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W. Similan Rujiwattanapong・Masahiro Yoshida

Waseda INstitute of Political EConomy
Waseda University
Tokyo, Japan

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W. Similan Rujiwattanapong† Masahiro Yoshida‡

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Abstract

Historically, unemployment peaks in the first and third quarters—the arrival of cold winters and hot summers. This paper attributes non-seasonally-adjusted (NSA) unemployment fluctuations to temperature shocks and assesses the impact of climate change on unemployment seasonality. Combining granular daily weather across US counties with monthly unemployment rates over the period 1990-2019, we find that extreme temperature days fuel unemployment by freezing hiring and triggering layoffs and thus, insurance claims and recipients. Climate change accounts for 40% of the decline in unemployment seasonality and 13% of the moderation in fluctuations in the overall NSA unemployment rate. Accelerated future warming will propagate the unemployment seasonality through milder winters and harsher summers.

Keywords: Climate change, Unemployment rate, Unemployment seasonality, Unemployment insurance.

JEL Codes: J63, J64, J65, Q54

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†Faculty of Political Science and Economics, Waseda University and Centre for Macroeconomics. Email: sruji@waseda.jp. Webpage: sites.google.com/site/wsrujiwattanapong.

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

1 Introduction

At least since the Great Depression, the containment of unemployment has been a historical theme of economic policy. Although the unemployment rate is monthly monitored as the "temperature" of the economy and serves as a central input to policy debates (e.g., unemployment insurance, minimum wage, fiscal/monetary policy), little is known about its regularity and the mechanism of its seasonal dynamics; in fact, most economists statistically smooth out these seasonal movements using statistical techniques. This lack of inquiry is surprising given this the rise of in-and-out type workers within years (Katz and Krueger (2019); Coglianese (2018)), increased female labor market entry as part-time workers, threat to consumption smoothing and association with UI policies. To reveal the mechanism of seasonal unemployment dynamics, this paper studies how temperature shocks shape unemployment, and assess the long-run implication of climate change on unemployment seasonality, given the forecast of accelerated warming in the new century.

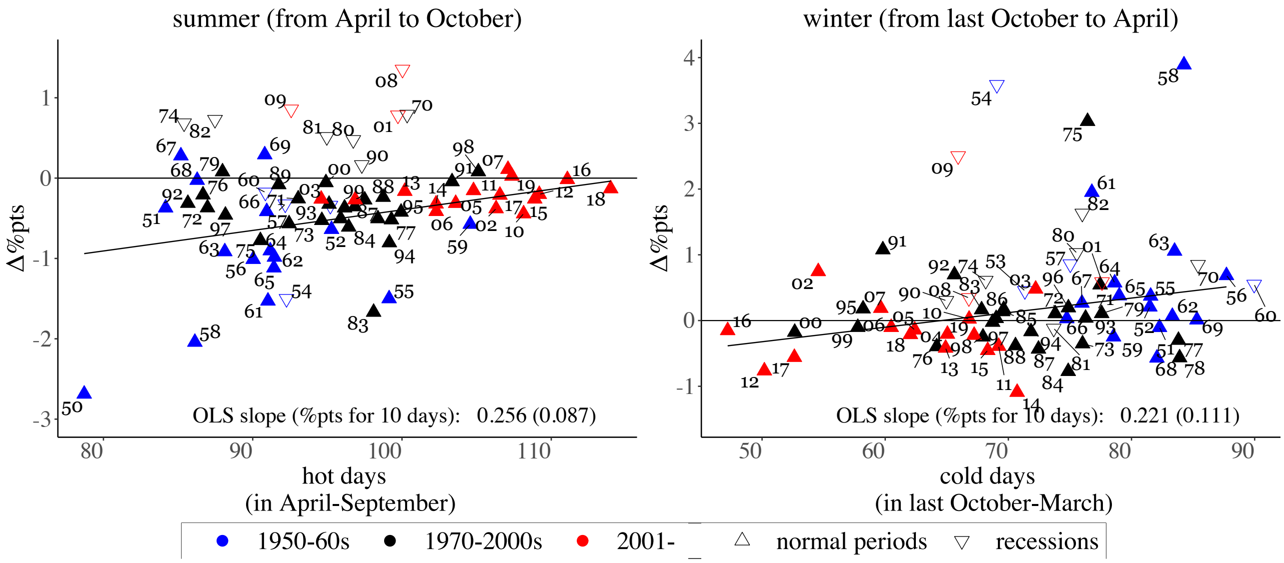
To motivate our investigation, we begin by contrasting a half-year change in the unemployment rate (in summer and winter) with its seasonal temperature exposure. Panel A of Figure 1 plots nationwide experience of hot days in summers (April to September, left) and cold days in winter (pre-year October to March, right), juxtaposed with half-year change of unemployment rates in 1950-2019. Despite the limited sample size of 70 years, the plots give a statistically significantly positive slope ($t = 2$).[1]Analogously, Panel B shows an adverse temperature-unemployment nexus across US commuting zones split by summers (left) vs. winters (right) in 2019. In summers, hot cities (e.g., Miami, FL, Austin, TX) experienced larger increase relative to cold days (e.g., Minneapolis, MN, Rochester, PA) in unemployment. In contrast, in winter, cold cities experienced a relative increase.

