and wealth variables in $\mathbf{W}^{g}_{i,\bar{I}_{-1}}$ 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 10 more 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.

[27]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., a one-hour lunch break). See also footnote 25.

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

	dependent variable: **Labor Force Participation Rate** (in % pts., prime-age males)				
	(1)	(2)	(3)	(4)	(5)
10 hot days	-0.345^{***}	-0.333^{***}	-0.321^{***}	-0.320^{***}	-0.347^{***}
	(0.062)	(0.063)	(0.063)	(0.064)	(0.066)
10 cold days	-0.377^{**}	-0.437^{**}	-0.431^{**}	-0.409^{**}	-0.379^{**}
	(0.176)	(0.174)	(0.190)	(0.186)	(0.170)
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

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 stacked 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 male population (see main text for details). *** $p < 1\%$, ** $p < 5\%$.

3.3 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 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 previous period covariates. The point estimates become generally larger for longer exposures, consistent with proposed mechanism of cumulative labor costs or physical/mental disability in the long run (Table A-2).

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.[28] 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).

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 comoved 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 3.1). 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)). The estimates are very stable, especially for hot days, suggesting

[28] 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.

that contemporaneous labor demand shocks do not confound the estimates in parallel with climate shocks (Table A-4).

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 7). I also rerun the analysis excluding the most agriculture-intensive regions, as measured by high shares of agriculture employment, but the estimates are unchanged (Table A-5). Thus, I judge that the result is unlikely to be mediated by agricultural productivity.

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 (cf., Barreca (2012)). To capture their complementarity, I compute the discomfort index (DI) using a standard meteorological formula[29], 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[30]. 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-6).

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

[30]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.

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-7).

3.4 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 4, 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 $g \in \{$HS dropouts, HS graduates, some college years, college graduates$\}$ with a reconstructed set of within-group controls $\mathbf{X}^g_{i,\underline{I}}$.

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 about 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. Worryingly, however, a significant harm remains even for college graduates, suggesting that college degrees are not

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 periods × 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. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

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).[31]

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 $\mathbf{X}^g_{i,\underline{I}}$. The climate effects of both hot and cold days are sharper for relatively younger males, especially for the young 25-34 and middle-aged 35-44.[32]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-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 Even when the outdoor jobs are damaged by heat shocks, adult males can move into the service sector, which offers low-skilled, climate-proof jobs (e.g., restaurant waiters, supermarket cashiers, office janitors). Given the law of the economics of agglomeration, it is well known that these low-skilled indoor services are disproportionately concentrated in densely populated cities. Thus, we predict that the impact of climate change on labor supply should be mitigated in densely populated cities.

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 ($\mid t \mid= 5$). Alternatively, when population density is replaced by the share of employment in the service sector, representing the struc-

[31] As shown in US automobile plants in Cachon, Gallino and Olivares (2012), even supposedly perfect indoor air-controlled factories suffered from productivity losses, possibly via door openings or spillover damage from transportation. Cold weather possibly harms cognitive performance for knowledge workers (Falla et al. (2021)). In Canadian universities, Cook and Heyes (2020) show that cold days reduced exam scores even in indoor classrooms, after commuting to the campus in the cold.

[32] 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.

tural development of the regional economy, the estimates are again statistically significant ($\mid t \mid > 3$). The exercise reveals strong regional regressivity, suggesting that climate damages to labor supply are magnified by the lack of a safety net of climate-sheltered service economies (Table A-8).

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. Somewhat reassuringly, 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-9). Alarmingly, 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 5.

3.5 Labor Market Attachment

To delve deeper into the source of the declining labor supply, 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-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

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)	**Employment** (3)+(4)	**Salaried emp.**	**Self-employed**	**Unemployments**	**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 periods $\times$ 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. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

work schedule that makes workers resilient to climate exposure[33]. 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.

3.6 Shrinking Employment across Sectors

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

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

employment-population ratio across ten private sectors (agriculture, construction/mining, two manufacturing and six services)[34]. 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.[35] 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.

Since typical manufacturing industries operate indoors, one would expect that climate damages should depend on the quality of climate control. In relatively labor-intensive, low-tech manufacturing (e.g., food, textile, glass), column 3 finds a significantly large job loss from hot days (-0.302), but not from cold days, speculatively because furnaces are supposedly to operate year-round to process raw inorganic materials (chemicals, petroleum/coal, plastics and glass)—sweating workers in the summer, but perhaps comforting them in the winter. Column 4, on the other hand, covers relatively capital-intensive, high-tech manufacturing (e.g., machine/automobile/instruments), and reports null effects from warming, and large job gains from cooling ($+0.842$). Although the air control statistics are comparable between the two manufacturing groups (57.9% vs. 57.2% of workers are under air control daily), the finding may indicate that high-tech machinery, due to its precise operation, requires even more stringent year-round air quality controls.

[34] 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.

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

Table 5: Climate Change and Sectoral Employment

Panel A: Climate Change and Sectoral Employment

dependent variables: **employment-to-population ratio**

(in %pts; prime-age males)

	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)
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)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
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 (≥ weekly)	73.3%	67.8%	30.0%	22.4%	31.3%	44.8%	68.9%	25.9%	23.3%	19.2%
Indoor uncontrolled (≥ 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 periods × 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 periods. 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 4 for definition of climate exposure.

Column 5 reports that retail/wholesale industries exhibit mild job growth (+0.089) from hot 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.[36]

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 29). 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.

Alarmingly, however, finance/real estate services in column 10 shows significant job losses from both extreme temperature days (−0.137 for hot days, −0.187 for cold days). Given the highest share of workers under daily climate control (76.0%), the job loss appears puzzling, but could be rationalized if the industry includes temperature-exposed jobs (e.g., sales per-

[36] 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.

sonnel or front-line customer service) or if labor demand is elastic due to higher capital intensity. This sector appears to be partly responsible for the decline in the LFPR for the highly educated.

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 influence from and response of outdoor jobs under climate change.

4 Mechanism

4.1 Outdoor Labor Market

Amplified effects of temperature exposure The previous section showed that shrinking salaried employment, especially in heat-sensitive sectors (e.g., construction), is a likely source of labor supply contraction. Because (supposedly) heat-protected indoor sectors include indoor jobs without air conditioning (e.g., grocery store workers facing frequent door openings; cooks using fire) or even outdoor jobs (e.g., lawn mowers, security guards), the previous broad industry analysis, while largely informative, appears to be elusive in reflecting temperature-related job losses.

To test the climate exposure mechanism, I enrich the baseline model by interacting the climate variables $\mathrm{hd}_{i,I}, \mathrm{cd}_{i,I}$ with a regional shifter $z^{e}_{i,\bar{I}_{-1}}$, a share of employment (measured by weeks worked) under different climate exposures e at pre-period outcome years $\overline{I}_{-1}$. Analogous to the procedure in Section 2.3, climate exposure $e \in \{$outdoor, outdoor under shelter, indoor uncontrolled, enclosed vehicles, indoor controlled$\}$ is constructed from several questions from the Work Context Survey.[37] Arranging equation (1), I construct a difference-in-

[37]The question includes "How often does this job require working *outdoors, under cover* (e.g., structure with roof but no walls)? "How often does this job require working indoors in *non-controlled environmental*

difference style formulation[38] such that

$$y_{i,\bar{I}} = \beta^h \mathrm{hd}_{i,I} + \beta^c \mathrm{cd}_{i,I} + \gamma^{e,h} \mathrm{hd}_{i,I} z^e_{i,\bar{I}_{-1}} + \gamma^{e,c} \mathrm{cd}_{i,I} z^e_{i,\bar{I}_{-1}} + \mu z^e_{i,\bar{I}_{-1}} + \mathbf{\Lambda} \mathbf{C}_{i,I} + \mathbf{\Psi} \mathbf{X}_{i,\bar{I}_{-1}} + \delta_i + \delta_I + \epsilon_{i,I}, \tag{2}$$

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 $z^e_{i,\bar{I}_{-1}}$, 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 2-5 interact a variant of workplace climate exposure. Column 2 reports even sharper adverse estimates for outdoor workplaces under shelter (e.g., gas stations, auto repair shops, hot dog stands), which protect workers from sun, rain and snow but may force them to work in inclement weathers. Column 3 uses the proportion of imperfectly controlled environments (e.g., old warehouses; factories with furnaces; restaurant kitchens), showing even greater harm than outdoor workplaces (column 1)—plausibly because heat and humidity are easily retained indoors.

Column 4 examines the link with driving tasks (e.g., taxi, truck, bus) performed outdoors in enclosed vehicles. Perhaps surprisingly, the estimates show similarly negative effects, despite the fact that car air conditioners are presumably installed throughout the study period, suggesting that door openings may counteract installed air conditioners. Given that the majority of US commuters use cars, this may partially explain why extreme temperature days hurt LFPR even among college graduates (Table 3). On the other hand, the interaction with the previous period shares of workers employed in daily-air-controlled jobs (e.g., cashiers,

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conditions (e.g., warehouse without heat)?" "How often does this job require working in a *closed vehicle or equipment* (e.g., car) "How often does this job require working *indoors in environmentally controlled* conditions?

[38]For this analysis, a superscript of group g (prime-age males) in equation (1) is omitted for brevity.

Table 6: Amplified Climate Impacts due to Temperature Exposure in the Workplace

	dependent variable: **LFPR** (in %pts., prime-age males) pre-period exposure (a share of employment)				
	× outdoor	**× outdoor under shelter**	**× indoor uncontrolled**	**× enclosed vehicles**	**× indoor controlled**
	Panel A: OLS estimates				
	(1)	(2)	(3)	(4)	(5)
10 hot days	−1.394***	−2.633***	−1.615***	−1.460***	0.847**
	(0.461)	(0.733)	(0.451)	(0.453)	(0.369)
10 cold days	−0.862	−3.468***	−1.876***	−1.591**	2.563***
	(0.788)	(1.236)	(0.720)	(0.725)	(0.623)
Adjusted R^2	0.877	0.877	0.878	0.877	0.878
	Panel B: IV estimates				
	(1)	(2)	(3)	(4)	(5)
10 hot days	−2.030**	−5.067***	−4.601**	−2.860***	1.928**
	(0.923)	(1.228)	(1.837)	(0.933)	(0.977)
10 cold days	−2.377*	−7.980***	−14.472***	−4.958**	6.330***
	(1.411)	(1.595)	(2.517)	(1.934)	(1.075)
Adjusted R^2	0.880	0.880	0.881	0.880	0.880

Note: $N = 3,610$ (5 periods × 722 commuting zones). 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. Only interaction estimates $\gamma^{e,h}, \gamma^{e,c}$ in equation (2) are reported for brevity. The model inherits 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 at Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

waiters, office clerks, engineers) is significantly positive in column 5. A sharp contrast between column 3 (imperfect control) and column 5 (perfect control) confirms the role of workplace air conditioning in maintaining their work efficiency.

IV estimates If climate change is causing workers to drop out of outdoor jobs, then there is a concern that the share of outdoor jobs in the previous period is a function of historical hot days and cold days, which are likely to be correlated with the current counterparts. If a regional climate is serially correlated at each CZ, the interaction terms could potentially be confounded. To address this concern, I exploit historical cross-CZ differences in industry specialization to isolate the nearly exogenous component of the occupation share of each environment e. A shift-share exposure to environment e in CZ i, $\widehat{z}^{e}_{i,\overline{I}_{-1}}$, is computed based on the previous period nationwide industry employment share such that

$$\widehat{z}^{e}_{i,\overline{I}_{-1}} = \sum_{k} \left(\omega^{i}_{k,1950} \frac{L^{e}_{k,\overline{I}_{-1}}}{L_{k,\overline{I}_{-1}}} \right)$$

where $\omega^{i}_{k,1950} \equiv \dfrac{L_{i,k,\overline{I}_{-1}}}{L_{i,\overline{I}_{-1}}}$ (total workweek share of industry k in CZ i in 1950), $L^{e}_{k,\overline{I}_{-1}}$ is the non-self employment weeks worked in each environment e in industry k in the pre-period outcome year $\overline{I}_{-1}$. I assume that this shift-share exposure extracts a component of exposure to each environment e that is dictated by the historical industry mix of each region, but is uncorrelated with subsequent climate exposure. Reassuringly, columns 1-5 give generally larger estimates with robust statistical precision. The overall analysis shows that labor supply is closely linked with exposure to the ambient temperature in workplaces, presumably through the biological structure of the human body.

