Climate Change and Outdoor Labor Markets: the Rise of Dropouts of Adult Males*

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Abstract

Male labor force participation in developed economies has ubiquitously declined since the 1970s. This paper shows that concurrent global warming fueled dropouts of prime-aged adult males by harming their traditional advantage of working outdoors. Exploiting climate change variation across U.S. commuting zones, constructed from granular weather station records, I find that 10 more annual hot days (above $75°F$) hurt labor force participation rate (LFPR) of prime-aged males by 0.3 percentage points during 1970-2019, more saliently for less-educated. In the new century, climate change accounted for 17% of the nationwide LFPR decline for non-college graduates. The effect of hot days is critically shaped by regional dependency on outdoor jobs. Climate change both hurt employment-to-population ratio and wages of outdoor workers, with limited transfer to indoor sector. I also find that the LFPR decline was partially induced by the labor supply side, fueled by the spread of residential amenity (e.g., air conditioners and colored TV sets) in the late 20th century. Collectively, the findings suggest that climate change exacerbates socio-economic inequality.

JEL Classification: J22, J12, J13, Q54

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1 Introduction

The globe has become and will be a hotter planet. Climate science established that a global temperature trended up around the 1970s[1]. The warming further accelerated in the 21st century, currently ends up being called as *global boiling* (Guterres, 2023)[2]. Climate scientists and economists have traditionally explored the climate impact on ecosystem and agricultural production at outdoor fields (e.g., Mendelsohn, Nordhaus and Shaw (1994); Deschênes and Greenstone (2007)) and countermeasures to cut CO2 emissions, however, surprisingly little is known about how climate change affects behavioral responses of people in the labor market.

This paper proposes a novel hypothesis that modern global warming loomed up since the 1970s contributed to a global decline in prime-aged male labor market participation rate (LFPR below) in developed countries[3]. I empirically features the U.S.: until 1970, a non-participation dropout rate[4] for U.S. prime-aged (aged 25-54) males had been 2-4%, in 2019, however, the rate has consistently risen to an alarming height of 12%[5], leading to rising income inequality, morbidity and poor subjective well-being (Krueger (2017)). Only consensus made in the long-standing debate is that a single dominant factors, both in demand and supply sides, cannot explain for the long-run decline (See Abraham and Kearney (2020) and Binder and Bound (2019) for a comprehensive survey)[6].

To motivate my inquiry, Figure 1 illustrates the long-run nationwide trend of hot days (with daily temperature exceeds $75°F$) and LFPR of prime-aged males during 1950-2019. As the number of hot days increased around 1970, one can see the parallel decline in LFPR. (Figure 1)

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[1]This temperature rise is unprecedented for two millennia since the dawn of 19th century industrialization. See e.g., Masson-Delmotte et al. (2021), Intergovernmental Panel on Climate Change (IPCC).

[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 the cross-country phenomenon on LFPR drop, e.g., Grigoli, Koczan and Topalova (2020).

[4]I define a person as a dropout if he is not either employed (including self-employed), nor searching for job (unemployed) and is not at school either.

[5]From U.S. Bureau of Labor Statistics. See a nationwide trend in the U.S. at Figure **??**.

[6]Conventional explanations include technology (Autor, Levy and Murnane (2003); Acemoglu and Restrepo (2020)), free trade (Autor, Dorn and Hanson (2013)) and institutions (Autor and Duggan (2003)). See related literature section for greater detail.

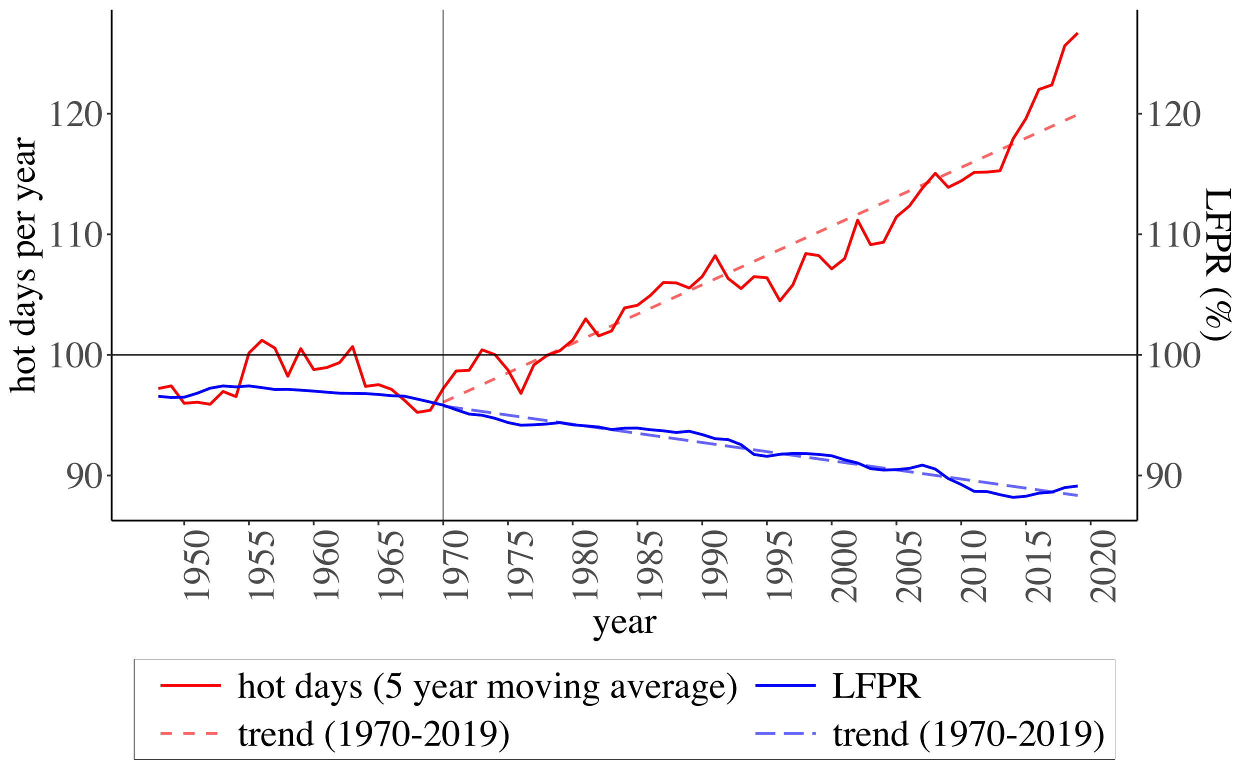

Figure 1: Nationwide trend of annual hot days (left axis) and labor force participation rate of prime-aged males (right axis; 1950-2019, U.S.)

Note: Nationwide hot days is a 5 year moving average of population-weighted average of exposure to hot days across counties in the U.S. mainland. Station records on weathers from National Oceanic and Atmospheric Administration (NOAA) are aggregated to county-level, weighted by annually interpolated county population from historical census (1940-1970 by decades) and Surveillance Epidemiology and End Results, National Cancer Institute (1970-2019, annually). A hot days has a mean temperature of $75°F$ ($23.9°C$) and a daily weight to maximum temperature is $\omega = 0.75$. Nationwide participation rate of prime-aged (25-54 years) males are taken from U.S. Bureau of Labor Statistics.

To help bridge a seemingly independent coincidence, I document that consistently 30% of prime-aged males have worked regularly outdoors since 1970, as identified by O*NET Work Context Survey, typically in primary, construction and transportation sectors. Intriguingly, over 75% of the outdoor workers have been consistently occupied by males. In parallel, during a half century, 1970-2019, I compute that 5-year average hot days per year (daily temperature above $75°F$) experienced by an average U.S. resident increased by 29.5 days (See Figure 1). Imagine a male working outdoors. Larger exposure to hot days would physiologically augment labor costs of manual tasks while standing, walking and sweating, and thus, suppress labor supply for outdoor jobs (*discomfort effect*). Intriguingly, since the

1960s, residential air conditioners and colored TV sets penetrated at home and relative cost of working outdoors vs. staying at home has expanded. Simultaneously, exposure to hot days would hurt labor productivity (Somanathan et al. (2021); Chen and Yang (2019)), and thus, shrink labor demand of outdoor jobs (*productivity effect*) by reallocation of labor, technical change, or exits of businesses. As both forces reduce outdoor jobs, global warming would nudge workers to get out of the market, even if he is unaware of climate change. In the age of global *boiling*, the reasoning conjures up a cautionary tale of frogs in the boiled water[7].

To assess the mechanism above, I build a balanced panel of exposure to climate change associated with LFPR across 722 U.S. commuting zones during 1970-2019. Containing a variety of climate zones, the continental U.S. provides an ideal testing ground for the climate-labor nexus. I construct a more than half-century series of daily weathers (e.g., humidity; precipitation; snowfall) of commuting zones from raw station records of nearly 15,000 U.S. weather stations from the National Climatic Data Center (NCDC).

To measure a daily temperature, majority of the literature conventionally uses the mean of daily maximum and minimum temperature. However, I show that the canonical measure significantly underrates the temperature during prime labor hours. Combining hourly temperature fluctuation from the separate U.S. Climate Normals dataset, I find that median temperature during business hours (8 am - 6 pm) has been substantially higher by 6.9F, and especially in the summer (July-September), by 9.0F compared to the conventional all hour daily mean.

Connected with prime-aged male LFPR computed from the Population Census and American Community Survey, this near-exogenous treatment permits a natural experiment, after controlling for extra climatological variables, demographics, health and wealth variables, regional traits, industry structure and Census division trend in addition to commuting zone and year fixed effects (See Dell, Jones and Olken (2014)).

The baseline results suggest that 10 more hot days (temperature $>75°F$) in decadal

[7]"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 tepid water and slowly warm it, the frog doesn't figure out what going on until it's too late." (Old proverb, rephrased in Meyer (2008)) This tale cautions that people may react to an acute shock, but fall into inaction under an incremental change.

baselines shrink prime-aged male LFPR by 0.24 percentage points. Cold days (temperature $< 35°F$) are also harmful, but with slightly less precision. The response is sharpest for less-educated (aged 35 and below). During 1970-2019, increase of hot days net of effects from decreased cold days depressed the nationwide LFPR by -0.108 *p.p.*. After 2000, however, the climate impact expanded to -0.320 *p.p.* (12.4% of the nationwide drop in LFPR) with little impacts from decreased cold days. Limiting to non-college graduates, the climate impacts was 17.7% of the total, and the impact was largest in the Southeast and Northeast regions, explaining 12.5% and 22.0% of the regional drop in LFPR, respectively.

I also find that climate change significantly reduced employment-to-population ratios of outdoor workers, and raised an unemployment-to-population ratio. I interpret that less-educated males working outdoors have less comparative advantage in indoor occupations, which are supposedly more intensive in communication or analytical skills. With controlling demographics, I find that extreme hot days *hurt* wages exclusively for outdoor workers. Combined with decreased employment-to-population ratio of outdoor workers, the adverse wage effect indicates that labor demand shrinkage is relatively at work to mask the supply-side contraction.

It appears very challenging to detach labor supply contraction from labor demand, because rising discomfort under heat (thus, suppress labor supply) would mechanically hurt labor productivity (thus, shrink labor demand). To directly isolate the labor supply response, I run a pair of exercises. First, I test whether regional prevalence of residential amenity (e.g., air conditioners and colored TV sets) magnified adverse climate impact on LFPR. Residential amenity presumably increases relative cost of work (by upgrading leisure utility at home) without harming labor productivity. Intriguingly, I find that prevalence of residential air conditioners and TV sets significantly augmented climate damages in the late prior century.[8] Second, I directly test whether climate change eroded preference for work, measured by repeated cross-sections of World Value Survey (WVS). Pairing interviewees' locations (longitudes and latitudes in 2017)[9] and regional climate change, I find that exposure

[8]The finding resonates with Aguiar et al. (2021), assessing the role of evolving video game technology to augment leisure utility and depress labor supply of young males.