Guided by the dynamic and spatial associations, we hypothesize that the arrival of hot summers and cold winters fuel unemployment rates. Extreme temperature days would significantly hurt labor efficiency by interrupted work, increasing physical / mental fatigue, lowering work morale, operational errors, and workplace injury risk (Park et al., 2021), and thus lead to a decrease in labor demand —- resulting in fewer hires and more separations. This prediction is consistent with our finding on seasonal regularity of unemployment cycle—starting with the peak in the first quarter (Jan-Mar), and re-peaking in the third quarter (Jul-Sep), when the average temperature hits the lowest and highest. To formally test this, we build a new panel data connecting plausibly-random monthly-level exposure to hot days and cold days, and non-seasonally adjusted (NSA) unemployment rates during 1990-2019, allowing for straightforward identification of temperature-unemployment nexus. We also add extra weather proxies (e.g.,

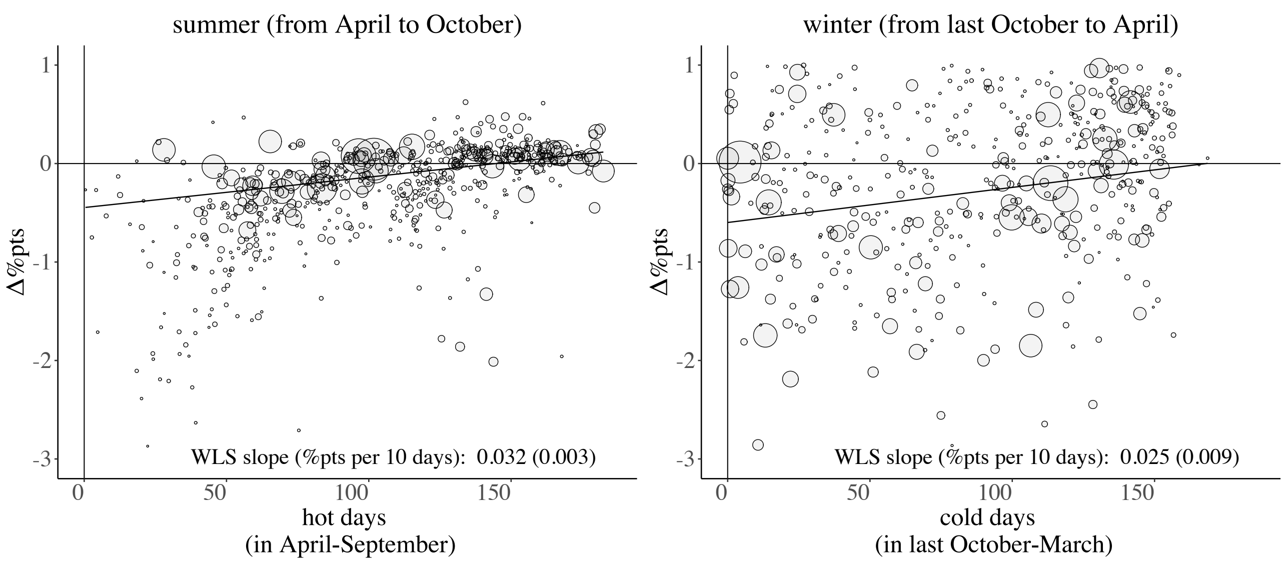
[1]Including or excluding recession years does not significantly change the estimate.

Figure 1: Temperature Shocks and Half-year Unemployment Dynamics in the US

(a) Nationwide Time Trend (1950–2019)



(b) Spatial Dispersion across Commuting Zone (2019)



Notes: Panel (a): County-level exposure to hot and cold days are aggregated at the national level, weighted by labor force, obtained from Bureau of Labor Statistics. Hot and cold days are defined as days with an average temperature during working hours (8 a.m. to 6 p.m.) exceeding 77°F and below 50°F, respectively. Nationwide monthly unemployment is taken from the Bureau of Labor Statistics. The fitted lines are trends without recession years, identified by NEBR-dated recession periods. Panel (b): County-level exposure to analogously defined hot and cold days is aggregated to commuting zone (CZ) level as the period average, 2015–2019, weighted by a county labor force. Each bubble represents a CZ, with its size corresponding to the labor force. Small CZs with labor force below 10,000 are dropped for clarity.

humidity, precipitation, snowfalls) which presumably prevents business operation outdoors or indoors without air conditioning. This granularity of analysis permits estimating climate impact on unemployment at within-county-by-year level, which are free from statewide institutional confounders (e.g., unemployment insurance; minimum wage; unionization). Importantly, we include year-month fixed effects to isolate temperature impacts from nationwide business cycle and institutional calendar effects (e.g., year-end contract; school graduation in May).