Within-sector effects on outdoor jobs The previous analysis showed that climate impacts are expectedly amplified by the prevalence of jobs under temperature exposure. To further highlight the role of outdoor jobs as a source of dropouts, I examine climate impacts on outdoor vs. indoor labor markets *within* sectors, a previous unit of analysis in Table 5. Table 7 examines the sensitivity of employments and wages under three work environments—outdoor, indoor uncontrolled, and indoor controlled.

Panel A of Table 7 reports climate impacts on prime-age male salaried employment within sectors across CZs, separately by each climate exposure environment with the repeated caveat that three are not mutually exclusive due to the design of the WCS. 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

Table 7: Climate Change and Outdoor vs. Indoor Labor Markets within Sectors

	Panel A: Employment-to-Population Ratio (in %pts; prime-age males)			**Panel B: Log Weekly Wages** (in percent; prime-age males)			
	units of analysis: CZs × sectors × periods			CZs × sectors × edu. groups × periods			
	Outdoor	**Indoor uncontrolled**	**Indoor controlled**	**Outdoor**	**Indoor uncontrolled**	**Indoor controlled**	**Total**
	(1)	(2)	(3)	(1)	(2)	(3)	(4)
10 hot days	-0.045^{***}	-0.025^{*}	-0.024^{*}	-0.036	-0.229	-0.197	-0.129
	(0.015)	(0.014)	(0.012)	(0.348)	(0.371)	(0.384)	(0.332)
10 cold days	-0.045^{**}	-0.039^{**}	-0.038	-1.712^{***}	-1.758^{***}	-1.772^{**}	-1.759^{***}
	(0.018)	(0.018)	(0.023)	(0.651)	(0.639)	(0.698)	(0.674)
				fixed effects			
CZ × sector	Yes	Yes	Yes				
sector × year	Yes	Yes	Yes				
CZ × sector × edu. groups				Yes	Yes	Yes	Yes
sector× state × year				Yes	Yes	Yes	Yes
				pre-period covariates			
employee demographics	✓	✓	✓	✓	✓	✓	✓
industry structure	✓	✓	✓	✓	✓	✓	✓
Observations	34,623	34,623	34,623	123,467	123,406	124,010	124,015
Adjusted R^2	0.914	0.915	0.950	0.878	0.883	0.894	0.906

Note: See definitions of work environments in the main text. 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. 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. Missing cells are dropped. Pre-period employee demographics for each occupational group is controlled at the CZ-sector level (in Panel A) and the CZ-sector-edu. group level (in Panel B). Pre-period industrial composition (average size of establishment and Herfindahl-Hirschman index) is controlled at the CZ-sector level. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

Panel A: Unit of analysis: 5 periods × 722 commuting zones× 10 sectors. 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. The regression weights are each cell's pre-period nationwide share of salaried employment. Panel B: Unit of analysis: 5 periods× 722 commuting zones× 10 sectors × 5 education groups. Weekly wages of each occupational category in each cell are computed for prime-age men in salaried employment. The regression weights are each cell's pre-period nationwide share of weeks worked in salaried employment.

because indoor environments block sunshine and cold wind. Even under indoor controlled environments, column 3 continues to report mild job loss from hot days (-0.024) and cold days (-0.038). Overall, significant job losses from both hot and cold days are observed in all workplaces, but the effects are magnified by more direct exposure to the climate, resulting in more severe and statistically sharper losses.

Standard theory suggests that the decline in employment is consistent with a contraction in both labor supply and demand. To further determine whether this is driven by labor supply vs. demand, I examine the wage responses of jobs across different work environments, which is theoretically ambiguous; on the 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, raising a purely empirical question.

Panel B of Table 7 reports climate impacts on weekly wages of salaried employees. To correct for compositional changes in skill levels within sectors, I take a detailed analysis of education groups-sector cells within CZs across years. To control for statewide institutional changes (e.g., minimum wage; right-to-work rules) in specific sectors, sector-state-year fixed effects are imposed.[39] Columns 1-3 examine the calculated weekly wages of each occupational category separately[40], and column 4 analyzes the aggregate wages. Intriguingly, in all specifications, despite the employment losses from hot days (shown in Panel A), wages show nearly null effects. The results are robust to alternative protocols; the use of hourly wages, alternative units of analysis, and the definition of workplace environments (see Table A-10).

From the perspective of the standard labor market model, the near-stability of wages, paired with shrinking employment, suggests that the contraction in labor supply is counteracting the contraction in labor demand. In fact, using the flexible semi-parametric bin

[39]Education takes five categories: high school dropouts, high school graduates, some college years, college graduates, above college. Sectors are inherited from the classification of Table 5. Acemoglu and Restrepo (2020) use a similar strategy to estimate the impact of the introduction of industrial robots on wages. See Table A-10 for an alternative unit of analysis.

[40]Analogous to employment, weekly wages of workers under different climate exposures are calculated by dividing labor income by weeks worked, each of which is an aggregation of sample weights interacted with the proportion of workers in each environment e of each worker's occupational title.

model, I find that scorching hot days (above 95°F) and mildly hot days (75-85°F) show an *increase* in total wages, revealing the hidden supply-side contraction (Figure A-11). Notably, this increase in wages in the 75-85°F bin coincides with the largest decrease in LFPR from hot days shown in Figure 6, highlighting the supply-side forces for suppressing LFPR.

Cold days, on the other hand, show uniformly negative wage effects across environments, indicating the relative dominance of labor demand contraction. This also ensures that the null wage effects of hot days are unlikely to be due to lack of power or wage rigidity. Analogous to hot days, applying the richer model of finer bins reveals hidden supply-side contraction that were also masked by the two-tailed model: severe cold days (< 20°F) bin shows an *increase* in total wages (Figure A-11). The wage analysis overall supports a mix of contractions in labor demand and supply, manifesting along a different distribution of temperatures.

For both hot and cold days, while wage effects are comparably similar across the workplace environment, the significant loss of outdoor jobs suggests that the labor supply contraction expand with direct exposure to ambient temperature, which I take to be a novel adjustment margin in the climate-labor literature. The implied decline in labor demand, on the other hand, is consistent with a number of theories, as exemplified by recent work 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 (Acharya, Bhardwaj and Tomunen (2023)), or labor-saving technological change (Qiu and Yoshida (2024)).

While conventionally discussed labor market shocks from technological revolution (e.g., ICT, industrial robots) and globalization (e.g., China shocks) are ostensibly labor demand shocks, my results collectively suggest that climate change not only undermines labor demand, but also the supply of outdoor jobs, and consequently, jointly pushes workers out of the labor force.

4.2 The Home as a Cooling Lounge

4.2.1 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 (2), substituting the previous period's workplace climate exposure, $z^e_{i,\bar{I}_{-1}}$, for the prevalence of residential amenities[41]. Because air conditioners and television sets became saturated in the U.S. after 2000, the analysis is limited to the 1970-2000 period with richer spatial variation in adoption.[42] 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 8 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[43] 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. [44]

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

[41] 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.

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

[43] 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.

[44] 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. Some study shows that global warming has hurt sleep quantity and quality, especially in developing countries (Minor et al. (2022)).

Table 8: 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	-0.277^{**}	-0.257^{***}	-0.353^{***}	-0.114^{*}	-0.036^{***}
	(0.108)	(0.079)	(0.072)	(0.064)	(0.008)
10 cold days	-0.123	-0.024	-0.351^{*}	-0.229^{**}	0.005
	(0.130)	(0.177)	(0.180)	(0.102)	(0.017)
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	-0.043^{***}	-0.093^{**}	-0.063^{**}	-0.005	-1.677^{***}
	(0.010)	(0.038)	(0.027)	(0.050)	(0.624)
10 cold days	0.003	-0.097	-0.008	-0.077	-1.787^{***}
	(0.018)	(0.064)	(0.049)	(0.074)	(0.545)
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 periods × 722 commuting zones) for columns 1-2 of Panel A, $N = 642$ (3 periods × 214 commuting zones) for column 3 of Panel A, $N = 3,610$ (5 periods × 722 commuting zones) for columns 4-5 of Panel A and Panel B. Only the interactive coefficients $\gamma^{e,h}$, $\gamma^{e,c}$ of equation (2) are reported. 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. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

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).[45]

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 attracted workers to stay home from labor.[46] 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 and television viewing is an almost exclusive leisure activity. 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 and begin a life as a dropout (Recall a rise of cohabitation with parents in Figure (3)). 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

[45]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.

[46]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.

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.

4.2.2 Access to Wealth

Panel A of Table 8 shows that climate change, coupled with a richer housing environment, promotes labor force exit throught the substitution effect. By contrast, climate-induced dropouts should be augmented through income effect, depending on the richness of their access to financial revenue.[47] 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.[48]

Motivated by the increasing dependence on family income (Figure 3), 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)[49]. 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

[47]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.

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

[49]62 is the minimum age for receiving Social Security benefits, which can include both retirement and disability benefits.

force[50].

These effects seem reasonable given 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 (Figure 3). As a placebo analysis, column 4 instead considers previous period personal non-labor incomes. As expected, no significant effects are observed, confirming the discussion in Figure 3 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.[51] 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 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.

4.3 Disability vs. Adaptation

Although adult males were found to secure a comfortable home and a stable non-labor income, the rise of the dropout lifestyle poses a puzzle as to why they do not settle for readily available jobs (including part-time, or gig-type jobs). This section explores their motivations for climate-induced dropouts—whether they involuntarily left the labor force due to disability or voluntarily changed their lifestyles to adapt.

Disability has long been cited as a major cause of male non-participation (Parsons (1980)). In the postwar period, governments in the rich world liberalized welfare systems that might otherwise have backfired by subsidizing dropouts. Autor and Duggan (2003) argue that

[50] 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.

[51] 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 ACS, a farm was any household on 1+ acres that yielded \$1000+ in produce in the previous year.

Congress's loosening of the US Disability Insurance eligibility rules and increase in the income replacement rate in 1984 acted as a disincentive to work. Given the growing number of studies reporting heat-related occupational injuries (Dillender (2019); Park, Pankratz and Behrer (2021)) and traffic accidents (Koetse and Rietveld (2009); Zou, Zhang and Cheng (2021)), it is natural to speculate that climate-induced dropouts reflect increased physical or mental disability. To test this possibility, I examine whether exposure to extreme hot days led to regional prevalence of disability during 1980-2019.

Difficulty in Daily Activities Panel A of Table 9 reports climate effects on disability reported by prime-age men in the Census and ACS, with a detailed breakdown of cold days below 25°F[52]. Column 1 uses a benchmark proxy for disability consistently measured from 1990 to 2019: a man is counted as disable if he reports either "Independent Living Difficulty" or "Self-care Difficulty", which separately represent functional difficulties outside or inside the home[53]. As speculated earlier, I find an adverse impact of hot days and severe cold days (< 25°F) on disability. Alternatively, using a broader definition that spans since 1980, subject to changes in the disability question from 1980-2000 (Census) to 2010-2019 (ACS), column 3 shows a larger loss of hot days (0.352) and severe cold days (< 25°F) (0.913).[54] Using the benchmark definition of disability at column 1, columns 3-4 show significant increase from warming in the share of the disabled within dropouts and disabled dropouts as a share of the population, respectively, indicating the strong association between disability and labor supply.

[52]In Panel A, using the baseline two-tailed model produces very similar effects from hot days, but no meaningful estimates from cold days below 35°F, seemingly masking the effects from cold days below 25°F.