[9]In the latest 2017 wave, interview locations are available by longitudes and latitudes. In 2013, residence

to hot days is associated with their lower willingness to work, expressed in nearly all work-related questions. A respondent's detail occupation is unavailable, however, the effect shows up exclusively for prime-aged males, and more sharply for the less-educated. Collectively, I conclude that the climate-induced dropout hypothesis operates both labor demand and supply sides. Under the forecast of accelerating global warming and with lacking evidence of adaptation, outdoor workplaces will further be a hotbed of dropouts to raise socio-economic inequality.

Related Literature Traditional research on global warming is centered around climate impact on agricultural productivity. First, and most significantly, the paper provides a new climate perspective on the long-standing literature of declining males' labor market attachment. Literature largely attributed the declining attachment to shrinking labor demand for non-colleged workers (See Juhn (1992); Acemoglu (2002); Card and DiNardo (2002)), later exemplified by skill-biased technical change of computerization (Autor, Levy and Murnane (2003)); skill-replacing technology of 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)). On the labor supply side, Krueger (2017) showed that physical and mental health is strongly worse in non-participants.[10] Highlighting the labor supply side, I feature a role of climate change to raise the labor discomfort, potentially damage physical or mental health. The paper introduces climate shocks across commuting zones——demonstrably a combination of regional labor demand and supply shocks.

Second, and related to the climate's impacts on health, this paper contributes to recent studies uncovering climate impact on human behaviors and psyche, exemplified by negative tweets (Baylis (2020)), increased suicides (Burke et al. (2018)) and violent crimes (Ranson (2014)), which could also work both within and beyond labor markets. A labor supply

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of a state is available. See Section 4 for greater detail.

[10] In 1960-1970s, the expansion of public benefits could be another factor to increase the opportunity cost of labor. Parsons (1980) and Autor and Duggan (2003) showed expansion of Social Security disability insurance benefits as a critical inhibitor for labor supply.

mechanism explored by my study shares a similar spirit with Graff Zivin and Neidell (2014). Using time use diaries in American Time Use Survey, 2004-2006, Graff Zivin and Neidell (2014) found that daily extreme weather shocks altered daily time allocation, by shrinking labor hours or shifting outdoor leisure to indoor. To the best of my knowledge, my paper is the first to associate climate change with modes of labor market attachment.

Third, my study complements burgeoning works uncovering declining labor productivity at establishment levels. Using an employer-side survey, Somanathan et al. (2021) (in India) and Zhang et al. (2018), Chen and Yang (2019) (in China), Cachon, Gallino and Olivares (2012) (in U.S. automobile industry) showed that higher temperature hurt labor productivity.[11]In contrast to their focus on indoor manufacturing plants, many of which are not air controlled, my study instead uses a population survey to feature individual labor supply and highlights outdoor workers prevalent across sectors .

The paper is organized as follows. Section 2 presents the data and proxies used for empirical analysis. The estimation results are provided in Section 3. Section 4 quantitatively assesses climate impacts in the aggregate level and discusses other mechanisms and policy implications. Section 5 concludes.

2 Data

To empirically isolate the climate impact, I assembled a newly constructed panel data of climate exposure, labor market attachments together with regional socioeconomic and industrial correlates during a half century during 1970-2019[12]. Along with Autor, Dorn and Hanson (2013), Autor and Dorn (2013) and Acemoglu and Restrepo (2020), I use a commuting zone (or CZ) as a combination of multiple neighboring counties, Tolbert and Sizer

[11]In the field of engineering, a series of 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)).

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

(1996)).[13]Given cross-county commuting, commuting zones most likely contain both workplaces and commuting routes of each worker, serving as a unit of regional labor market.

2.1 Climate change

The weather station data is drawn from Global Historical Climatology Network Daily (GHCN-daily) from the National Climatic Data Center (NCDC) 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 available under universal quality assurance checks. I use weather variables of the daily d's maximum and minimum temperature T_d^{max}, T_d^{min}, precipitation, snowfall and dew points. Following the literature, 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 $\omega \in (0,1)$. Majority of the literature uses $\omega = 0.5$[14], however, taking an arithmetic mean significantly underrates day time temperature as shown below.

Climate meets labor markets To see this, I compute a monthly $\times$ weekly CZ-specific $\omega_{week,month,i}$ to match the median temperature during the typical business hours including commuting hours (8am-6pm), employing within-day hourly temperature fluctuation averaged during 1980-2010 from alternative Climate Normals dataset (from National Centers for Environmental Information).[15] A seasonal distribution of $\omega_{week,month,i}$ is found to be substantial: a median ω is 0.8 in the summer vs. 0.68 in the winter. (Figure 2; left) Driven by a strong seasonality of within-day temperature cycle, temperature in the labor market are higher than the conventional daily mean with $\omega = 0.5$, substantially underrating the temperature exposed to outdoor workers during daytime. (Figure 2; right).

[13]To consistently measure LFPR since 1980, a commuting zone is a finest geography units publicly available. Only employment-to-population ratios are publicly available for counties by BLS.

[14]Alternatively, some literature adopts extreme weathers by using either maximum (e.g., Graff Zivin and Neidell (2014)) or minimum temperature (e.g., Cook and Heyes (2020)). Overall, the literature is silent at discussing an optimal weight of max and min temperature to compute a daily temperature (See my computation of daily weight ω in Section 2.1).

[15]See Appendix for details. Instead of targeting T_d^{median}, using T_d^{mean} does not significantly change the estimates. In the robustness check section, I shall test the robustness of the choice of ω.

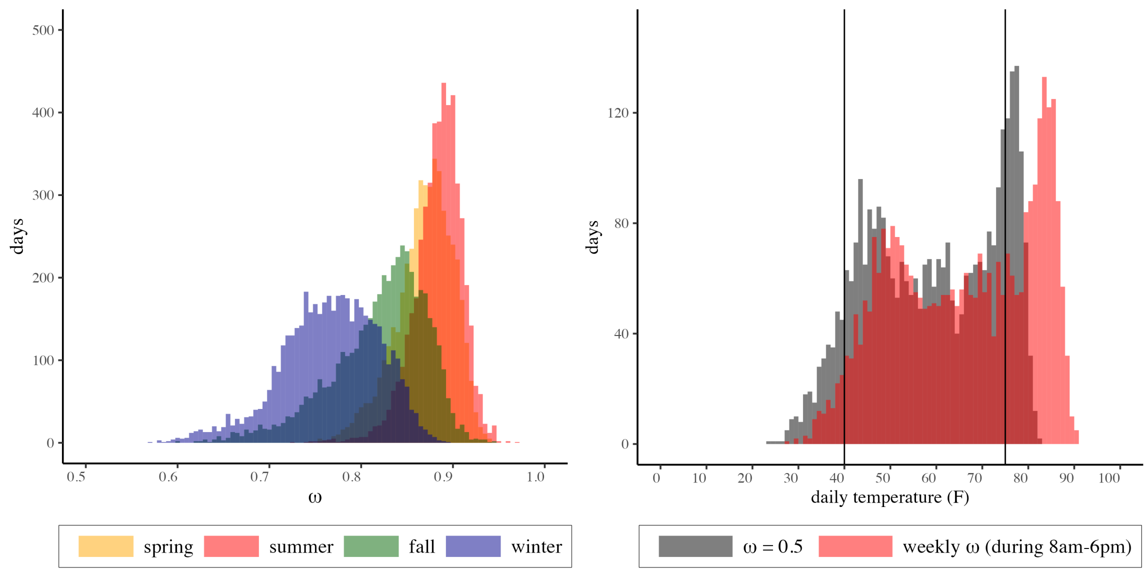

Figure 2: Distribution of daily temperature weight across seasons (left) and annual distribution of temperature by weight choice (right)

Note: (left) A unit of observation is $\omega_{i,t}$, computed in weekly average among four weeks within each month, constructed from station records by Climate Normals, 1980-2010. Each year is split to four seasons: Summer; June, July and August. Fall; September, October and November. Winter; December, January and February. Spring; March, April and May. (right) A unit of observation is a daily temperature averaged during 2011-2019, allocated to each bin. $\omega_{i,t} = 0.5$ is an arithmetic mean of max and min temperature of Global Historical Climatology Network Daily, while weekly $\omega_{i,t}$ is set to fit median temperature during 8am-6pm using Climate Normals. (See text for more details.)

To construct CZ-level climatological variables, I follow an inverse-distance weighted method to aggregate each station-level data record (e.g., Barreca et al. (2016) and many others) Limiting to weather stations with complete records in any given year, records from closest 10 stations from each CZ population centroid[16] is aggregated weighted with an inverse of squared power of distance from the centroid.

Climate is typically characterized by a distribution of realized daily weathers. Proxying climate change as 5-year prior average of annual number of hot and cold days, with median daily business hour temperature cutoffs $75°F$ and $35°F$, respectively, I document a dramatically rich variation of climate change, both between and within nine NOAA climate regions,

[16] 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 Appendix for details)

where some regions experienced even cooling[17].

Initially hot regions (especially Southeast, South and Southwest) experienced the severest warming and initially cold regions (Northeast, Northwest) experienced the mildest warming, or even, cooling with decreased hot days.[18] Notably, regional climate shocks are both conceptually and geographically distinct from conventional labor demand shocks, including ICT shocks (on indoor occupations with routine analytical tasks across sectors), globalization (import competition) and automation (industrial robots primarily in manufacturing).

2.2 Labor supply and market outcomes

As outcome variables of analysis, I construct commuting zone level LFPR, weekly wages and other regional covariates for prime-aged (age 25-54) males and other demographic group of interest. The age scope largely excludes the concern of adjustment margins by education and retirement. I use repeated cross-sectional surveys of IPUMS of Census (1950-2000, by decade) and American Community Survey (2010 and 2019)[19]. These datasets include between 1 and 5 percent of the U.S. population and provide a comprehensive set of information at the individual level with socio-demographics characteristics and labor market attachment. A data offers the place of residence at the household level, permitting a linkage to climate variables. All the analysis is limited to non-institutional samples in the U.S. mainland.

In 1970, most of commuting zones had a high LFPR above 90%. In 2019, however, the U.S. underwent a significant LFPR drop, albeit with great regional divergence. Intriguingly, intensive warming areas (Southeast and South) suffered from significant LFPR drops, while mild warming areas (Northwest, Northeast) kept relatively higher LFPR, signaling a climate-induced dropout hypothesis (See Appendix for a visual expression).

[17]Nine climate regions consist of Northwest, West, Southwest, West North Central, East North Central, Central, South, Southeast and Northeast. See Appendix for heat maps.

[18]Typically, the histogram of days across daily temperature bins is single-peaked. Suppose that climate change upshifts the temperature distribution. Then, one can see that climate change increases more hot days at initially hotter areas.

[19]To secure the sample size, I followed the literature to stack each ACS samples with 2-year sample of 2009-2010 and 2018-2019, respectively.