[53]The Census and ACS questions are "Because of a physical, mental, or emotional condition, does this person have difficulty doing errands alone, such as visiting a doctor's office or shopping?" (Independent Living Difficulty) and "Does this person have difficulty dressing or bathing?" (Self-care Difficulty).

[54]A man is disabled if he reports "Disability limits but does not prevent work" and "Disability prevents work" (IPUMS of the 1970-1990 Census), and "Disability causes difficulty working" (IPUMS of the 2000 Census) on the "Work disability" question. For the 2009-2010 and 2018-2019 ACS, a man is disabled if he reports any of the sensory difficulties (Cognitive, Ambulatory, Vision, Hearing), Independent living difficulty, or Self-care difficulty.

Table 9: Climate Change and Disability

	Panel A: Self-reported Disability (in %pts; prime-age males)				
	Benchmark				
	Disability share (outside & home)	**Disability share (add work disability)**	**Share of the disabled within dropouts**	**Disabled dropouts (share)**	**Non-disabled dropouts (share)**
	(1)	(2)	(3)	(4)	(5)
10 hot days	0.186***	0.352***	1.872**	0.044***	0.100**
	(0.047)	(0.078)	(0.767)	(0.015)	(0.039)
10 cold days ($\geq$25°F & $<$ 35°F)	−0.303	−0.246	−0.454	0.015	−0.008
	(0.188)	(0.273)	(2.334)	(0.048)	(0.104)
10 cold days ($<$25°F)	0.216*	0.913***	3.814	−0.019	0.162*
	(0.114)	(0.220)	(2.606)	(0.047)	(0.085)
Observations	2,888	3,610	2,888	2,888	2,888
Adjusted R^2	0.852	0.831	0.894	0.846	0.880

	Panel B: Public Transfer Benefits on Disability (in %pts; prime-age males)				
	Social Security (SS) recipients	**Welfare recipients**	**Share of SS receipts within dropouts**	**Dropouts with SS**	**Dropouts without SS**
	(1)	(2)	(3)	(4)	(5)
10 hot days	0.034*	0.088***	0.606*	0.030*	0.089***
	(0.018)	(0.027)	(0.333)	(0.016)	(0.032)
10 cold days ($\geq$25°F & $<$ 35°F)	−0.009	0.165**	0.932	−0.025	0.124
	(0.038)	(0.071)	(0.888)	(0.028)	(0.093)
10 cold days ($<$25°F)	−0.034	0.036	3.236***	−0.045	0.263***
	(0.044)	(0.053)	(0.941)	(0.036)	(0.078)
Observations	3,610	3,610	3,610	3,610	3,610
Adjusted R^2	0.823	0.770	0.847	0.844	0.895

Note: $N = 2,888$ (4 periods (1990-2010, 2019) $\times$ 722 commuting zones) for columns 1, 3-5 of Panel A. $N = 3,610$ (5 periods (1980-2010, 2019) $\times$ 722 commuting zones) for column 2 of Panel A and for Panel B. All models inherit definitions of hot days, treatment windows (5-year average), full controls, two-way fixed effects, regression weights, and clustering of standard errors from the baseline model, column 5 of Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

Public Transfer Benefits The results in Panel A are based on surveys that ask a yes/no question about self-reported *difficulties* with activities of daily living, which plausibly reflect their impaired physical and mental conditions but do not necessarily discourage work. The snapshot surveys are best viewed as symptoms of seriously deteriorating health rather than smoking guns of permanent disability[55]. Panel B instead examines the sensitivity of recipients of disability programs—Permanent Disability Insurance (DI) benefits and Supplementary Security Income programs—that require identical health requirements. To receive a benefit, an individual must have a medically certified physical or mental impairment that prevents the individual from engaging in a "substantial gainful activity" for at least one year. Given the scrutiny of the Disability Determination Services, although sometimes claimed to be loose, public transfer should supplement self-reporting to better proxy for permanent disability. According to the Social Security Bulletin Annual Report, musculoskeletal disabilities (e.g., back pain) or mental disorders (e.g., mood and schizophrenic disorders) increased substantially after 2000, accounting for two of the largest diagnostic groups (Figure A-12).[56]

Importantly, the prominence of physical pain is well-aligned with the long experience of outdoor jobs—often straining the joints of the back, knees, and shoulders through repetitive bending, squatting and carrying heavy loads under climate stress, which has supposedly fueled the aging wear and tear of joint cartilage. This is consistent with Krueger (2017), who documents that non-participant men disproportionately report physical pain and poorer mental health in the Princeton Pain Survey. The increase in mental disorders also coincides with reported heat-induced dysfunction of the human psyche, as exemplified by increased suicides (Burke et al. (2018)), violent crime (Ranson (2014)), and negative tweets (Baylis (2020)) in response to hot days.[57]

[55]I emphasize, however, that the lack of medical evidence does not mean that dropouts are free of poor health. The diagnosis of mental disorders is based on systematic series of questionnaires (see Hyman (2010) for a review). Similarly, the diagnosis of physical pain depends on self-reporting, not necessarily by scientific measurement by MRI (New Yorker, 2018). Neuroscience suggests that all physical pain is essentially a "subjective" alarm from the brain, emanating from the damaged joints and nervous system (Tracey and Bushnell (2009)).

[56]In contrast, injuries continued to account for less than 5% of all DI beneficiaries (see Figure A-12), suggesting that injuries are unlikely to be a primary cause of disability.

[57]In IPUMS of Census and ACS, Social Security income consists of Social Security pensions, survivors' benefits, or permanent DI, and US government Railroad Retirement Insurance payments. Welfare income

Panel B reports results similar to those in Panel A to support this argument. Columns 1 and 2 examine Social Security (SS) income and welfare recipients as reported in the Census and ACS, respectively. In the sample of prime-age men, these are roughly equivalent to recipients of permanent DI benefits and Supplemental Security Income disability benefits, respectively. Two columns show positive effects for hot days.

Columns 3-4 in Panel B consider the share of Social Security (SS) recipients among dropouts and the share of SS-receiving dropouts among prime-age males. Again, both have positive estimates ($t \approx 1.8$) from hot days. The findings are reasonable because separation from "substantial gainful activity" is a requirement for DI claimants to signal their disability in the DI review process.

Disability vs. Adaptation Columns 1-4 in Panel A and B of Table 9 demonstrate that the climate-induced dropouts are closely associated with disability. However, I find that disability does not seem to be a necessary condition. Column 5 of Panel A reports the warming impact on dropouts *without* reporting difficulties, which is more than twice that of dropouts with disabilities (0.100, $t = 2.6$ vs. 0.044, $t = 2.9$ in column 4).[58] Similarly, in Panel B, dropouts *without* Social Security benefits have much larger and more precise estimates (0.089, $t = 2.8$) for hot days than that of dropouts with Social Security benefits ($0.030, t = 1.9$), confirming that DI receipt is also not a prerequisite for dropping out either.[59] In fact, during the study period, I find that 72% of dropouts report no difficulties in daily activities, 75% of dropouts do not receive Social Security benefits, and 59% of males who report difficulties are not dropouts. Thus, DI recipients should be considered as a minority of climate-induced dropouts.[60]

includes low-income disabled persons, as well as federal/state Supplemental Security Income payments to the elderly (age 65+), Aid to Families with Dependent Children (AFDC), and General Assistance (GA).

[58] Similarly, severe cold days (< 25°F) significantly increased non-disabled dropouts, ($1.62, t = 1.9$ in column 5), but did not affect disabled dropouts (column 4).

[59] Analogous to Panel A, severe cold days (< 25°F) significantly increased dropouts without Social Security benefits, ($2.63, t = 3.4$) in column 5, but not dropouts with benefits in column 4.

[60] This is aligned with an influential work, Ruhm (2000), which argues that people become healthier by working less in recessions. This is supported by time diary records in recessions (Aguiar, Hurst and Karabarbounis (2013)), who document that people reallocate work to time with family and self-care.

The observed wedge between disability and dropout would be best reconciled if dropout is not a consequence of disability, but a preventive avoidance before their health becomes permanently impaired. Consistent with band-aid solutions on hot days reported in previous work, such as reduced work hours and absenteeism (Graff Zivin and Neidell (2014); Somanathan et al. (2021)), my findings so far present a set of symptoms of adaptation; the heterogeneity analysis revealed that a small adaptation to hot days occurred over years and in initially hot areas (Section 3.4). The bin analysis (Figure 6) shows that climate damage is slightly mitigated, when the daily temperature is above 80 ℉. In contrast to the acute mortality episodes often reported in the climate-health literature[61], male LFPR responds only in the longer treatment of 3 years and longer, suggesting their sensible behavioral adjustment (Table A-2). Moreover, the labor supply of permanently disabled males should not respond to richer residential amenities and family wealth (Table 8). Putting all the pieces together, I conclude that climate-induced dropouts are not a byproduct of public health disasters, but adaptation of the lifestyles to prevent their health from deteriorating.

4.4 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 (Molloy, Smith and Wozniak (2011); 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

[61] The climate-health literature reports acute mortality on hot days among hard-to-adapt, physically vulnerable populations, including the elderly (Deschenes and Moretti (2009)), the homeless (Ramin and Svoboda (2009)), pregnant mothers (Kuehn and McCormick (2017)), and infants (Deschênes, Greenstone and Guryan (2009)).

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-11). 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-11). If extreme temperature days reduce in-migrants, out-migrants must respond by shrinking to maintain population size[62].

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, perhaps consistent with an increase in dropouts living with their parents (Figure 3). 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, but by the exit of the local labor force.

5 Assessment

5.1 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

[62] 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.

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 $\overline{I}_0$ (e.g., 2000) to $\overline{I}_1$ (e.g., 2019) is calculated as

$$\Delta \text{LFPR}_R^g = \sum_{i \in R} \omega_{R,\overline{I}_0}^{g,i} \beta^{g,h} (\text{hd}_{i,I_1} - \text{hd}_{i,I_0}) + \sum_{i \in R} \omega_{R,\overline{I}_0}^{g,i} \beta^{g,c} (\text{cd}_{i,I_1} - \text{cd}_{i,I_0}), \tag{3}$$

where $\omega_{R,\overline{I}_0}^{g,i}$ is the population share of CZ i's group g within region R in the initial year $\overline{I}_0$ and $\text{hd}_{i,I}, \text{cd}_{i,I}$ are the average number of hot days and cold days during each 5-year period I. Given that my estimates come from two-way fixed-effects models, and that there is little evidence for climate-induced migration (Section 4.4), the results of the formula (3) 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" between greater warming and milder cooling. Figure 7 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 $I_0 = [1966, 1970], I_1 = [1995, 2000]$ into the formula (3), 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 recalculation with $I_0 = [1996, 2000]$ and $I_1 = [2015, 2019]$ yields a net climate