2.3 Outdoor jobs

To define the outdoor labor market under direct climate exposure, an important measurement challenge is to document *who* works outdoors. To directly proxy a person working outdoors, I adopt a task-based approach (e.g., Autor, Levy and Murnane (2003)) to probe occupational requirements of work environments. I use Work Context survey of O*NET (Occupational Information Network by the US Department of Labor), containing hundreds of standardized and occupation-specific descriptors on nearly 1,000 occupations. In the category of "physical and social factors that influence the nature of work", I use a question of *How often does this job require working outdoors, exposed to all weather conditions?* The answer is from 5 choices: *5. Every day; 4. Once a week or more but not every day; 3. Once a month or more but not every week; 2. Once a year or more but not every month; 1. Never*. Combining answers 4 and 5, I compute an occupation-level likelihood of working outdoor regularly at least weekly (extensive-margin) and an imputed weekly frequency of working outdoors (intensive-margin)[20] across 873 ONET-SOC occupations.[21] Analogous questions were separately asked how often each interviewee of one occupation work under non-air controlled or air-controlled environments. Then, an ONET-SOC identifier can be connected to occupation code (*occ*2010) in the Census and American Community Survey [22].

To illustrate the typical examples of outdoor jobs, Table 1 lists up the ranking of major occupations (over 0.5 million employment in 2019) with a highest ratio of working outdoors every day. One can see that all top 10 occupations are predominantly served by males and the less educated with very fewer college ratio, typically below 10%, in agriculture, construction and service sectors.

Defining "outdoor workers" as engaged in working outdoors regularly at least weekly, Figure 3 (top) shows an imputed share of outdoor workers within sectors and sectoral mix

[20] I take a middle point of each answers; 5 Everyday for 4.5, 4 Once a week or more for 3. Then, the frequency is weighted averaged with the number of replies.

[21] Using Work Context Survey, Dingel and Neiman (2020) defined a job which can be done *at home*. Conceptually, jobs which can be done at home and outdoor jobs are mutually exclusive, but not exhaustive. Jobs at indoor facilities (e.g., restaurant waiters; janitors; laboratory scientists) away from home do not belong to either category.

[22] See Appendix for details.

Table 1: Occupation rankings of outdoor exposure (2019)

ranking	description	sector of largest employment share	work outdoors everday (ratio)	work outdoors at least weekly (ratio)	male ratio	colleged worker rartio	employment (2019)
1	Construction Laborers	construction	81%	81%	96%	4.8%	1,894,577
2	Driver/Sales Workers and Truck Drivers	service	76%	92%	93%	5.8%	3,693,300
3	Police Officers and Detectives	service	66%	85%	84%	34%	914,692
4	Agricultural workers, nec	agriculture	66%	83%	75%	5.8%	775,746
5	Grounds Maintenance Workers	agriculture	65%	66%	94%	6.1%	1,313,674
6	Laborers and Freight, Stock, and Material Movers, Hand	service	57%	63%	79%	5.2%	2,343,733
7	Industrial Truck and Tractor Operators	service	57%	60%	92%	2.9%	634,116
8	First-Line Supervisors of Construction Trades and Extraction Workers	construction	56%	91%	96%	9.1%	779,073
9	Carpenters	construction	54%	71%	98%	5.9%	1,254,008
10	Maintenance and Repair Workers, General	service	51%	85%	96%	6.9%	582,332

Note: An occupation ranking is ordered by a ratio of employees working outdoors everyday inferred from Work Context Survey, from ONET, limiting occupations (*occ2010*) with over 0.5 million annual employment in from IPUMS of 2018-2019 stacked American Community Survey (population-weight is adjusted in 2019). A sector of largest employment share is the largest sector where workers of each occupation belongs from agriculture, construction, manufacturing, utility and service. (See the main text for details.)

of outdoor workers. Over 50% of agriculture, near-half of construction, one third of transportation and mining/utility, and less than 10% of manufacturing and service employees work outdoors. Given that even heat-sensitive sectors include a substantial portion of non-outdoor workers, I posit that an occupation is more direct proxy to characterize outdoor labor than sectors. By contrast, Figure 3 (right) shows the sectoral composition of outdoor workers. Although heat-sensitive sectors of agriculture and construction consistently accounted for near-half, outdoor jobs are prevalent across all sectors of the U.S. economy.

To capture demographic profiles under direct exposure of climate change, Figure 3 illustrates a share and composition of outdoor workers by sex and education attainments.

Figure 3 (middle; left) shows that one-third of males vs. 10-15% of females (aged 16 and above) work outdoors. As 75-80% of outdoor jobs are served by males, it is safe to presume that outdoor jobs are largely "male occupations". (middle; right) Limiting to prime-aged

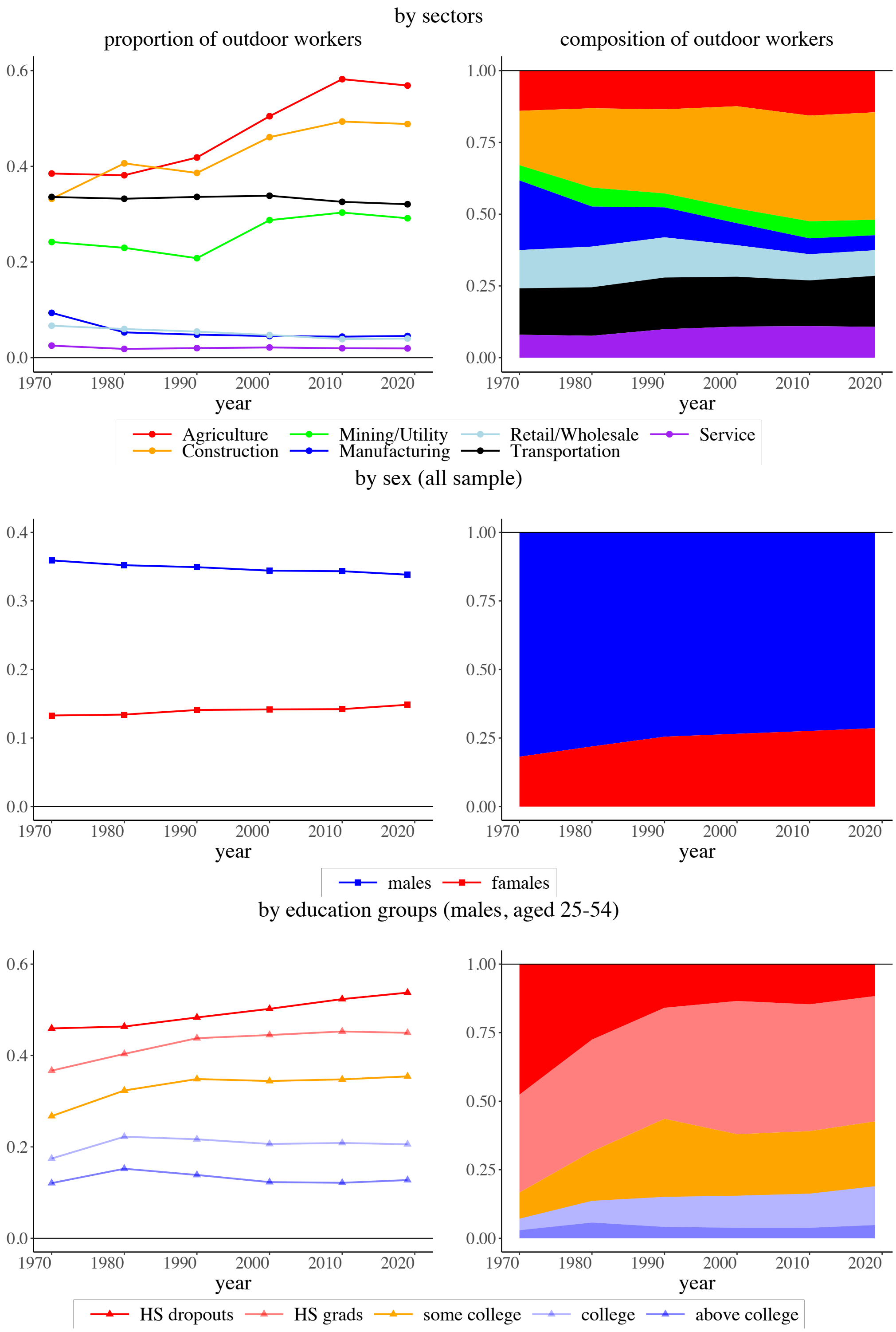

Figure 3: Descriptive statistics of outdoor workers (proportion (left) and composition (right))

Note: Computed from IPUMS of Census 1970-2000 by decades and stacked American Community Survey 2009-2010 (for 2010) and 2018-2019 (for 2019). Employment of outdoor worker is computed by a sample weight multiplied with a likelihood of regularly working outdoors at least once a week recorded in Work Context Survey from the O*NET (See the main text).

males (bottom)[23], I analogously document the share of (left) and composition by (right) workers' education attainment. Intriguingly, non-college workers are increasingly more likely to work outdoors. Given that outdoor jobs provide hard-to-automate, non-tradable service, shrinking indoor manufacturing employment were absorbed by outdoor jobs, which are immune from automation and trade competition. This is aligned with a well-rehearsed narrative of labor market polarization (Autor and Dorn (2013))[24] that middle-wage employment with routine tasks were shifted to low-wage non-routine manual occupations, exemplified by outdoor jobs in this study.

Figure 3 (right column) overall implies that 70% of outdoor jobs are predominantly served by prime-aged less educated males prevalent across all sectors. Given that the overwhelming majority of labor market dropouts have high-school graduates and less, the data signals that an outdoor labor market is presumably a hotbed of dropouts (as is tested below).

3 Analysis

Employing the newly created panel of regional labor markets linked with exposure to climate change, this section estimates the impacts of global warming on LFPRs and other related market outcomes.

3.1 Empirical Model

To isolate the effect of climate change from other correlates, I start by building a following binned specification for a demographic group g (e.g., a baseline sample g is prime-aged (25-54) males) across CZ i and 5 year periods $I = [\underline{I}, \overline{I}] \in \{(1976, 1980], [1986, 1990], [1996, 2000], [2006, 2010], [2016, 2020]$:[25]

[23] I compute that prime-aged (25-54) workers, a primary scope of this study, have consistently accounted for 70-80% of outdoor workers.

[24] Intriguingly, the total employment share of outdoor workers is fairly stable despite the rising share of working outdoors for less educated males. This is reconciled by a decline of high-school dropouts and rise of college enrollments.

[25] To avoid the Covid 19 pandemic shock in the year 2020, I used a linearly extrapolated outcome in a linear extrapolated value s.t. $y^g_{i,2020} = (y^g_{i,2019} - y^g_{i,2010}) \times (10/9) + y^g_{i,2010}$. Likewise, for the final period

$$y^g_{i,\overline{I}} = \sum_{b \in \{1,\cdots,11,13,\cdots,16\}} \beta^{g,b}\text{days}^b_I + \underbrace{\boldsymbol{\beta}^g \mathbf{X}^g_{\overline{I}_{-1}}}_{\text{a vector of pre-period controcs}} + \delta_i + \delta_I + \underbrace{\mathbb{I}(CensusDivision)\overline{I}}_{\text{Census division trend}} + \epsilon_{i,I} \tag{1}$$

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 mean number of days with median business-hour daily temperature during the period I, falling into 16 bins $\{(-\infty, 20), [20, 25), \cdots, [65-70), [75-80), [80-85), [85-90), [90, \infty)\}^{\circ}F$ ordered by $b \in \{1, \cdots 16\}$.[26] As an annual sum of bins is constant, I omitted a twelfth ($b = 12$) bin, $[70, 75)^{\circ}F$ (or $[21.1,23.9)^{\circ}C$) [27] as a benchmark. Aligned with the convention of climate literature, I assume that a daily weather is meteorologically random at each region endowed with its unique geographic features (e.g., elevation and distance to coasts); annual distribution of weather cannot be affected by regional economic activities, which could be simultaneously shaped by labor market attachments of prime-aged males.[28]. $\beta^{g,b}$ is an estimand of interest, interpreted as replacement of 10 days in bth bin with the pre-set benchmark temperature of bin $[70, 75)^{\circ}F$.

Given a demographic group g, $X^g_{\overline{I}_{-1}}$ is a vector of commonly listed covariates at the pre-period outcome year $\overline{I}_{-1}$, with corresponding coefficients $\boldsymbol{\beta}^g$, consisting of 5 components such that $\mathbf{X} = \{\mathbf{C}_{i,I}, \mathbf{D}^g_{i,\overline{I}_{-1}}, \mathbf{E}_{i,\overline{I}_{-1}}, \mathbf{M}^g_{i,\overline{I}_{-1}}, \mathbf{W}^g_{i,\overline{I}_{-1}}\}$. $\mathbf{C}_{i,I}$ includes other climatological variables except temperature (relative humidity; precipitation; snowfalls) averaged during the period I. $\mathbf{D}^g_{i,\overline{I}_{-1}}$ contains a rich vector of demographic composition of a group g: a share of race and ethnicity groups, 10-year age bins, non-migrants[29], immigrants and veterans at the end of pre-period I^{-1}. $\mathbf{E}_{i,\overline{I}_{-1}}$ is an industry structure to capture labor demand side dynam-

$[2016, 2020]$, I use a 5-year average of days under each bin during 2015-2019.

[26]For leap years, the number of days in each bin is adjusted by multiplying 365/366

[27]Graff Zivin and Neidell (2014) specified the breakpoint of hot day as similar to mine, 25C. Chen and Yang (2019) used 21-24C as baseline bin in China, very close to mine.

[28]I also presume that each region (or even a country) is small enough to affect the entire data generating process of weather. Given the well-rehearsed narrative of collective actions (observed in The Intergovernmental Panel on Climate Change (IPCC)), climate change proceeds in the planet scale shaped by miscellaneous global factors (e.g., greenhouse gas emission, a polar vortex and fluctuations of volcanic activities).

[29]Non-migrants are people who had not crossed state borders within 5 years.

ics (employment share of manufacturing, agriculture and construction; mean establishment size). $\mathbf{M}_{i,\bar{I}_{-1}}$ characterizes a pre-period regional factors (a ratio of over-65 seniors above; poverty ratio; population density). $\mathbf{W}^{g}_{i,\bar{I}_{-1}}$ is a health and wealth factors (ratio of the disabled; mean family income; mean social security benefits; a ratio of house renting; regional housing values) to shift a labor supply dynamics. All the covariates $\mathbf{X}$ are constructed from the Population Census and ACS (See Appendix for details) except mean establishment size (from County Business Pattern, Eckert, Fort and Yang (2021)).

Inclusion of two-way fixed effects (δ_i in CZ-level and δ_I in period-level) essentially formulates a difference-in-difference model, producing the estimates from within-CZ variation net of common time shifter (e.g., business cycle; technology shocks; federal-level institutional change) (Dell, Jones and Olken (2014)). To cover regional trend of labor demand and supply, I include a common trend of nine Census divisions $I(CensusDivision)\bar{I}$. $\epsilon_{i,\bar{I}}$ is a normally distributed error term. Because weather variables are spatially correlated, robust standard errors are clustered at CZ levels, a spatial unit of analysis. The model is weighted by a pre-period CZ share of national prime-aged male population.

Armed this full-battery of meteorological and socioeconomic controls with Census division common trend after isolating two-way fixed effects, one would hardly consider other confounders to shape the labor market outcomes and $\beta^{g,b}$should be presumably given a causal interpretation. For sensitivity of estimates to measurements and time windows of hot and cold days and more stringent fixed effects, see the robustness check in Section 3.3.

3.2 Baseline results

Semi-parametric bin estimates Setting LFPR as an outcome in (1) ($y^{g}_{i,\bar{I}} = \text{LFPR}^{g}_{i,\bar{I}}$) in the period end year $\bar{I}$, Figure 4 illustrates estimates of the semi-parametric bin model (1).

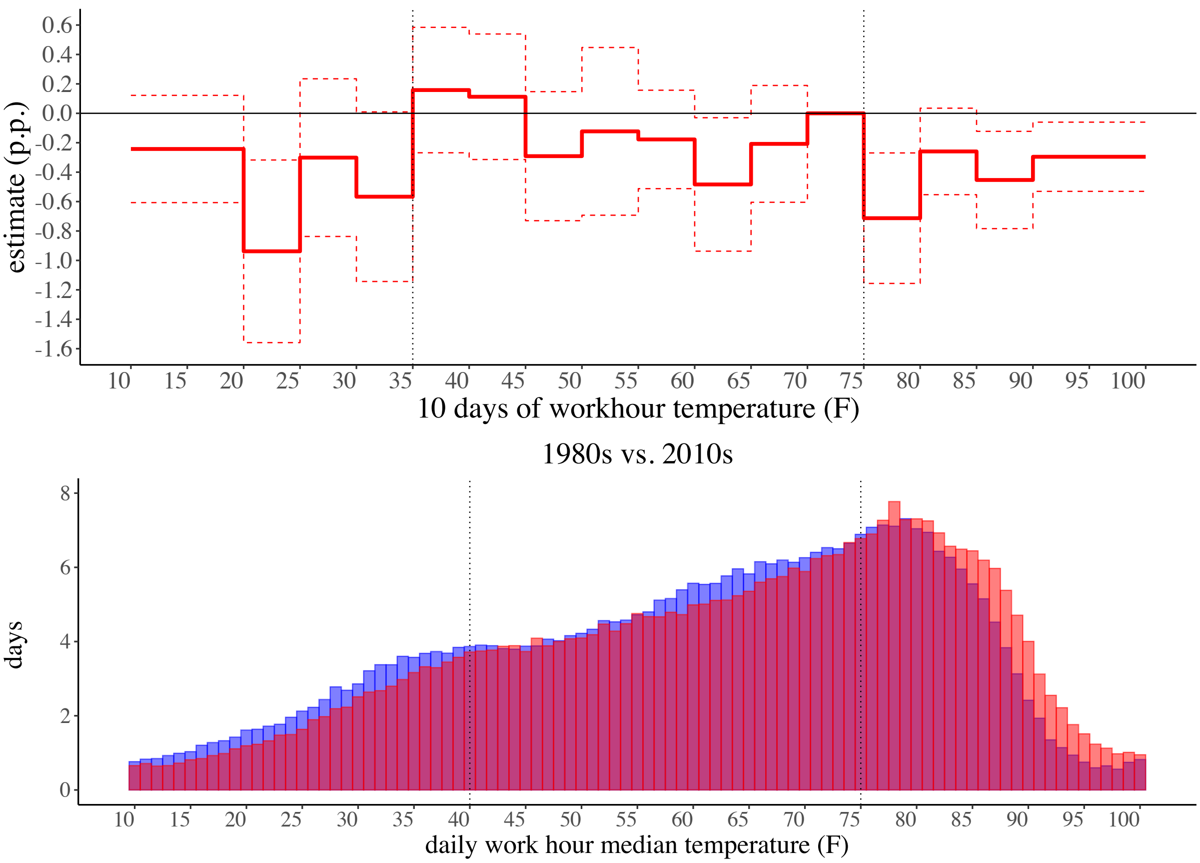

Figure 4: Bin estimates of climate change on labor force participation rate (prime-aged males)

Note: (Top) Estimates of β^b in equation (1) are illustrated with 95% confidence intervals (red dashed lines). Baseline bin is a 70-75$°F$. (Bottom) Nationwide temperature exposures normalized in 365 days are allocated over 1$°F$ bins (truncated with 10$°F$ and 100$°F$) along the mean work hour temperature during 1971-1980 and 2011-2019. The nationwide exposure is computed as a weighted average of regional exposure with start of period CZ prime-aged male population during each period. Dotted lines are thresholds of hot ($> 75°F$) and cold days ($< 35°F$) in the baseline specification.

The analysis shows clear non-linearity of climate effects along daily temperature. Replacement of 10 days (i.e.; business days in two weeks for typical full-time workers) in a benchmark bin ([70-75)$°F$) to hotter days above 75$°F$ significantly drops LFPR of prime-aged males by approximately -0.4 *p.p.*. Likewise, 10 day replacement to cold days below 35$°F$ yields slightly larger negative impacts, but with wider 95% confidence intervals. Replacement to other "normal days" with moderate temperature (35-70$°F$) does not significantly affect LFPR, as the confidence interval crosses the outcome axis.

This inverted-U non-linearity is canonically reported in prior climate literature on agricultural productivity (Schlenker and Roberts (2009)), labor productivity (Somanathan et al. (2021)), mortality (Barreca et al. (2016); Deschenes and Moretti (2009)) and GDPs (Burke, Hsiang and Miguel (2015)) and indoor laboratory studies (Seppanen, Fisk and Faulkner (2003)).

As a core mechanism to connect climate change with labor markets, extreme temperatures harm physical and mental health of workers; high temperatures can increase heart and respiratory rates, reduce blood pressure, sweat the body, cause fatigue. Cold temperatures narrows blood vessels, tightens muscles and depletes energy to sustain the body temperature. The non-linearity signals that a production function of labor is closely tied with the biological structure of their human bodies.

Baseline estimates Given the inverted-U non-linearity, I proceed to use a more parsimonious model featuring with upper and lower tails of weather distribution to further improve precisions of estimates (*a la* Barreca et al. (2016); Somanathan et al. (2021)). Operationally, I replace the climate change terms in the main specification (1), $\sum_{b=1} \beta^{g,b} days_I^b$, by $\beta^{g,h}\mathrm{hd}_{i,I} + \beta^{g,c}\mathrm{cd}_{i,I}$, where $\mathrm{hd}_{i,I}, \mathrm{cd}_{i,I}$ are average number of hot and cold days exposed to region i during period I, respectively. Guided by the previous 5°F bin estimation and also informed by the literature, thresholds of hot days and cold days are set with 75°F and 35°F of median business hour temperature, respectively[30]. Therefore, $\beta^{g,h}, \beta^{g,c}$ captures the climate effect of interest of group g, capturing an impact of replacing 10 "normal days" with $[35, 75)^{\circ}F$ by 10 hot or cold days, respectively. Table 2 reports estimates of a parsimonious model.

Founded by the equation (1), a preferred specification Column (5) inherits a full battery of controls and Census division trend under two-way fixed effects, indicating that a decadal baseline shift of 10 more hot days decreases the LFPR by 0.239 $p.p.$ ($p < 0.1\%$). Remarkably, the effect is fairly stable for exclusion of pre-period controls in Column (1)-(4). In addition to

[30] See Footnote 27 for reference to prior works. A robustness check is also provided for alternative thresholds of hot and cold days (Section 3.3).

Table 2: Climate change and labor force participation rates (LFPRs) across commuting zones (prime-aged male population; outcome years, 1980-2019)

	dependent variable: LFPR (percentage point) (prime-aged (25-54) males)				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
10 hot days	-0.286 ***	-0.294 ***	-0.280 ***	-0.246 ***	-0.239 ***
	(0.065)	(0.068)	(0.068)	(0.066)	(0.071)
10 cold days	-0.444 ***	-0.487 ***	-0.498 ***	-0.454 ***	-0.451 ***
	(0.152)	(0.153)	(0.155)	(0.115)	(0.122)
			pre-period covariates		
climate	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
demography	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
industry structure	No	**Yes**	**Yes**	**Yes**	**Yes**
labor market	No	No	**Yes**	**Yes**	**Yes**
health and wealth	No	No	No	**Yes**	**Yes**
Census division trend	No	No	No	No	**Yes**
adjusted R-squared	0.863	0.866	0.867	0.880	0.881

Note: $N = 3,610$ (5 time periods × 722 Commuting Zones). LFPR is computed in prime-aged (age 25-54) males in the U.S. mainland in years 1980-2000 by decades from Population Census and in 2010, 2019 from stacked American Community Survey 2009-2010 and 2018-2019, respectively. Hot days and cold days are prior 5-year averages of the number of days with mean temperature of business hours (8am-6pm) over 75°F and less than 35°F, respectively. Pre-period covariates are constructed at pre-period outcome years (See main text for details). All models include commuting zone and year fixed effects. Robust standard errors in parentheses are clustered by commuting zones. All models are weighted by pre-period commuting zone share of national prime-aged male population. *** $p < 1\%$.

climate variables $\mathbf{C}_{i,I}$ (relative humidity, precipitation, snowfall), (1)-(5) sequentially adds demography controls $\mathbf{D}^g_{i,\bar{I}_{-1}}$, industrial structure, $\mathbf{I}_{i,\bar{I}_{-1}}$, labor market status, $\mathbf{M^g}_{i,\bar{I}_{-1}}$ and health and wealth variables, $\mathbf{W}^g_{i,\bar{I}_{-1}}$, and a Census division trend. However, the magnitudes and precision are largely unchanged, corroborating the identification assumption that climate change is quasi-random independent of other correlates for LFPR of adult males.