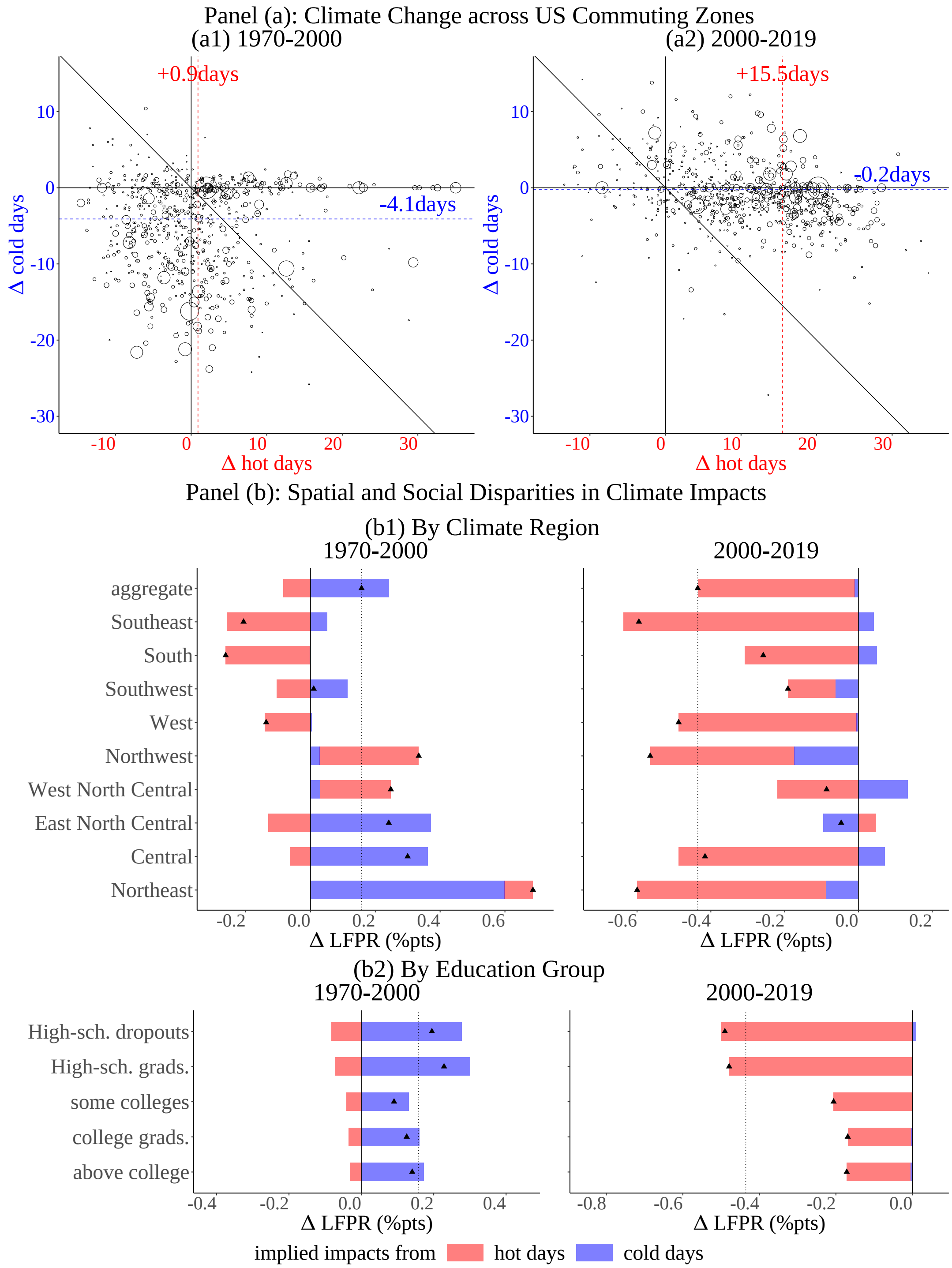

Figure 7: Implied Climate Impacts on the Labor Supply of Adult Males

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 (3), 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.

impact of -0.436 $\%pts,$ almost exclusively due to more hot days[63]. 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.[64]

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 temperature rise may be underestimated because of the strong interaction of high temperature and high humidity from the neighboring Gulf of Mexico[65]. 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 A-6). 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

[63]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 23). The calculation is robust to a number of alternative models of splitting by education group, dynamically variable effects, and interaction with outdoor exposure (see Figure A-12). Estimates from alternative models suggest that the contribution of climate change is in the range of 11.2%-15.1% (baseline).

[64]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.

[65]Recall that using uncomfortable days measured by the interaction of temperature and humidity provides much larger estimates (see Table A-6).

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 (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 29), 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.

5.2 Policy Implication—Heat Regulation Law

Global temperatures are projected to rise in the coming decades of the 21st century (Masson-Delmotte et al. (2021)). 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[66]. 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. This appears to be particularly effective for mildly warm temperatures of 75-85°F, where an increase in wage was found (see a discussion around Table 7 and Figure (A-11)). Because the number of days with 75-85°F days is large, rapidly increasing, and widespread compared to severe temperature extremes, I consider this mild temperature range to be particularly alarming; if the hot temperature remains tolerable, employers or employees are unlikely to take countermeasures seriously, and cumulative exposure to this temperature will be detrimental to physical and mental health in the long run, as the cautionary tale of the "frogs in the boiled water" warns[67].

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 (Ponticelli, Xu and Zeume (2023)), exit of relatively smaller firms (Acharya, Bhardwaj and Tomunen (2023)), and adoption of automation (Qiu and Yoshida (2024)).

[66] 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)).

[67] See footnote 5 in the Introduction.

Despite the null nationwide wage response (in Section 4.1) and its implied counterbalance of shrinking regional labor demand and supply, the net benefit of the regulation appears to be a purely empirical question. Either ex-post regional case studies or ex-ante net welfare evaluations are beyond the scope of this paper, and are left for future work.

6 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 socioeconomic inequality.

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APPENDICES FOR ONLINE PUBLICATION

Climate Change and Outdoor Jobs: the Rise of Adult Male Dropouts

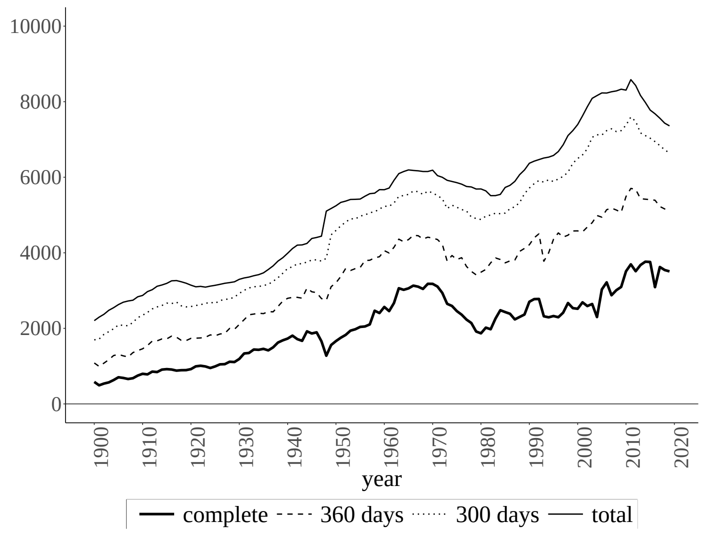
Masahiro Yoshida

April 12, 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.



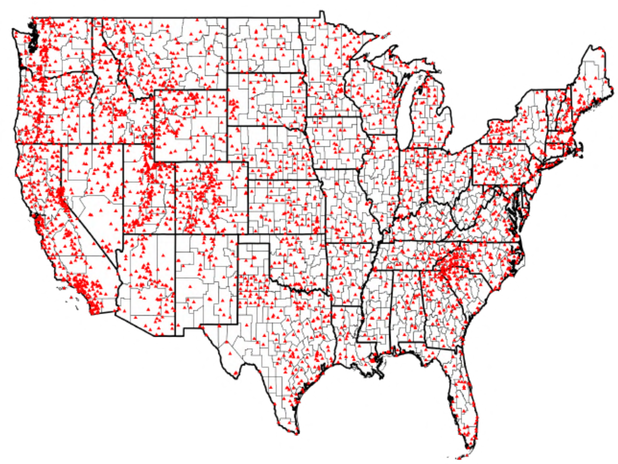


Figure A-1: Availability of US Weather Stations (left: trend in 1900-2019; right: distribution in 2019)
Note: (left) Weather stations are Global Historical Climatology Network Daily (GHCN-daily) from the NCEI. (right) Borders are commuting zones, and red dots indicate stations with full days available 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).

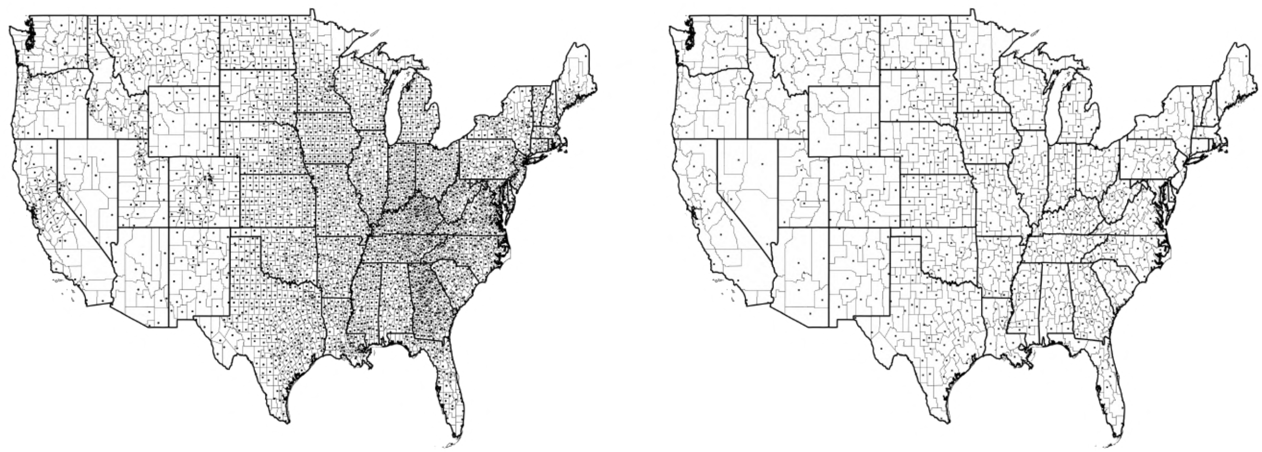


Figure A-2: County (left) vs. Commuting Zone (right) Level Population Centroids

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

Compute daily weight for a maximum temperature I obtain the hourly temperature variation at each day d at each CZ i from January 1 to December 31, averaged over 1980-2010 from the Climate Normals dataset of the NCEI. Then, for a day $d \in (w, m)$ in month m-by-week w, I compute a daily temperature of day d, using a weight to the maximum, $\omega_{m,w,i}$ at CZ i. Each month m is divided into 4 weeks: the first, second, third week consists of 8, 8, 7 days. The fourth week consists of $n - 23$ days, where n is the number of days in each month.

First, I match a nearest available station, reordered in the Climate Normals, to the population centroid of each CZ i (computed above) on a month m-by-week w basis. Second, I construct a daily median temperature $T_{d,i}^{median}$ during business hours (8 am - 6 pm), and daily maximum and minimum temperatures $T_{d,i}^{max}, T_{d,i}^{min}$ at CZ i. I drop 0 am because a significant portion of the data is missing. Omitting 0 am is harmless because 0 am rarely hits the minimum of a subsequent day or an earlier day. Third, for each month m-by-week w at CZ i, I compute a daily weight $\omega_{d,i} \in (0, 1)$ to the maximum s.t. $\omega_{d,i} = \dfrac{T_{d,i}^{median} - T_{d,i}^{min}}{T_{d,i}^{max} - T_{d,i}^{min}}$. Finally, I take an average $\omega_{d,i}$ for $d \in \{m, w\}$ to get $\omega_{m,w,i}$.

Temperature Figure A-3 shows the calculated levels and changes of hot days and cold days with temperature thresholds of 75°F and 35°F, respectively.