3.3 Robustness checks

Before applying the model to other outcomes, or dive into the mechanism, this section explores the robustness of the baseline results around the following drivers of estimation. Other auxiliary exercises are also provided in Appendix.

Proxies of weathers In the baseline model, thresholds of hot and cold days are set as $75°F$ (23.9F) and $35°F$ (1.7C), guided by a 5˚F bin semi-parametric estimates in Figure 4 and informed by the literature using two-tail temperature models (See Footnote 27). I examined alternative cutoff pairs with $70°F$, $75°F$, $80°F$ (hot days) and $30°F$, $35°F$, $40°F$ (cold days). Adverse climate effects remain (Table A3), however, a baseline pair of $75°F$ and $35°F$ generates the most precise estimates both for hot and cold days. I also examined alternative formulation of precipitation and snow, however, the results are qualitatively unchanged (See Appendix).

Treatment windows In the baseline model, climate change is proxied by a medium-run 5 year average of hot and cold days (4 year for the latest period $[2016-2019]$) . Instead, I test the sensitivity in shorter or longer treatment windows, ranging from 1 year, 10 year, 15 year. The estimates would get weaker, but qualitatively similar. (Table A4, Appendix) Given that workers might relocate the regions (See Section **??** for concern for migration) or even exceed the prime age limit of 55 after a decade, time window of 10 year appears too long. 1-year temporary shocks does not yield a significant estimates despite its negative sign, suggesting that labor supply would not immediately react to contemporaneous weather shocks, but in cumulative years——aligned with the tale of “frogs in the boiled water”.

State-year fixed effects Readers may worry that two-way fixed effects and Census division trend are elusive on time-variant statewide institutions (e.g., welfare system; health care; minimum wages; unionization; heat regulation law), which might independently affect both regional labor supply and demand. Given that each state has only 15 CZs (median) and within-state climate change is similar, unsurprisingly, inclusion of state-year fixed effects is challenging; it neglects most of useful stark cross-regional climate variation, which has been central for identification. (c.f., Pierce and Schott (2020)) Despite the drastically limited treatment variation, however, estimates of hot days survive (-0.136 *p.p.* for 10 hot days ($p = 7.0\%$)), suggesting that statewide institutions does not critically drive the results.

Discomfort index On extreme hot days, discomfort could be fueled by humidity (c.f., Barreca (2012)). Instead of controlling relative humidity in $C_{i,I}$, I directly used an average number of discomfortable days with discomfort index (DI) above 75, computed from a standard meteorological formula, a function of temperature and relative humidity. Expectedly, replacing hot days by discomfortable days yields larger and more robust estimates.[31]

3.4 Heterogeneous analysis by demographic sub-samples

As a predominant share of outdoor workers are less-educated and the less-educated workers have presumably less outside options indoors, climate impact should be much more salient for less-educated workers. To explore the heterogeneity of impacts, I reestimate the model, splitting to male subsamples by education attainment group $g \in \{$HS dropouts, HS graduates, some colleges, college graduates$\}$with group-specific controls $\mathbf{X}^g_{i,\underline{I}}$, in Table 3.

Aligned with the speculation, the effect is drastically sharper for less-educated males, especially, high-school dropouts (-0.684 ($p < 1\%$)). Coefficients for workers with above high-school degrees (3)-(5) are not statistically significant, consistently with their few entry to outdoor jobs and richer outside options in indoor jobs. Overall, the impact of climate shocks is systematically regressive for non-colleged workers.

Analogously, I split male samples into 5 age bins with subsample g consisting of males aged in $\{[18, 25), [25, 35), [35, 45), [45, 55), [55, 65)\}$, with group-specific controls $\mathbf{X}^g_{i,\underline{I}}$. Aligned with our scope of the analysis to prime-aged (25-54) males, climate effects of hot days is significant, especially for the middle-aged 35-44 (-0.320 ($p < 0.1\%$)). The harm of cold days is severest for 25-34 males (-0.479 ($p = 0.1\%$)), and less significant for 45-54 males (-0.253 ($p = 14.5\%$)). The dropout of this period is alarming for sustaining a standard of living till the elderly age and child rearing (if any). The effect is insignificant for non-prime aged males (aged 18-24 young males and aged 55-64 senior males), aligned with relatively lower ratio of outdoor workers.

[31] If a DI exceeds 75, more than half of people supposedly feel discomfort. See construction of discomfort index in Appendix. Analogously, combining temperature and humidity via WBT (wet bulb temperature), Somanathan et al. (2021) obtained more adverse effects on plant productivity relative to conventional daily mean temperature.

Table 3: Climate impacts by education attainments and age groups (males; outcome years, 1980-2019)

	Dependent variable: LFPR (percentage points)				
	Panel A: by education (prime-aged (25-54) males)				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	HS dropouts	**HS graduates**	**HS graduates and less ((1)+(2))**	**some college**	**college graduates**
10 hot days	-0.600 ***	-0.246 ***	-0.329 ***	-0.111	-0.112 *
	(0.193)	(0.087)	(0.091)	(0.070)	(0.061)
10 cold days	-0.134	-0.012	-0.257	-0.253 **	-0.208 ***
	(0.292)	(0.211)	(0.187)	(0.102)	(0.069)
adjusted R-squared	0.815	0.868	0.862	0.755	0.699
	Panel B: by age (males)				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	18-24	**25-34**	**35-44**	**45-54**	**55-64**
10 hot days	-0.228	-0.219 **	-0.320 ***	-0.179 **	0.020
	(0.208)	(0.095)	(0.076)	(0.087)	(0.152)
10 cold days	-0.300	-0.479 ***	-0.396 **	-0.253	0.384
	(0.216)	(0.143)	(0.166)	(0.173)	(0.261)
adjusted R-squared	0.836	0.769	0.815	0.852	0.866

Note: $N = 3,610$ (5 time periods $\times$ 722 Commuting Zones) LFPR is computed in prime-aged (age 25-54) males in the U.S. mainland in years 1980-2000 by decades from Population Census andin 2010, 2019 from stacked American Community Survey 2009-2010 and 2018-2019, respectively. Hot days and cold days are prior 5-year averages of the number of days with mean temperature of business hours (8am-6pm) over 75°F and less than 35°F, respectively. All models include a full battery of controls in Column 5 at Table 2 constructed within each subsample and commuting zone fixed effects. Robust standard errors in parentheses are clustered by commuting zones. All models are weighted by pre-period commuting zone share of national population of each sub-sample. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

3.5 Employment, non-employment and unemployment

To further investigate the climate impact on mode of labor market attachment, I decompose labor force to employment, unemployment[32], full-time students and a dropout in Table 4.

[32] My unemployment measure is a ratio of unemployed to regional prime-age population instead of labor force participants.

Table 4: Climate change and labor market attachment across commuting zones (prime-aged males; 1970-2019)

	dependent variables (percentage point)			
		employment rate		
	LFPR	salaried workers	self-employed	total (2) + (3)
	(1)	(2)	(3)	(4)
10 hot days	-0.244 ***	-0.421 ***	0.080	-0.341 ***
	(0.067)	(0.112)	(0.052)	(0.094)
10 cold days	-0.461 ***	-0.642 ***	0.019	-0.623 ***
	(0.131)	(0.210)	(0.082)	(0.179)
adjusted R-squared	0.880	0.841	0.850	0.852
	dropout 1-(1)-(7)	unemploy-ment-to-population ratio	full-time student ratio	self-employed at home
	(5)	(6)	(7)	(8)
10 hot days	0.213 ***	0.096 *	0.031 **	0.054 **
	(0.061)	(0.056)	(0.013)	(0.024)
10 cold days	0.382 ***	0.162 *	0.079 ***	0.082 **
	(0.120)	(0.097)	(0.022)	(0.032)
adjusted R-squared	0.890	0.837	0.690	0.751

Note: $N = 3,610$ (5 time periods × 722 commuting zones. Each outcome proxy is computed in prime-aged (age 25-54) males in the U.S. mainland in years 1980-2000 by decades from Population Census and in 2010, 2019 from stacked American Community Survey 2009-2010 and 2018-2019, respectively. Hot days and cold days are prior 5-year averages of the number of days with mean temperature of business hours (8am-6pm) over 75°F and less than 35°F, respectively. All models include a full battery of controls in Column 5, Table 2 and commuting zone and state × year fixed effects. Robust standard errors in parentheses are clustered by commuting zones. All models are weighted by pre-period commuting zone share of national prime-aged male population. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

As a baseline result, Column 1 inherits the main specification Column 5 in Table 2. Compared with LFPR in (1), employment rate (or employment-to-population ratio) in Column 4 shows even larger estimates $-0.341 p.p.$ ($p < 0.1\%$), ensuring that LFPR drop is not driven by decrease in unemployment. Within employment rates, salaried employment received severer effect with both economic and statistical significance $-0.570 p.p.$ ($p < 0.1\%$) in Column 2, while the effect on self-employment was $+0.177 p.p.$ in Column 3 and self-employees working at home[33] was $+0.054p.p.$ in Column 8, respectively ($p < 5\%$). Interpretably, self-employment (including "gig works" such as ride share drivers and freelancers), especially at home, permits elastic labor supply with a flexible work schedule[34], resilient to outdoor climate shocks. Consequently, Column 8 shows that dropout-to-population ratio is fueled by $+0.221p.p.$ ($p < 5\%$). Intriguingly, the effect is partially offset by rise in full-time student ratio shown in Column 7. Given the scope of adult males over 25, this might be surprising, but somewhat reasonable if college life is mostly indoors.

Theoretically, climate's impact on an unemployment-to-population ratio is ambiguous. On one hand, outdoor workers become unemployed by layoffs or exits to search for alternative jobs. On the other hand, unemployed workers might quit job search to become a dropout from larger search costs.[35] Column 6 shows a positive estimate for unemployment rates, indicating that on a net basis, employments are pushed out to an unemployment pool, suggesting that homes provide solid air-conditioned cooling shelters from climate change (as tested below in Section 4.2.1).

3.6 Outdoor vs. indoor labor markets

Previous section showed that the LFPR drop is driven by declining employment-to-population ratio. By splitting the employment by environments of outdoor exposure, this section first tests whether the employment shrinkage is triggered by regional outdoor labor markets. Then, I turns to explore the wage responses of outdoor jobs.

Employment rates I test whether climate change reduced employment rate of outdoor jobs relative to indoor jobs. To see this, using Work Context Survey questions, I split the employments to outdoor jobs, indoor jobs with non-controlled environments, and air-controlled indoor jobs in a mutually exclusively way. Outdoor jobs are imputed number

[33] To detect workers at home, I use an answer of "working at home" in a question on commuting mode (i.e., how do you commute?).

[34] See Katz and Krueger (2019) for recent rise in alternative work arrangements.

[35] Especially before the Internet era, extreme weathers would have raised search cost because job search requires a series of outdoor activities (e.g., going to a job agency; on-site interviews).

of employees who work outdoors at least once a week. (See section 2.3 for details). Aside from outdoor jobs, indoor non-controlled jobs are who work indoors under non-controlled environment at least once a week. The rest is air-controlled indoor jobs.

Setting an employment rate of each job category in the main specification, Table 5 summarizes the results. Consistent with the theory, I find that an outdoor employment rate significantly shrunk in (1) in response to more hot days. By contrast, employment rates with indoor workplaces show a statistically insignificant point estimate. No evidence was found for transfers from outdoor to indoor workplaces, indicating that outdoor workplaces would be a hotbed of dropouts. One explanation is that skills in outdoor cannot be transferrable to indoor occupations.

wages I proceed to investigate the response of wages of outdoor employment, which not only informs the benefit of surviving employees, but signals the relative labor demand vs. supply forces at work. In parallel to employment rates across occupations, I examine how wages in outdoor vs. indoor employment responded with climate change. Theoretically, climate impact on wages of outdoor jobs is ambiguous. On one hand, diminishing labor productivity would suppress their wages from contraction of labor demand. On the other hand, as labor cost increases, we should expect that survivors' wages rose from shrinkage of labor supply. By a worker-level analysis, I examine how a weekly wage[36] responds with climate change, controlling for individual demography and education, and three-fold fixed effects in CZ-occupation group, state-year and occupation group-year levels.

Table 5 (Panel B) shows a significantly negative impact of hot days on wages of outdoor workers. A standard labor market model suggests that the negative wage response indicates relative dominance of labor demand reduction.[37]

[36] I compute weekly wages of full-time full-year workers excluding self-employees, by dividing annual labor income by weeks worked during a year.

[37] Deryugina and Hsiang (2014) reported negative impacts of temperature on mean annual income across U.S. counties. By contrast, my analysis found an adverse impact on weekly wages and annual income specifically for outdoor workers.

Table 5: Climate change and employment rates across climate exposure (prime-aged males; 1980-2019)

Panel A: dependent variables: employment-to-population ratio (percentage point; czone-level)

	occupaton category		
	outdoor	**indoor non-controled**	**indoor controled**
	(1)	**(2)**	**(3)**
10 hot days	-0.167 **	-0.028	-0.127
	(0.066)	(0.025)	(0.106)
10 cold days	-0.135	0.006	-0.415 **
	(0.097)	(0.053)	(0.190)
observations	3,610	3,610	3,610

Panel B: dependent variables: log (weekly wage) (worker-level)

	occupaton category		
	outdoor	**indoor non-controled**	**indoor controled**
	(1)	**(2)**	**(3)**
10 hot days	-0.953 ***	-0.901	-0.089
	(0.320)	(0.701)	(0.385)
10 cold days	-0.451	-1.000	-1.590 *
	(0.717)	(1.160)	(0.865)
observations	48,300,679	19,320,272	135,241,900

Note: An employment-to-population ratio is computed in prime-aged (age 25-54) males in the U.S. mainland in years 1980-2000 by decades from Population Census and in 2010, 2019 from stacked American Community Survey 2009-2010 and 2018-2019, respectively. Occupation categories are defined mutually exclusive based on O*NET Work Context Survey (see text for definitions). Hot days and cold days are prior 5-year averages of the number of days with mean temperature of business hours (8am-6pm) over 75°F and less than 35°F, respectively. All models include a full battery of controls in Column 6, Table 2 and commuting zone and state $\times$ year fixed effects. Robust standard errors in parentheses are clustered by commuting zones. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$. (Panel A) $N = 3,610$ (5 time periods $\times$ 722 commuting zones). All models are weighted by pre-period commuting zone share of national prime-aged male population. (Panel B) Limited to prime-aged (age 25-54) salaried full-time full-year employees in the U.S. mainland. Weekly wage is computed from IPUMS of Population Census and American Community Survey. All models include an experience, experience squared, a dummy of races and immigrants, veteran, education attainments, interacted with a year dummy. All models also include commuting zone, state $\times$ year, occupation group $\times$ year fixed effects. Robust standard errors are clustered by commuting zones. All models are weighted by sampling weight share of each subsample employment.

If this is the case, global warming should be readily comparable to other conventional labor demand shocks from technological revolution (Autor, Levy and Murnane (2003); Acemoglu and Restrepo (2020)) and free trade (Autor, Dorn and Hanson (2013)). The finding is aligned with a few recent establishment-level studies on climate impact on labor demand adaptations on the employer side. Across U.S. counties, Ponticelli, Xu and Zeume (2023) showed temperature shocks increased energy costs and lowered the productivity of small manufacturing plants, and led to higher production concentration in large plants. Acharya, Bhardwaj and Tomunen (2023) showed that firms operating in multiple counties reallocated employment in warming counties elsewhere, whereas single-county firms just shrunk. Using an individual dataset, my paper complements their works by showing disproportionately adverse climate impacts on outdoor labor markets.

4 Mechanism

4.1 The role of outdoor labor market

To explore the mechanics behind the main result, this paper highlights the understudied role of regional outdoor labor markets. As directly exposed to climate change without air conditioners, one would presume that climate impact moves with regional dependency on outdoor jobs. To see this, I interact climate variables $\mathrm{hd}_{i,I}, cd_{i,I}$ with a pre-period dependency on outdoor jobs in a modified model of difference-in-difference formulation such that

$$\begin{aligned} y^g_{i,\overline{I}} = \beta^{g,h}\mathrm{hd}_{i,I} + \beta^{g,c}\mathrm{cd}_{i,I} + \gamma^{g,h}\mathrm{hd}_{i,I} r^{g,out}_{\overline{I}_{-1}} + \gamma^{g,c}\mathrm{cd}_{i,I} r^{g,out}_{\overline{I}_{-1}} + \gamma^{g,out} r^{g,out}_{\overline{I}_{-1}} \\ + \boldsymbol{\beta^g} X^g_{\overline{I}_{-1}} + \delta_i + \delta_I + \mathbb{I}(CensusDivision)\overline{I} + \epsilon_{i,I}, \end{aligned} \tag{2}$$

where $r^{g,out}_{\overline{I}_{-1}}$is dependency on outdoor workers of group g at the end year of pre-period. $\gamma^{g,h}, \gamma^{g,c}$ captures a shifter effect of outdoor exposure to the climate impact of interest. Setting g as prime-aged males, Table 6 shows the results.

Table 6: The climate effects and regional dependency on outdoor jobs across commuting zones (prime-aged male population; outcome years, 1980-2019)

	dependent variable: LFPR (percentage point) (prime-aged (25-54) males)			
	extensive-margin outdoor pre-share		**intensive-margin outdoor pre-share**	
	OLS	**OLS**	**IV**	**IV**
	(1)	**(2)**	**(3)**	**(4)**
10 hot days	0.117	0.088	0.071	0.068
	(0.157)	(0.153)	(0.076)	(0.076)
10 cold days	-0.731 **	-0.687 **	-0.181	-0.163
	(0.302)	(0.283)	(0.143)	(0.143)
10 hot days × outdoor pre-share	-1.221 **	-0.254 *	-1.042 ***	-0.239 ***
	(0.582)	(0.131)	(0.328)	(0.073)
10 cold days × outdoor pre-share	0.705	0.118	-1.361 ***	-0.328 ***
	(0.829)	(0.174)	(0.525)	(0.120)
outdoor pre-share	0.128	0.027	0.141 **	0.033 **
	(0.112)	(0.025)	(0.064)	(0.014)
adjusted R-squared	0.879	0.879	0.879	0.879

Note: $N = 3,610$ (5 time periods × 722 Commuting Zones). LFPR is computed in prime-aged (age 25-54) males in the U.S. mainland in years 1980-2000 by decades from Population Census and in 2010, 2019 from stacked American Community Survey 2009-2010 and 2018-2019, respectively. See definitions of outdoor pre-share in the main text. The model inherits full-controls, division trend and fixed effects at Column 5, Table 2. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

(1) and (2) identify the effects mediated via outdoor labor market with different proxies of outdoor exposure $r^{g,out}_{\bar{I}_{-1}}$. (1) uses an extensive margin, a imputed ratio of full-time workers who regularly work outdoors at least weekly. (2) uses an intensive-margin, an imputed frequency of working outdoors within a week, weighted by work weeks of each observation. In both (1) and (2), interaction terms $\gamma^{g,h}$ show significantly negative estimate ($\gamma^{g,c}$ was insignificant). This indicates regions initially dependent on outdoor jobs underwent larger subsequent harms.

This approach raises the question of what determines pre-period outdoor exposure to vary across commuting zones. One might worry that pre-period outdoor exposure is correlated with the current period warming trend, if the previous period warming reduces a ratio of outdoor workers (shown below). Consequently, if a regional warming trend is consistent, the interaction term might merely reflect an intensification (i.e., hotter areas experience larger adverse effects from 10 more hot days). To address this potential bias, I exploit historical cross-CZ differences in industry specialization to isolate the near-exogenous component of an outdoor occupation share, r^{out}_{1950}. A shift-share outdoor exposure is computed as an imputed outdoor employment based on the pre-period national share of industry employment such that

$$r^{g,out}_{i,\bar{I}_{-1}} = \frac{\sum_k \omega^{g,i}_{k,1950} L^{out}_{k,\bar{I}_{-1}}}{P_{i,\bar{I}_{-1}}}$$

where $\omega^{g,i}_{k,1950} \equiv \frac{L_{k,i,\bar{I}_{-1}}}{L_{k,\bar{I}_{-1}}}$ (industry k 's share of region i in group g in 1950), $L^{out}_{k,\bar{I}_{-1}}$ is an outdoor employment at industry k in the pre-period $\bar{I}_{-1}$ and $P_{i,\bar{I}_{-1}}$ is a prime-aged male population at region i in the pre-period $\bar{I}_{-1}$. I presume that this imputed outdoor exposure extracts an outdoor exposure dictated from the historical industry mix, but is uncorrelated with subsequent climate exposure. Reassuringly, (3)-(4) gives a slightly smaller in magnitude, but with higher precision for $\gamma^{g,h}$. Intriguingly, $\gamma^{g,c}$ also shows significantly (and even larger) negative estimates.

4.2 Labor supply mechanism

A standard labor market model suggests that the negative elasticity of outdoor job wages (shown in Table 5) indicates relative shrinkage of labor demand curve. Armed with a pair of empirical strategies in Section 4.2.1 and 4.2.2, this section investigates an understudied mechanism on the labor supply side, which is potentially masked by the behavior of wages.

4.2.1 Role of residential amenity

A fundamental barrier to distinguish labor supply detachment and labor demand shrinkage is that climate change would not only augment labor cost (thus, suppress the supply) for outdoor workers, but hurt labor productivity (thus, reduce the demand). The first strategy exploits the regional spread of residential amenities (i.e., air conditioners and colored televisions) since the late 1960s as a shifter to augment the labor costs without harming the labor productivity. To implement this, I presume that residential amenities increase opportunity costs of labor by upgrading the value of leisure at home, but do not harm labor productivity[38]; watching televisions at home (at least, if moderate) does not presumably affect labor productivity outdoors.[39] Air conditioners would even help sustain labor productivity by sheltering workers from outdoor heat waves, especially under extreme hot days.[40]

In 1955, air conditioners were only implemented in office buildings, supermarkets and movie theaters, but fewer than 2% of the residences had air conditioning (Biddle (2008)). According to the Census of Households, an ownership rate of air conditioners for a median commuting zone has surged from 37.0% (in 1970) to 58.9% (in 1980). Although 97.0% of households owned a television set in 1970, partially fueled by the rapid spread of cable TV subscription, television sets per capita increased from 1.46 television sets (in 1970) to 1.62 (in 1980) for a median CZ[41]. Applying the extrapolation strategy of Barreca et al. (2016), I impute a CZ-level adoption rate of residential air conditioners for all CZs and per capita television sets for a subset of 214 CZs[42], covering 80% of prime-aged male population, during 1970-1990 (See Appendix for proxy construction). This analysis is limited to the previous century during 1970-2000 because both air conditioners and television sets have completed penetrating the entire U.S. after 2000.