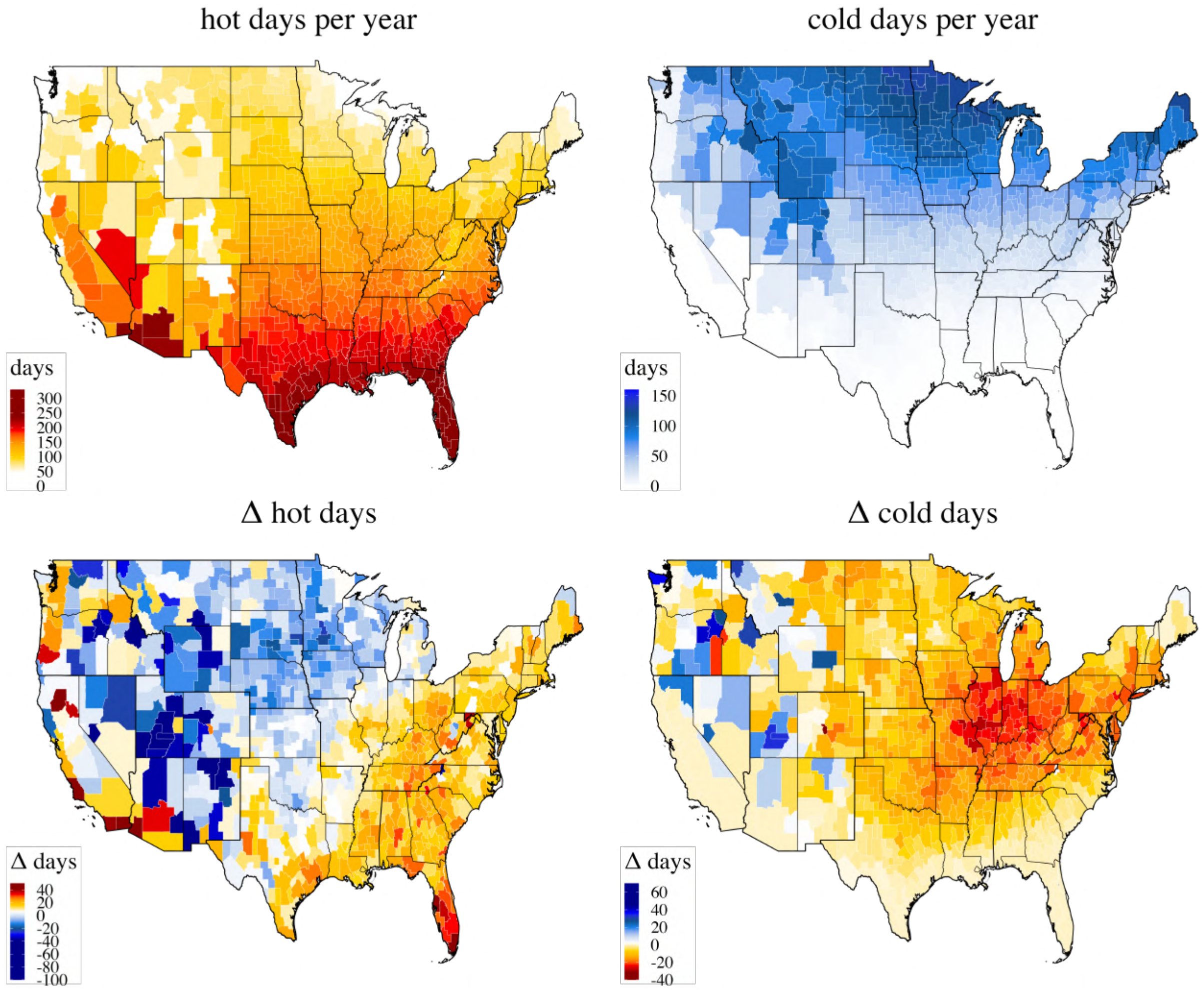


Figure A-3: Hot and Cold Days in US Commuting Zones (level in 2019; change from 1980-2019)

Note: The thresholds for hot days and cold days are set at 75°F and 35°F of the median temperature during business hours (8am-6pm). I use an average number of hot and cold days during 2015-2019 for 2019, and during 1976-1980 for 1980.

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-4 shows heat maps of the extensive margin and intensive margin of precipitation and snowfall over the CZs in the most recent period, 2015-2019.

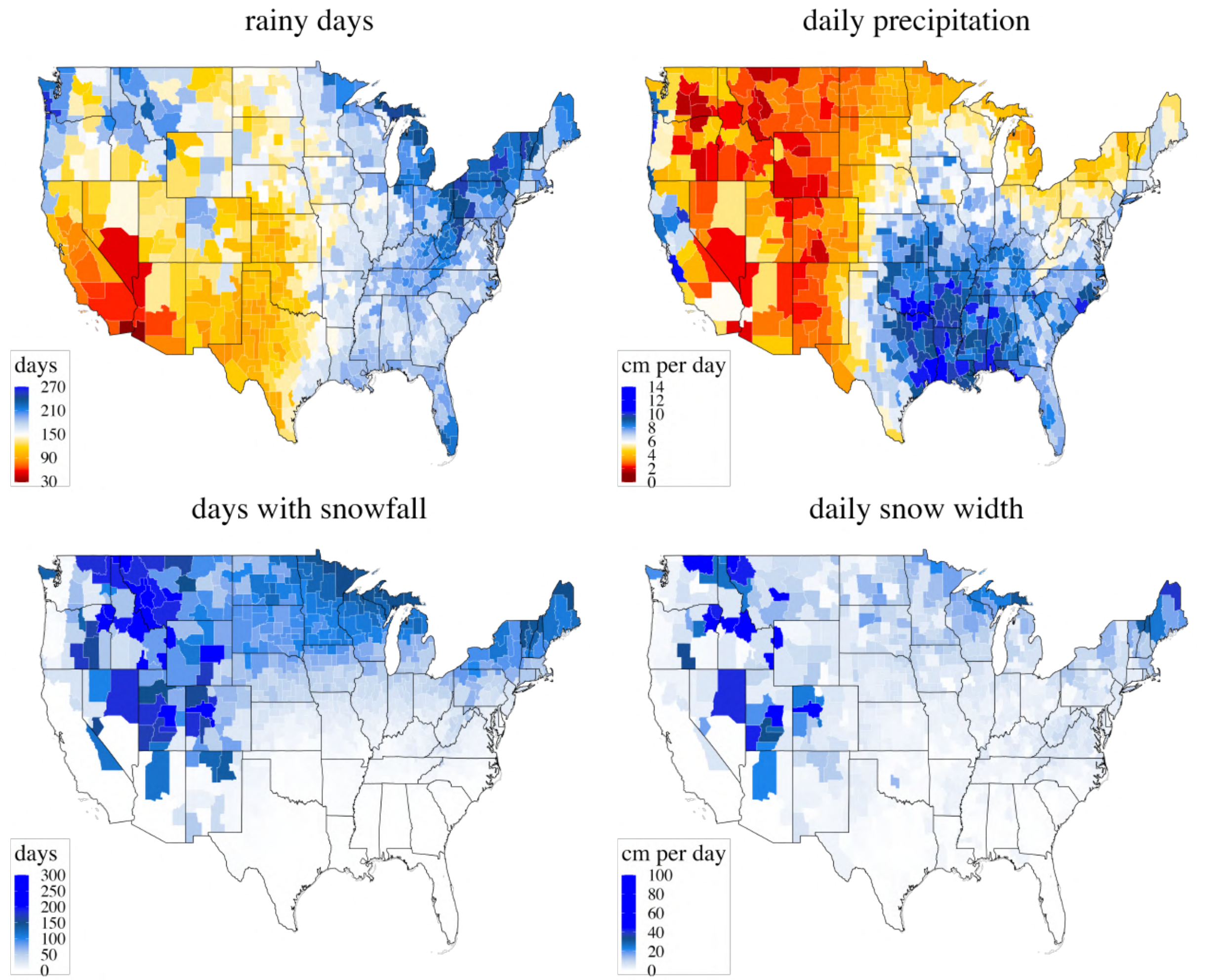


Figure A-4: Precipitation and Snowfall (2019)

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.

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 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-5 shows heat maps of relative humidity and uncomfortable days with Discomfort Index is above 75.

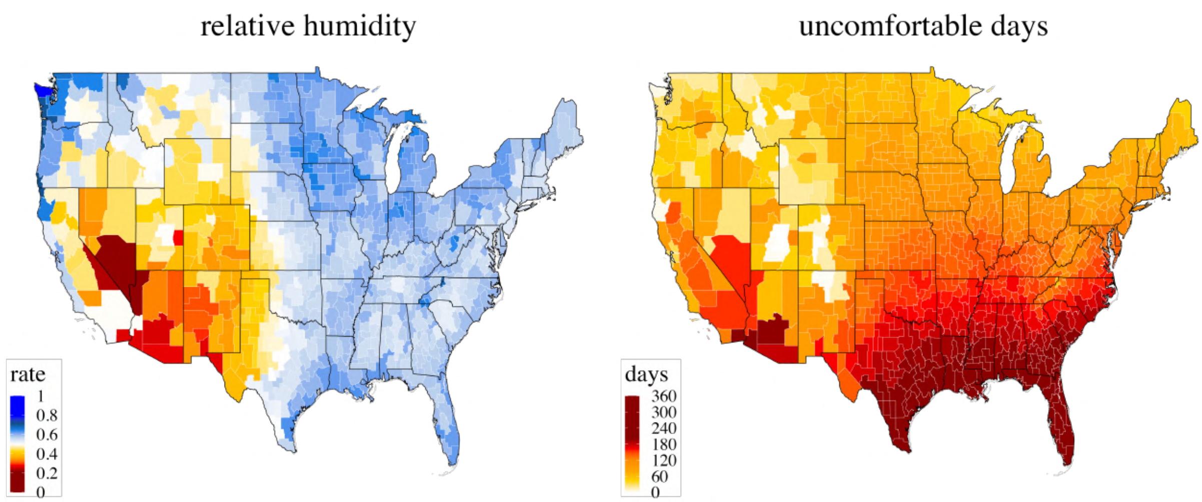


Figure A-5: Relative Humidity and Uncomfortable Days (2019)

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 2019, I use an average of each proxy during 2015-2019.

A1.2 Labor Force Participation Rates (LFPRs)

Figure A-6 contrasts LFPRs of non-institutionalized prime-age (25-54) males across commuting zones in 1980 to pre-pandemic levels in 2019. Using David Dorn's crosswalks, county groups (1980) in the 1980 Census and Public Use Microdata Areas (1990-2019) in the 1990-2000 Census and 2009-2010, 2018-2019 ACS are converted to CZs.

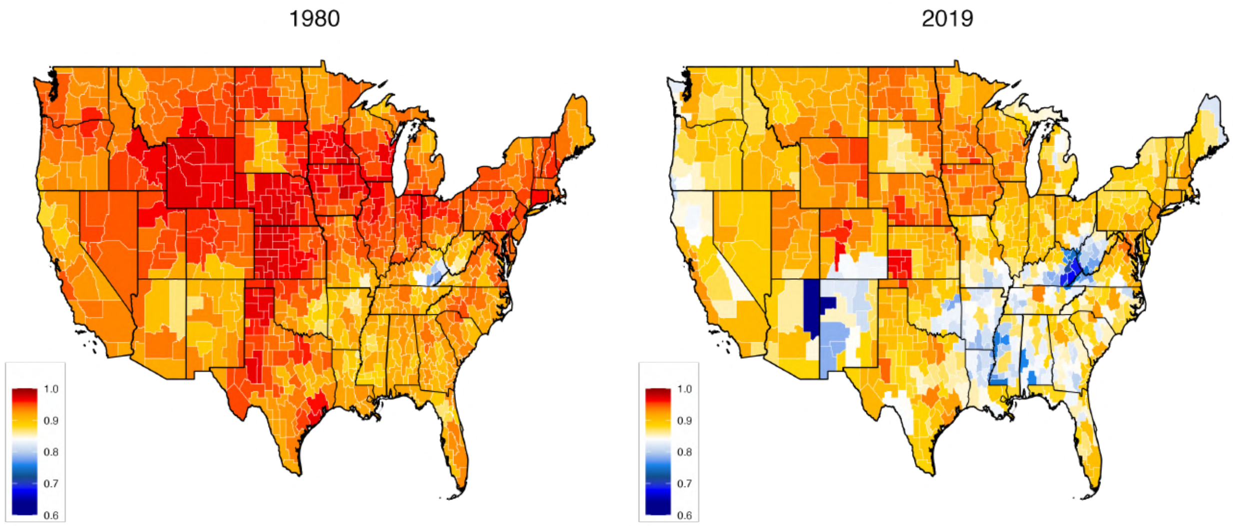


Figure A-6: LFPRs across Commuting Zones (1980 vs. 2019)