[38]Aguiar et al. (2021) assessed the impact of quality evolution of video game for labor supply of young males. Albeit not prime-aged males, Waldman, Nicholson and Adilov (2006) documented that spread of cable TV subscriptions induced children's autism.

[39]I am not aware of studies associating television watching and labor productivity, especially of physical tasks in this context. Watching television more likely affects cognitive ability, but no evidence is found that watching TV would harm cognitive abilities (Gentzkow and Shapiro (2006); Gentzkow and Shapiro (2008)). Using American Time Use Survey, Well-Being Module, however, Krueger (2017) (Table 3) reports that watching TVs is associated with more tiredness and less sense of meaning for males aged 16-35, which might jointly hurt labor productivity and increase labor costs.

[40]Barreca et al. (2016) document the benefit of air conditioners on reducing mortality under extreme hot days during the twentieth century. Global warming hurt quantity and quality of sleep especially under developing countries (Minor et al. (2022)), and air conditioners are shown to be effective.

[41]I use an extensive margin of TV sets due to wider geographic variations than a saturated near 100% intensive margin of ownership rate.

[42]The limit of geographical coverage comes from Census 1960, recording a subset of counties, which are mapped to commuting zones.

Table 7: The role of residential air conditioners across commuting zones (prime-aged males; 1980-2000)

	dependent variables (percentage point) (prime-aged (25-54) male population)			
	LFPR	employ-ment rate	unemploy-ment rate	LFPR
	(1)	(2)	(3)	(4)
10 hot days	-0.131	0.008	-0.140 **	0.170
	(0.085)	(0.108)	(0.062)	(0.135)
10 cold days	-0.496 ***	-0.530 ***	0.034	-0.439
	(0.137)	(0.186)	(0.117)	(0.290)
10 hot days × air conditioner share	-0.165 *	-0.398 ***	0.233 ***	
	(0.099)	(0.117)	(0.068)	
10 cold days × air conditioner share	-0.094	-0.113	0.019	
	(0.131)	(0.193)	(0.119)	
10 hot days × TV sets per capita				-0.230 ***
				(0.061)
10 cold days × TV sets per capita				-0.176
				(0.176)
air conditioner share	0.020	0.042 **	-0.022 *	
	(0.016)	(0.019)	(0.012)	
TV sets per capita				0.024
				(0.018)
czone fixed effects	Yes	Yes	Yes	Yes
state × year fixed effects	Yes	Yes	Yes	Yes
adjusted R-squared	0.963	0.943	0.886	0.974
observations	2,166	2,166	2,166	642

Note: $N = 2,166$ (3 time periods × 722 Commuting Zones) for (1)-(3) and $N = 642$ (3 time periods × 214 Commuting Zones) for (4). Dropout rates and LFPR are computed in prime-aged (age 25-54) males in the U.S. mainland in 1980, 1990 and 2000. Hot days and cold days are prior 5-year averages of the number of days with mean temperature of business hours (8am-6pm) over 75°F and less than 35°F, respectively. All models include a full battery of controls with division trend, commuting zone and year fixed effects in Column 5, Table 2. All models are weighted by pre-period commuting zone share of national prime-aged male population. Robust standard errors in parentheses are clustered by states. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

To test the role of residential amenities as a shifter of climate impact, I use an analogous difference-in-difference formulation in an equation (2), by replacing outdoor exposure by spread of residential amenities at pre-period outcome years. Table 7 highlights the results. Remarkably, all columns show expectedly complementary negative estimates with hot days, suggesting that improved residential amenity facilitated climate impacts.

(1) and (4) interacts hot and cold days with pre-period (1970-1990) adoption rate of residential air conditioners and per capita TV sets. One can see the significantly adverse interactive estimates for hot days (-0.165, -0.230). The interacted estimates for cold days are negative, but not precisely estimated. For air conditioners, this could be reasonable because air conditioners specialize in cooling down.[43] Splitting LFPR into employment rate in (2) and unemployment rate in (3), employment rate displays larger negative impacts which is significantly offset by the rise of unemployment rate. As discussed in climate-induced unemployment in Table 4, this could be consistent that homes endowed with residential air conditioners provide comfortable shelters from outdoor climate change. Overall, the analysis corroborates that climate change augments opportunity costs of labor, fueled by richer residential amenities.

4.2.2 Preference for work

The first strategy features the spread of residential amenities as augment *opportunity* costs of labor, instead of a direct costs of discomfort. As a complementary second strategy, I directly measure preference for labor, which are supposed to shape labor costs, using a series of work-related questions at World Values Survey (WVS). WVS 2017 wave started to record a longitude-latitude of each interviewee, allowing for connection with regional temperature and their affiliation of commuting zones. I use 5 questions regarding willingness to work spread across modules. As each question has different formats and number of choices, I normalize every answer from 0 (most negative response) to 1 (most positive response) for work value[44]. (For raw description of survey questions, see Appendix.) I test how a recent 5 year experience of hot and cold days affected their value on works, controlling for their demography, experience and education. Under state fixed effects, the estimates comes from

[43] Alternatively, I use residential electric heaters to see interaction with climate change. Intriguingly, only cold days show positive estimates, suggesting that prevalence of modern heaters by contrast mitigate the climate impact, presumably by sustaining labor productivity from the cold. (See Appendix).

[44] To be comparable across questions, I adjust that larger number indicates a positive response for work-related values.

within-state cross-CZ variation.

Table 8: Climate impact on work-related values (prime-aged males; 2017)

	dependent variable: work values (prime-aged males, 2017; normalized value (0-1))				
	work is important	non-working is lazy	work is a duty	work should always comes first	hard work improves life
	(1)	(2)	(3)	(4)	(5)
10 hot days	-1.00 ***	-1.02 *	-2.03 ***	-1.20	-2.09 **
	(0.37)	(0.57)	(0.62)	(0.94)	(0.89)
10 cold days	4.07 **	-0.73	3.57	6.53	-4.31
	(1.88)	(3.43)	(5.72)	(4.60)	(3.65)
Observations	671	668	668	669	669

Note: Prime-aged (25-54) males in World Value Survey, 2017. Main climate variables are 10 year average of hot days and cold days in the year before (2007-2016). See text for interpretation of each outcomes. Other individuals controls include age, age squared, and dummies of race, immigrant and education attainments. Start of period commuting zone level controls include commuting zone population density, share of agriculture employment, a ratio of above 65 population, a ratio of people born in the same state, and a ratio of renting a house. All the models include state fixed effects and weighted by a sampling weight of WVS. Robust standard errors in parentheses are clustered by states. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

Table 8 summarizes the results. Perhaps surprisingly given the limited sub-sample of prime-aged males, I find that experienced hot days significantly hurt value for work measured in (1), (2), (3), (5), of different format of multiple choice ((4) was less statistically significant). The response is not observed in other samples of prime-aged females, older (above 55) males and younger (under 25) males. Though occupation categories in WVS prevents me to identify outdoor workers, the effect is stronger for less-educated and younger workers under larger outdoor exposure, consistently with my main regional analysis. The data is admittedly cross-sectional, and thus, low-morale adult males systematically self-select warming locations within states. However, I view selection bias is limited given that WVS near-randomly selects respondents along the national demographic composition.[45] Collec-

[45] Analogously, selective attrition might be at work such that people with higher work value are less likely to reply in WVS.Although I cannot entirely rule out the possibility, given that people with high work value have smaller work costs and replying to WVS is an 2-3 hour part time job, I believe this is unlikely.

tively, this auxiliary analysis suggests that climate change undermined the social norm for labor force attachment together with subjective well beings.

4.3 Product market

Readers familiar with prior climate literature with focus on agriculture (e.g., Deschênes and Greenstone (2007); McLeman and Smit (2006))[46] would worry that the estimate LFPR drop and adverse climate effect on outdoor labor market might be driven by product market shocks; especially in the heat-sensitive agriculture, climate-driven damage and the decline in agricultural productivity might reduce labor demand of farm laborers.

Although the story is plausible in development economies, I posit that it does not fit the advanced economy, the U.S., where agriculture accounts for less than 1% of the total GDP and only 1.5% of employment in 2019. Moreover, agriculture accounts for a non-negligible, but still a minority ratio of 20% of outdoor employments (Section 2). To assess the role of the agriculture sector, I exclude most agriculture-intensive regions (mostly agglomerated in the West North Central). As exclusion of agriculture-intensive areas does not significantly change the main estimates (See Appendix), I conclude that the product market is not likely to be the primary channel to drive the results.

5 Assessment: climate impacts

Founded on the baseline estimates interacted with relative change in regional exposure to hot vs. cold days, this section quantitatively assesses the contribution of climate change on the observed decline of LFPR of adult males. In parallel to nationwide implications, I also examine whether climate change exacerbated the socio-economic inequality across climate regions and education groups.

[46] Peri and Sasahara (2019) reported urban-rural migration from climate-induced damages in agriculture sector across the globe.

5.1 Climate impacts

Global warming not only increases exposure to hot days, but decreases exposure to cold days (shown at Figure 4 (Panel B)). Having established that both hot days and cold days hurt labor market attachment (Table 2), the net impact would be an empirical question, depending on the horse race between extreme temperature days.

An implied impact ΔLFPR^g_R for a group g in region R (a set of i) from a end of period year $\overline{I}_0$ to $\overline{I}_1$ is computed as

$$\Delta\text{LFPR}^g_R = \sum_{i\in R} \omega^{g,i}_{R,t^*}\beta^{g,h}(\text{hd}_{i,I_1} - \text{hd}_{i,I_0}) + \sum_{i\in R} \omega^{g,i}_{R,t^*}\beta^{g,c}(\text{cd}_{i,I_1} - \text{cd}_{i,I_0}), \tag{3}$$

where ω^i_{g,R,t^*} is a i's group g population share within region R at a weighting year $t^*\in[\overline{I}_0, \overline{I}_1]$ and $\text{hd}_{i,I}, \text{cd}_{i,I}$ are average numbers of hot days and cold days during 5-year period I.

Figure 5 illustrates regional exposure to climate change (Panel A) and their implied climate impacts (Panel B). Figure 5 (Panel A) highlights the well-known reversal of climate change during (1) 1970-2019 vs. (2) 1950-1970 (pre-study period). One can see a stark contrast of climate change; in 1950-1970, a median CZ underwent 2.6 less hot days and 1.4 more cold days, sometimes framed as the age of global *cooling*. As meteorology science established, by contrast, the period during 1970-2019 is the age of modern global warming. The U.S. is no exception; a median CZ experienced 5.5 more hot days and 0.2 less cold days.[47]

Nationwide Pairing the baseline estimates with regional exposure to climate change, the impacts of climate change are evaluated in Figure 5 (Panel B). Setting g as prime-aged males, R as the entire 722 commuting zones, and specifying $I_0 = [1966, 1970], I_1 = [2015, 2019]$, and a weighing year $t^* = 2000 \in [1970, 2019]$ in the formula (3), the overall impact of the hot days during the period is -0.378 *p.p.,* accounting for 5.6% of the nationwide drop in LFPR.[48].

[47] Hot days and cold days are computed as prior 5-year average such that an average of years 1946-1950 used for 1950, 1966-1970 for 1970, and 2015-2019 for 2019.

[48] As my two-way fixed effect model identifies the within-CZ climate effect on LFPR, I contrast an implied impact with within-CZ component of nationwide LFPR drop. (See Appendix for construction of comparable data moments).

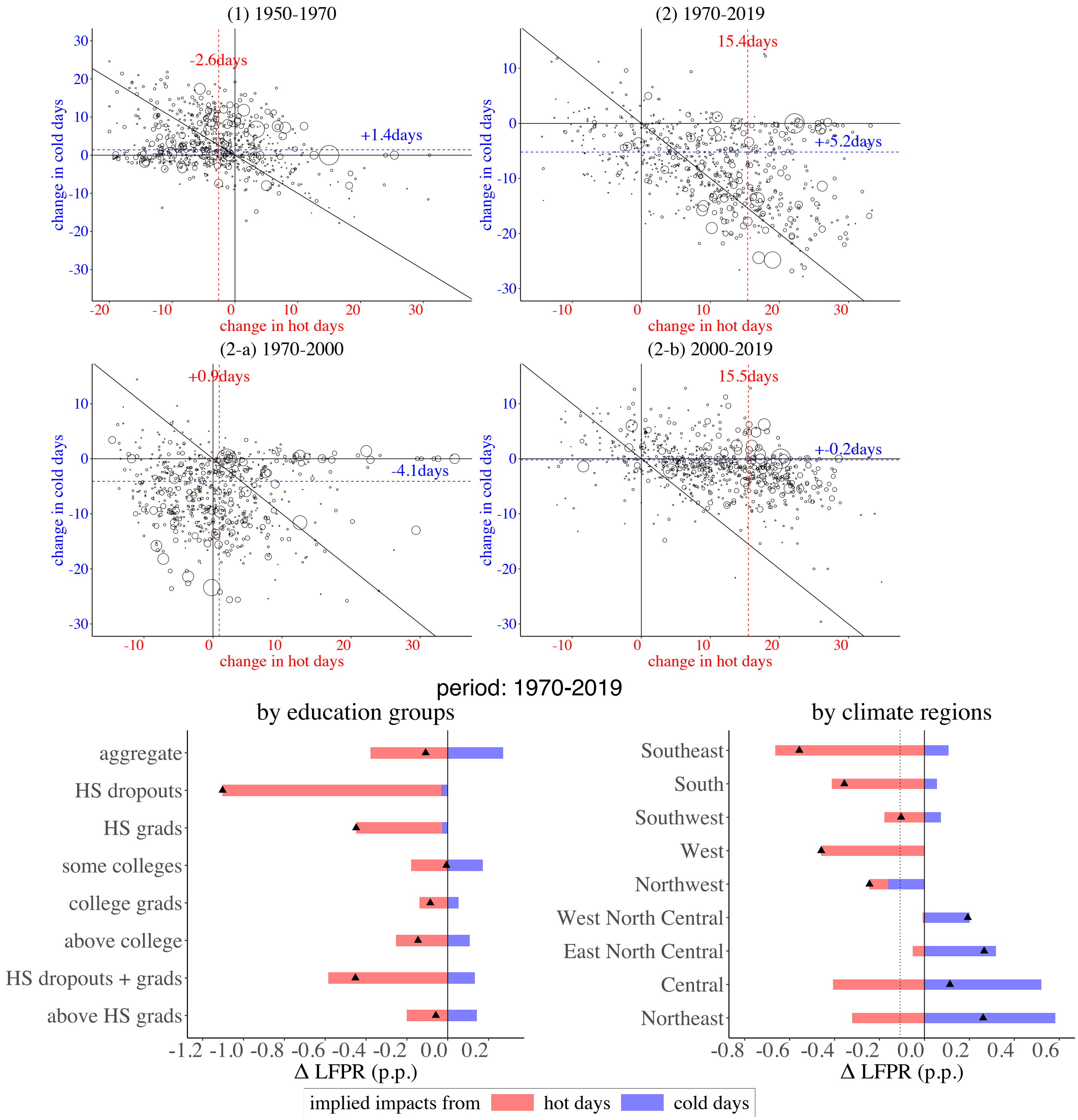

Figure 5: The implied impacts of climate change on prime-aged male labor force participation rate, 1970-2019

Panel A: Hot days and cold days are prior 5-year averages of the number of days with median temperature of business hours (8am-6pm) over 75°F and less than 35°F, respectively. Panel B: Aggregate effects are computed based on the full specification Column 5 at Table 2 and CZ-level climate exposure nationwide, weighted by CZ-level prime-aged male population. Effects by climate regions (by NOAA) are computed by baseline estimates and CZ-level climate exposure within each region. Effects by education groups are analogously computed group-specific estimates from sub-sample analysis at Table 3.

The effect from reduced cooling is $+0.270$ *p.p.*, non-negligibly counteracting the effect on harm of warming. In net, the overall climate impact is -0.108 *p.p.*.

By education groups and climate regions As exposure to climate climate drastically differs across locations and given the stark heterogeneity of labor supply elasticity across education groups (Table 3), the nationwide assessment presumably masks between- and within-region inequality of the climate impact. Panel B (left) depicts the simulated impacts across education attainments, employing $\beta^{g,h}, \beta^{g,c}$ for each education groups g, borrowed from the sub-sample analysis at Table 3. Mirrored by the divergence of elasticities, the less educated groups (with high school graduates or less education attainment) underwent significant drops by -0.347 *p.p.* (-0.904 *p.p.* for dropouts and -0.367 *p.p.* for HS graduates), accounting for 3.3% of their LFPR drop.

Panel B (right) illustrates the regionally computed weights limiting R to each NOAA climate region under baseline estimates. With salient difference of climate exposure, the regional gap is notable. Initially hot areas (Southeast, South, West) areas underwent more hot days, these areas received significant drop (-0.557 *p.p.* in Southeast, -0.356 *p.p.* in South, -0.459 *p.p.* in West). Each corresponds to 7.7%, 5.4% and 7.6% of their LFPR drop, respectively.[49] By contrast, Northeast and Central area were harmed less, as the areas had enjoyed fewer cold days, especially before 2000.[50]

Non-colleged under the global *boiling* Limiting our focus on the new century after 2000 under severer global warming, however, increase in hot days typically dominates decrease in cold days. Figure 5 (Panel A) separately illustrates the climate change before and after 2000 (in (2-a) vs. (2-b)). The new century period (2000-2019) underwent significant increase of hot days (+ 15.5 days) relative to negligible decrease of cold

[49]Give the their closeness to Mexican Gulf, Southeast and South have higher humidity than other climate zones. As using discomfort index instead of hot days offers much larger estimates (See a robustness check in Section 3.3), the assessment is likely to be a lower bound.

[50]A simulation after 2000 would suggest that these areas also received an intensive increase in hot days. See Appendix for after-2000 counterpart of the impact assessment.

days (-0.2 days), which is a stark contrast to pre-century period (1970-2000)[51]. Specifying $I_0 = [1996, 2000], I_1 = [2015, 2019]$, and a weighing year $t^* = 2000 \in [2000, 2019]$ in the formula (3), the simulation suggests that netting out competing forces after 2000, climate change significantly hurt LFPR by -0.320 *p.p.*, explaining for 12.4% of the nationwide drop in LFPR during 2001-2019[52]. Remarkably, regarding high-school graduates and less, climate change explained even larger 17.7% of the nationwide LFPR drop.[53] By climate regions, Southeast experienced the largest drop -0.482 *p.p.* (12.5% in total), however, other areas Northeast and Central also underwent concerning adverse effects -0.383 *p.p.* (22.0% in total) and -0.364 *p.p.* (6.2% in total), respectively. (See Appendix for a simulation during 2000-2019).

5.2 Policy implication

Global temperatures are projected to rise further in the coming decades of the 21st century. Alarmingly, no evidence was found for any adaptation for increased hot days. Interacting years with hot and cold days, the coefficient for hot days does not significantly improve over time, consistent with more severer hot days.[54] This paucity of adaptation is reported in a series of prior works, including Deryugina and Hsiang (2014). This naturally raises a normative question on the role of public intervention in this intensified harm from heat.

Heat regulation law as a place-based policy One common idea in the policy arena is a heat regulation law, which has been implemented in a few states[55], and debated for

[51]Increase of hot days was very modest with 0.9 days, while decrease of cold days was -4.1 days.

[52]Warming impact from additional hot days reaches -0.346 *p.p.* (13.4% of the nationwide drop) while cooling impacts from less cold days was suppressed to $+0.019$ *p.p.*. In the same period, I compute that climate change accounted for X% of drop in employment rate of prime-aged males.

[53]When the thresholds of cold days is set as $40°F$ or $30°F$, counteracting effect from cold days are much weaken and the net climate impact is even larger. I report more conservative estimates. The assessment is robust to a series of alternative procedures across models, population weights $\omega^{g,i}_{R,t^*}$ for aggregation, and corresponding observed data moments of LFPR. (See Appendix).

[54]By contrast, as cold days decreases and become less severer, the coefficient for cold days appears smaller.

[55]My estimates might be interpret as net of state-level regulations. Excluding the three states (accounting for approximately X% of prime-aged male population), however, do not change the estimates.

a federal-level implementation[56]. A typical policy package contains a mixture of primitive solutions: prohibiting labor under extreme hot weathers, flexible time schedule, mandating personal heat-protective equipments (cooling vests, or personal air fans), and frequent access to watering and shading.

What happens when the heat regulation act is implemented in a state? Given the discussion on mechanism at work, my empirical findings create policy implications at regional labor markets. For regions where labor supply response is dominant, mandating protection would expectedly serve to prevent further dropouts. For regions where labor demand response is dominant, however, heat regulation law might backfire to trigger unintended consequences of employment shrinkage; because mandating investments would facilitate heat avoidance by labor reallocation (Ponticelli, Xu and Zeume (2023)) and/or exits of relatively smaller businesses (Acharya, Bhardwaj and Tomunen (2023)). As exposure to climate change highly differs across regions, and relative market force depends on differential demographic composition and industry mix, the regulation should be better implemented as placed-based policies (Austin, Glaeser and Summers (2018)) rather than the federal-level. Despite the estimated adverse wage response nationwide (in Section 3.6) and its suggestive dominance of shrinking regional labor demand, the net benefit appears to be a pure empirical question.[57] Either ex-post regional case studies or ex-ante net welfare evaluation are out of the scope of the paper, and left for future work.

6 Concluding remark

Throughout the human history, males have enjoyed comparative advantage in working outdoors. Exploring the secular trend of their declining labor attachment, the paper posits that modern climate change hurt the traditional advantage of adult males. Employing a plausibly random variation of climate change across U.S. commuting zones as a natural experiment, the paper demonstrates that climate change impaired their labor force attachment. The de-

[56]Only a handful of states (e.g., California, Washington) adopt heat regulation law.

[57]I am not aware of experimental studies to test the impact of state-level heat regulation law or to validate the efficacy of the countermeasures to heat.

tachment appears to be intermediated by outdoor labor markets——seemingly an absorbing place for unskilled workers, immune from modern technology revolution and globalization, but unsheltered from planetary change. I find that climate change both shrink outdoor employment and wages exclusively for outdoor workers, suggesting that outdoor labor markets is a hotbed of dropouts. The evidence for adaptation is limited. The harm is alarmingly uneven among adult males both within- and between-regions. Because outdoor labor markets are chiefly served by noncollege workers and disadvantaged regions critically depends on outdoor jobs, accelerating climate change would exacerbate the socio-economic inequality.

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