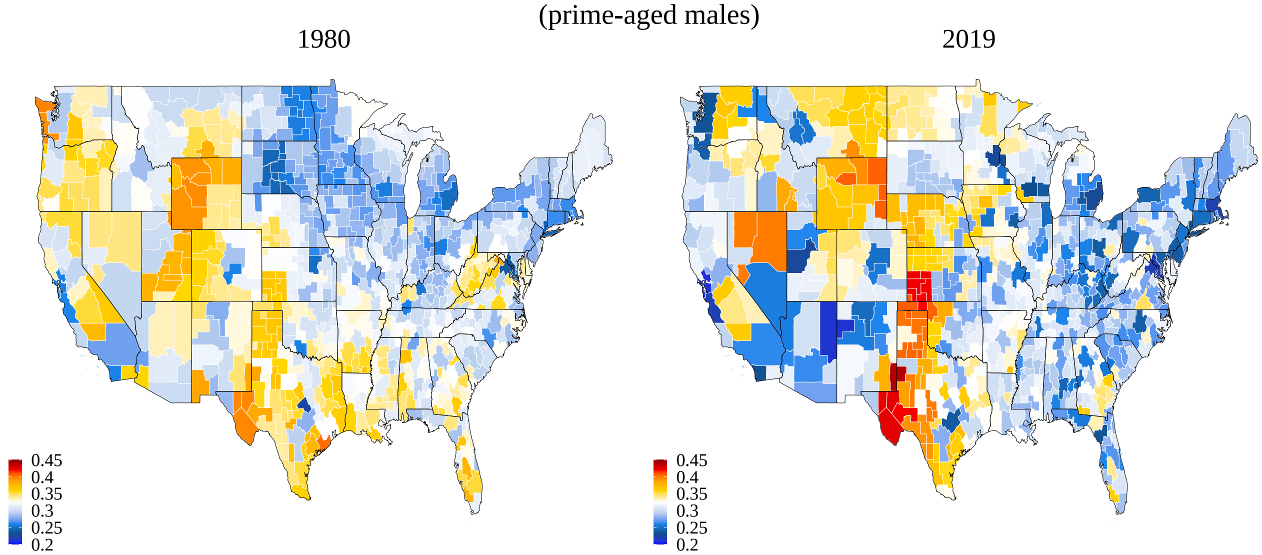
Note: LFPR is the share of the labor force in non-institutionalized prime-age (25-54) male population from the 1980 Census and the 2018-2019 stacked ACS.

A1.3 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 prevalence of outdoor jobs as a share of the prime-age male population to regional development, proxied by the median weekly wage of all workers and 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)).

Panel (a): A Population Share of Outdoor Jobs
(prime-aged males)



Panel (b): Economic Development and Dependence on Outdoor Jobs

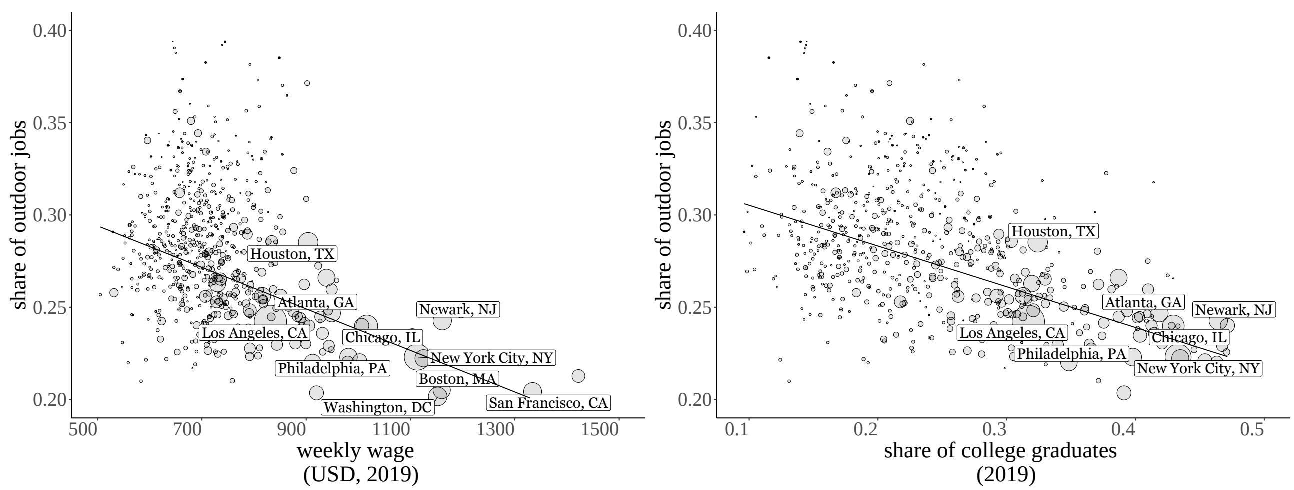


Figure A-7: Outdoor Jobs across Commuting Zones (1980-2019)

Note: Computed from IPUMS of the 1980 Census and the 2018-2019 stacked 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): A share of outdoor workers in prime-age male population. Panel (b): Weekly wages in prime-age male workers (left) and the share of non-college graduates in prime-age male population (right).

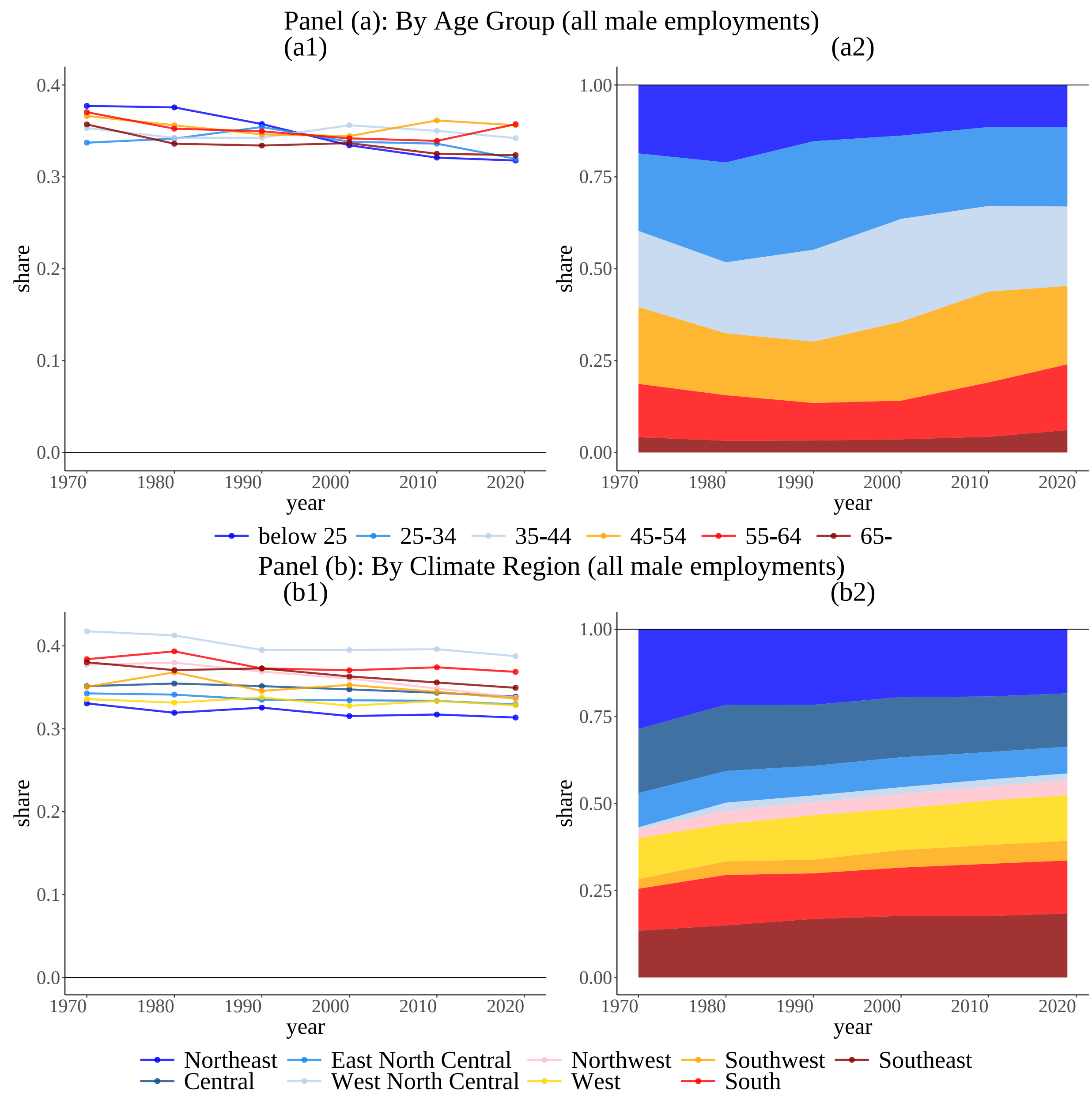


Figure A-8: Outdoor Workers by Age Group and Climate Region (Selection and Composition)

Note: Computed from IPUMS of 1970-2000 Census by decades and stacked 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 4. 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.

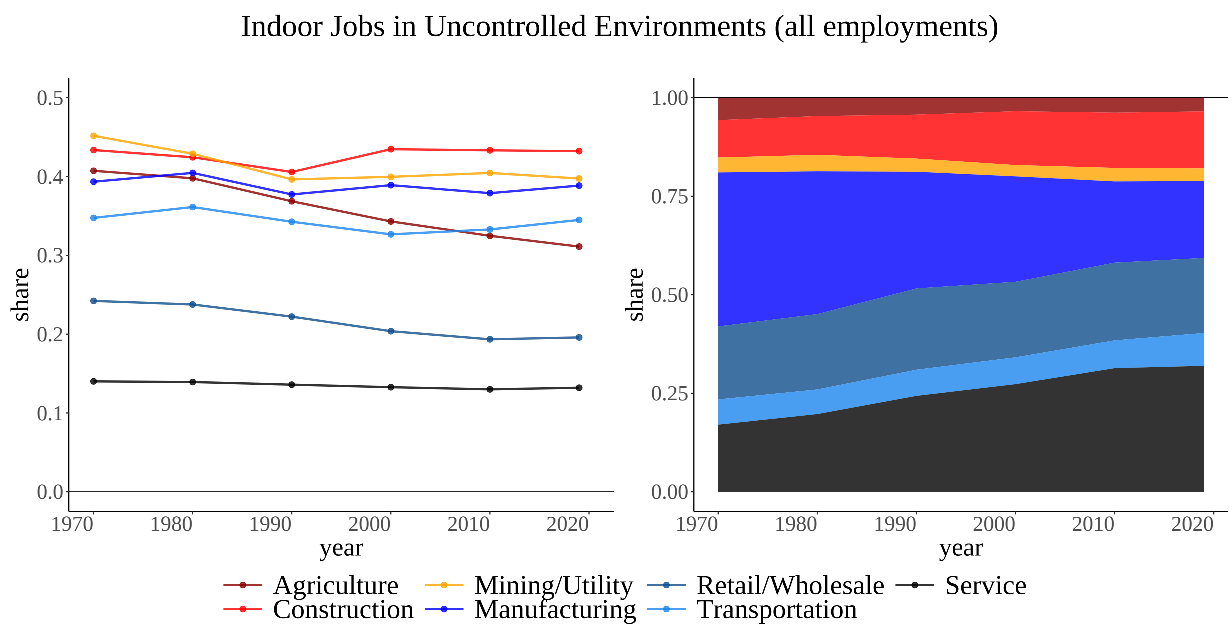


Figure A-9: Indoor Jobs in Uncontrolled Environments by Sector (Selection and Composition)

Note: Calculated from IPUMS of the 1970-2000 Census by decades and stacked 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.

A1.4 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.

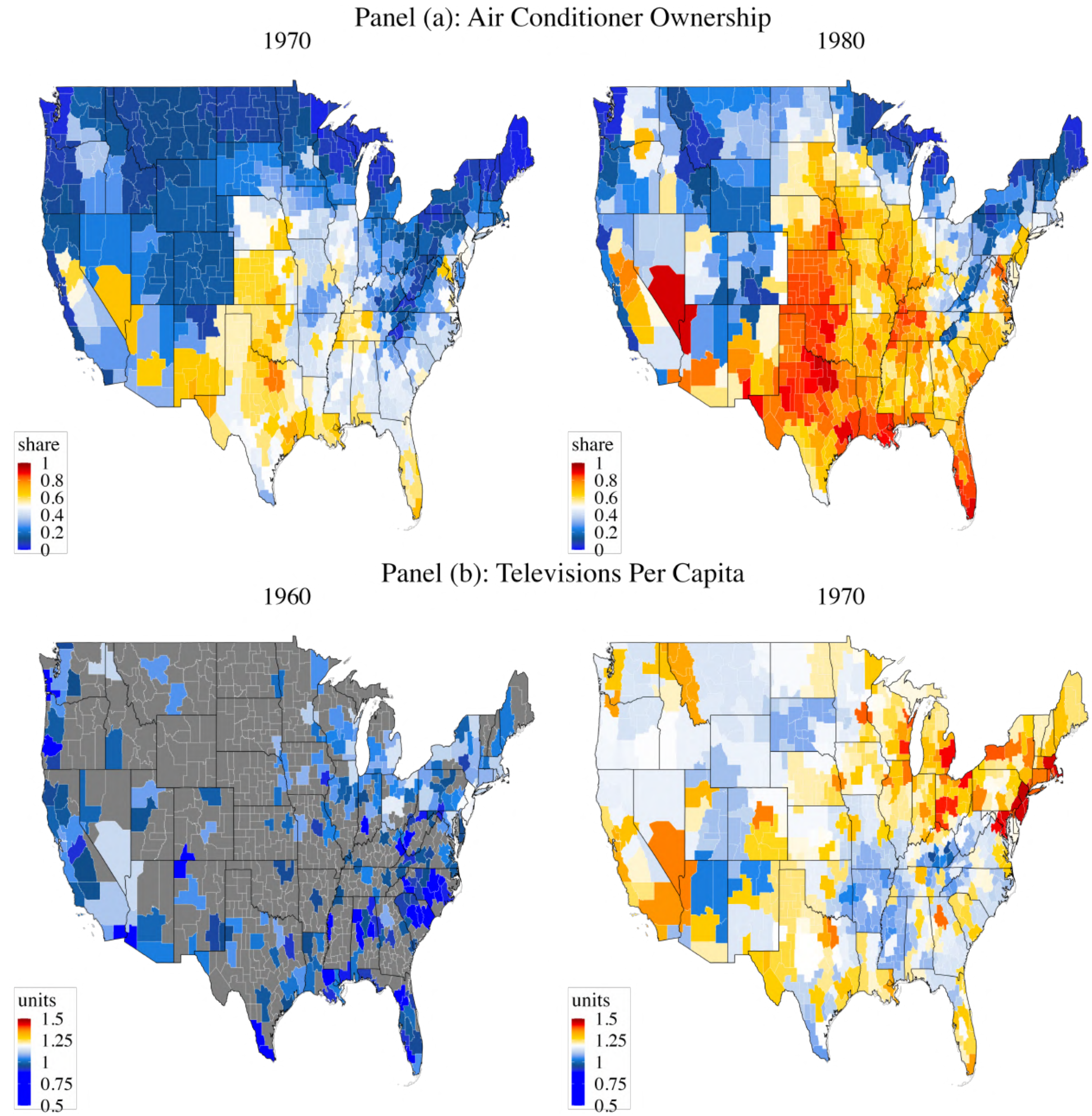


Figure A-10: Prevalence of Residential Amenities

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. $\mathbf{C}_{i,I}$ are taken in 5-year average for each period I.

- $\mathbf{C}_{i,I}$ (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)

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

- $\mathbf{D}^g_{i,\bar{I}_{-1}}$(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)

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

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

- $\mathbf{W}^g_{i,\bar{I}_{-1}}$(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-11), 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 climate variable treatment windows. Longer treatment windows increase the magnitude of the climate effect with stable statistical significance. In particular, in column 1, 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 cumulative labor discomfort mechanism.

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 periods × 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 pretrends 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.

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 × year FE**	**+ state × 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 periods $\times$ 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. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

Labor demand shocks Table A-4 reports the estimates from subsamples that exclude CZs that were severely affected by a particular labor demand shock. Computer shocks are changes in exposure to PCs per employee in 1980-2000, borrowed from Autor and Dorn (2013). Robot shocks are changes in industrial robots per employee in 2004-2014, constructed from Acemoglu and Restrepo (2020). China shocks are proxies for international trade competition with China in 1990-2007, constructed from Autor, Dorn and Hanson (2013). A set of CZs particularly affected by these shocks is specified by prime-age male population-weighted percentiles (25 pct. or 50 pct.) of CZ-level shocks. Excluding these areas does not weaken the robustness of the main warming estimates. The negative cooling estimates are largely inherited, although with slightly less precision, possibly due to reduced power.

Table A-4: 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^{***}	-0.379^{***}	-0.302^{***}	-0.339^{***}	-0.319^{***}	-0.382^{***}	-0.402^{***}
	(0.066)	(0.084)	(0.106)	(0.075)	(0.102)	(0.075)	(0.110)
10 cold days	-0.379^{**}	-0.452^{***}	-0.593^{***}	-0.214	-0.268	-0.351^{*}	-0.398
	(0.170)	(0.148)	(0.128)	(0.168)	(0.216)	(0.183)	(0.249)
Observations	3,610	3,185	2,620	2,625	2,090	2,455	2,110
Adjusted R^2	0.876	0.877	0.875	0.884	0.876	0.887	0.879

Note: Unit of analysis: 5 periods × 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. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

Agriculture Table A-5 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-5: 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 periods $\times$ 722 commuting zones) for column 1 and 5. Columns 2-4 respectively uses 610, 434, and 217 commuting zones for 5 periods. 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-6 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-6: 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^{**} (0.170)	-0.408^{**} (0.172)	-0.393^{**} (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 periods × 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-7 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-7: 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***	−0.406***
			(0.143)	(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***	−0.713***
			(0.184)	(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 periods $\times$ 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. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

A2.3 Regional Heterogeneity

Table A-8 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 previous period's outcome year 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 previous period's the outcome year, 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-8 supports that climate impacts are regressive for rural areas, where alternative indoor jobs, presumably in personal services, are poorly available.

Table A-8: Regional Heterogeneity: Urban vs. Rural Areas

	LFPR		**dropout rate**	
	(in %pts; prime-age males)			
	(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 periods × 722 commuting zones). log(pop density) and share of employment in services are taken at the end year of the previous period. 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-9 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 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-9: 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 periods × 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. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

A2.5 Wages

Semi-parametric bin model Figure A-11 illustrates the semi-parametric bin (10°F and 5°F) estimate of the climate impact on weekly wages, following Panel B of Table 7. 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 (< 20°F), relative to the benchmark bin of $[65, 75)$°F.

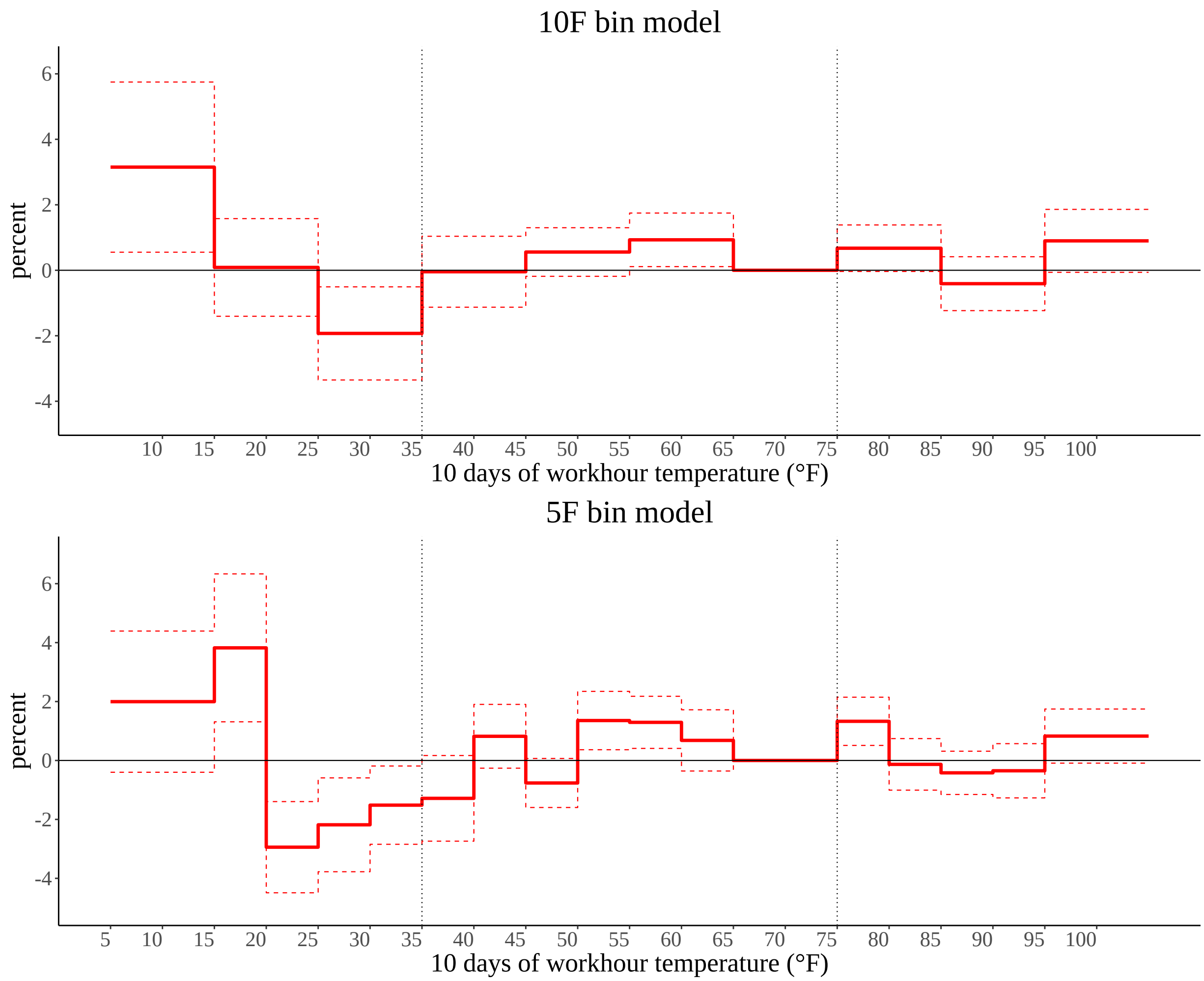


Figure A-11: Semi-parametric Climate Impacts on Weekly Wage within Sectors

Note: Unit of analysis: 5 periods× 722 commuting zones× 10 sectors × 5 education groups. Weekly wages in each cell are calculated for prime-age male workers, excluding the self-employed. Bin estimates of log weekly 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 CZ-sector-education groups and sector-state-year, regression weights, and clustering of standard errors in Panel B of Table 7.

Robustness of wage impacts Table A-10 shows the robustness of Panel B of Table 7 across protocols. I find that the null results for hot days and the negative effects for cold days are very robust.

Table A-10: Robustness on Climate Impacts on Weekly Wages within Sectors

	dependent variables: **Log (Wages)** (in percent; prime-age male salaried employment)														
	Hourly Wages cell: CZs × sectors × education groups				**Weekly Wages** cell: CZs × sectors				**Weekly Wages** cell: CZs × sectors× age groups				**Weekly Wages** cell: CZs × sectors × education groups		
													Alternative Exposure		
	Outdoor	**Indoor uncontrolled**	**Indoor controlled**	**Total**	**Outdoor**	**Indoor uncontrolled**	**Indoor controlled**	**Total**	**Outdoor**	**Indoor uncontrolled**	**Indoor controlled**	**Total**	**Outdoor** (every day)	**Indoor Uncontrolled** (every day)	**Indoor controlled** (≥ weekly)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)			
10 hot days	−0.179	−0.266	−0.220	−0.133	−0.159	−0.232	−0.179	−0.157	−0.085	−0.106	−0.143	−0.084	−0.254	−0.372	−0.157
	(0.362)	(0.337)	(0.321)	(0.307)	(0.397)	(0.363)	(0.384)	(0.366)	(0.396)	(0.369)	(0.367)	(0.357)	(0.379)	(0.377)	(0.338)
10 cold days	−1.361**	−1.176**	−1.106*	−1.012*	−2.220***	−1.948***	−1.712**	−1.805***	−1.962***	−1.882**	−1.842**	−1.823**	−1.845***	−1.660**	−1.753**
	(0.573)	(0.578)	(0.590)	(0.582)	(0.710)	(0.716)	(0.664)	(0.674)	(0.718)	(0.731)	(0.734)	(0.741)	(0.616)	(0.643)	(0.683)
	Pre-period covariates														
demography	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
industry structure	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
cell-level FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
sector-state-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	123,467	123,406	124,010	124,015	34,595	34,595	34,595	34,595	316,748	316,566	319,540	319,641	122,907	122,519	124,014
Adjusted R^2	0.875	0.883	0.893	0.902	0.911	0.917	0.918	0.934	0.816	0.827	0.849	0.859	0.844	0.860	0.898

Note: Unit of analysis: 5 periods×cells. Weekly wages of each occupational category in each cell are computed for prime-age men in salaried employment. See the main paper for definitions of climate exposure. Sectors are inherited from the classification of Table 5. Education takes five categories: high school dropouts, high school graduates, some college years, college graduates, and above college. Age groups takes three groups, [25, 35), [35, 45), and [45, 54). Pre-period employee demographics for each occupational group is controlled at the cell level. Pre-period industrial composition (average size of establishment and Herfindahl-Hirschman index) is controlled at the CZ-sector level. Other elements of the models inherit from Panel B of Table 7. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

A2.6 Migration

Table A-11 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.[68].

[68]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-11: Climate Change and Cross-regional Migration

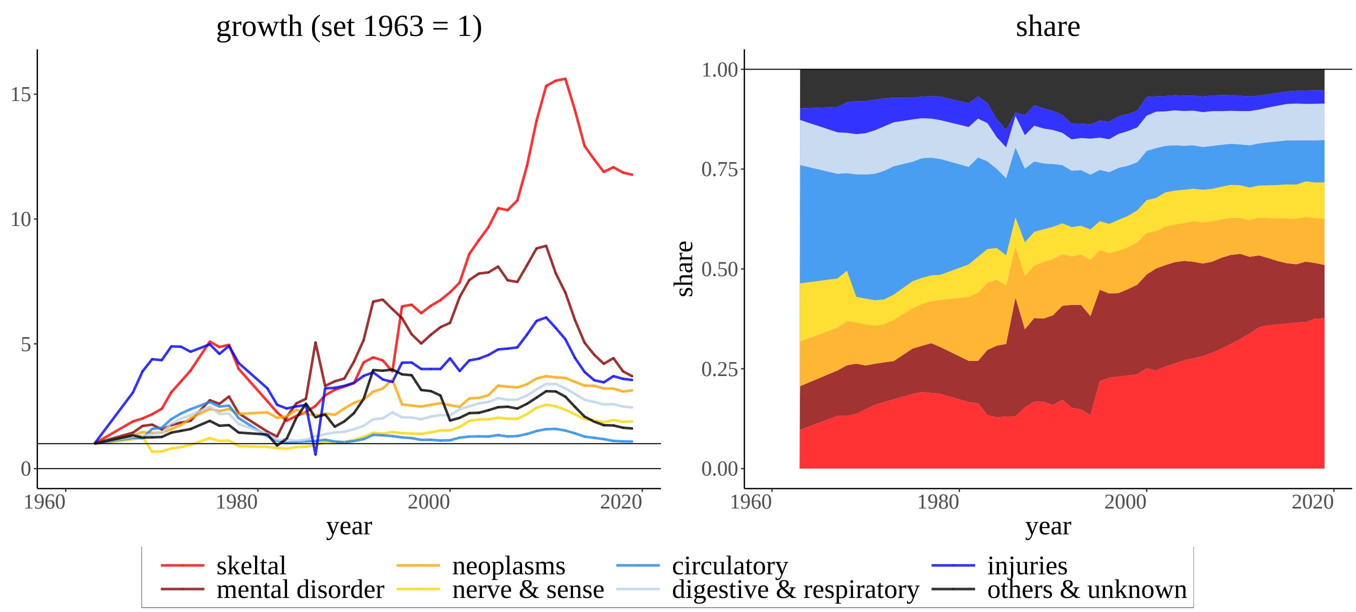
	dependent variable: **Population Size (log-scaled)** (in percent; prime-age males)					
	Total	**Non-college grads**	**College grads**	**Moved-in between states**	**Moved-in in 5 yrs**	**Born at the state of residence**
	Panel A: Baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
10 hot days	−0.902	−0.422	−0.830	−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 periods $\times$ 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 stacked 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. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

A2.7 Disabilities

Disability insurance awards by diagnostic group Figure A-12 shows a trend and share of Social Security Disability Insurance (SSDI) recipients by diagnostic group, crafted from the Annual Statistical Report on the Social Security Disability Insurance Administration. Since 1980, the growth of skeltal cases and mental disorders are salient, consisting of the two largest groups after 2000. Other prominent cases including neoplasms, nerve & sense, digestive & respiratory are largely stable. Injuries account for a very small proportion between 3-5%.

Figure A-12: Social Security Disability Insurance Awards by Diagnostic Group (1963-2019)



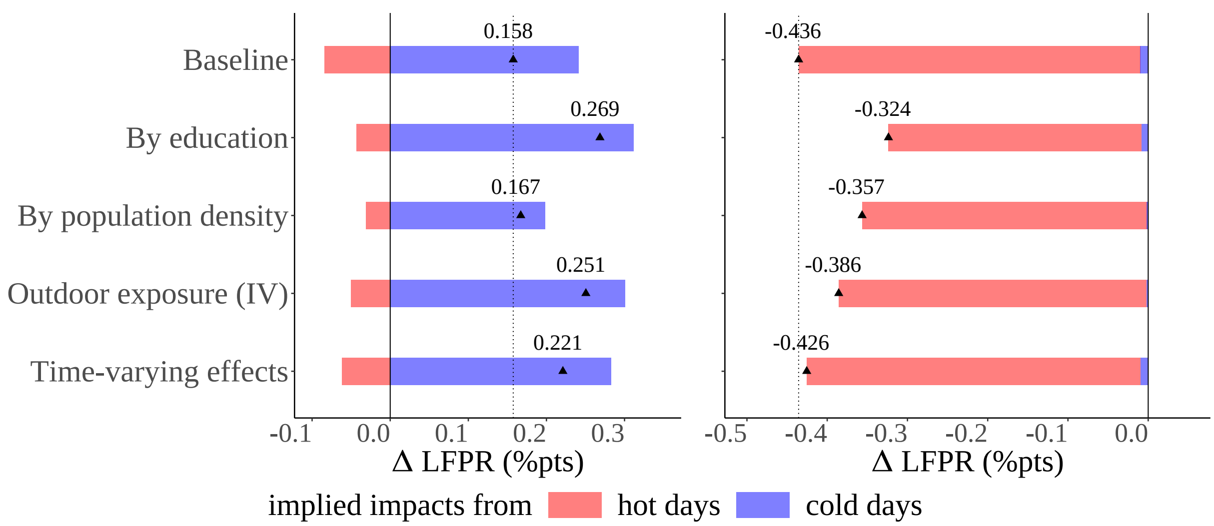
Note: Computed from the Annual Statistical Report on the Social Security Disability Insurance Program, 2023, Social Security Administration. "others & unknown" includes *congenital, infection, endocrine, blood, skin, other, unknown*. "digestive & respiratory" include *digestive, genitourinary, respiratory*. Discontinuous spikes in mental disorder and injury cases in 1986 reflect the raw data.

A3 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-8). "Outdoor exposure (IV)" indicates a model that interacts instrumented outdoor exposure (column 1, Panel B of Table 6). "Time-varying effects" suggests a model that estimates time-varying effects during the period end years $\overline{I} \in \{1980, 1990, 2000\}$ 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%, 14.8%, 12.4%, 13.4% of the an overall decline in LFPR during 2000-2019, $-2.88\%pts$ (linear trend) from the BLS headline figure.

Table A-12: 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 shows 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-8. 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.

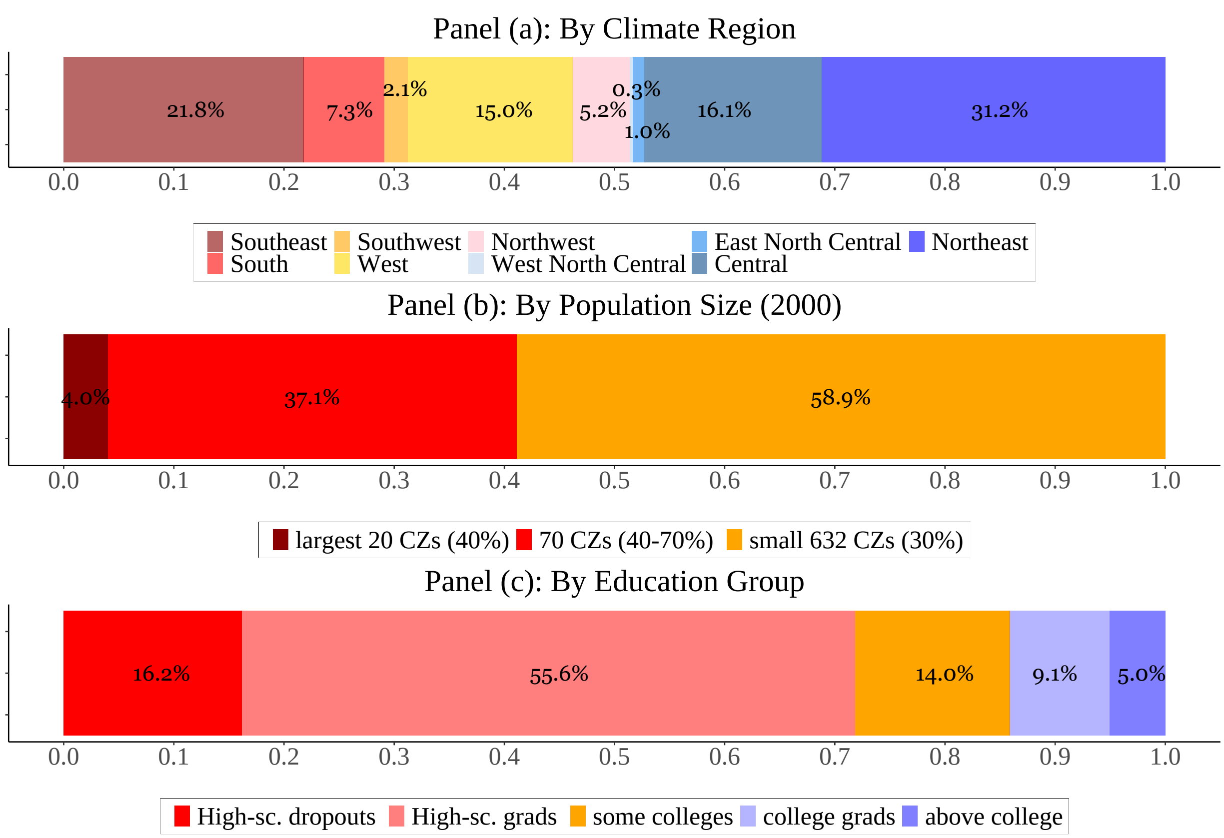


Figure A-13: Implied Composition of Climate-induced Dropouts during 2000-2019

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.