We find that 10 more extreme temperature days per month (hot days over 75°F and cold days below 45°F) increases monthly unemployment rate by 0.2-0.3%pts. The results are robust to alternative thresholds of hot and cold days, pre-trends, and combination of fixed effects.

To unpack the mechanism behind, we next track the quarterly job and employment flows by county-by-sector during 2001-2019. We find that both hot and cold days freeze job creation (or hiring) and induce job destruction (or separations) in wide range of sectors. Especially, job destruction was most severe in heat-sensitive sectors (e.g., construction, manufacturing). Fewer job hiring was observed in in-person service sectors, suggesting that temperature shocks might have reduced labor-intensive service demand. Return hiring of possibly seasonally laid-off workers to the previous employers was severely hurt, contributing to the expansion of unemployment pool. In addition, we find that more layoffs, instead of quits, are responsible for more separation, and suppressed job openings, suggesting that labor demand shrinkage is at work.

As is well known, layoffs are most likely lead to unemployment, we view this as especially alarming. To examine the reasons of mass layoffs during 1996-2013, we find that seasonal layoffs acyclically accounts for 20-30% of total mass layoff cases, and most responsive to extreme temperature days. One would expect that the increase layoffs would lead to receipts of unemployment insurance (UI). We find that experience of hot and cold days raises statewide monthly UI claims, reduce exits from UI exits, and thus, expand a pool of continued recipients, suggesting seasonal fiscal burdens. Guided by our findings, we turn to assess how climate change, especially, global temperature warming, activating since 1970-1980s, shapes the seasonality of unemployment. Aligned with the ongoing climate change, we document that unemployment seasonality has tarnished overtime especially around the recessionary peak in 1983. Unemployment in the first quarter (e.g., New Year's Day, Super Bowl Sunday) has declined, while that in the third quarter (e.g., Independence day; Labor Day) has risen overtime. Consistently, we show that climate change through fewer cold days and more hot days accounts for about a half of the decline in unemployment seasonality, measured by a variance of seasonal unemployment rate. In the coming decades, however, temperature rising scenario predicts that climate change will increase the volatility of unemployment—threatening the welfare, especially seasonal workers, and calls for countermeasures of unemployment forecast and job security.

Related Literature. Bridging temperature shocks and unemployment dynamics with an empirical approach, this paper contributes to the intersection of macro labor economics and climate science. First, this paper provides a descriptive contribution by documenting the status and change of seasonality of unemployment as an empirical regularity. To our surprise, we are not aware of papers explicitly codifying the unemployment seasonality from unadjusted raw records, presumably due to the dominance of the conventional practice of seasonal adjustment. In particular, we also document that unemployment seasonality is time-variant and shrinking.

Second, the paper proposes temperature shocks as a novel determinant of unemployment dynamics. The literature has long interested in macroeconomic outcomes such as growth (Dell et al., 2012; Colacito et al., 2019), income (Deryugina and Hsiang (2014)), labor share (Qiu and Yoshida (2024)) and labor force participation (Yoshida (2025)). Our paper is the first to associate unemployment rate, varying across time and space with arguably most seasonal factor—climatic temperature. [2] Leveraging granular spatial and monthly variation, we run a "natural" experiment to attribute the incidence and changing nature of seasonality to climate change. We show that climate change, characterized by a long-run change of temperature shock smooth out a within-year temperature fluctuation.

Third, the proposed mechanism of temperature-induced unemployment builds on establishment-level studies in climate science, exploring climate impacts of employments factory productivity (Chen and Yang, 2019; Somanathan et al., 2021). The findings are aligned to burgeoning studies showshrinkage and destruction of employment of small establishments (Ponticelli et al. (2023)), reallocation across areas (Acharya et al. (2023)). By adding on the literature by looking at employment inflows and outflow, we bring the insights of labor demand response to unemployment dynamics. Importantly, we identify not only frozen hires, but increased layoffs on the firm side. From a policy perspective, our finding speaks to policies on job security, especially in summers.

The remainder of the paper is structured as follows. Section 2 describes the data sources used in the study. Section 4.1 presents the baseline results, validated by robustness checks in Section 4.1.1. Section 5 explores the mechanism via layoffs and frozen hires. Section 7 evaluates the role of climate change to moderated fluctuation of both unadjusted and seasonal unemployment. Section 6 creates implication to unemployment insurance claims and recipients, and Section 8 concludes.

[2] As a notable exception, recently, Kim et al. (2025) analyzes the effect of temperature shocks on outputs, prices and unemployment, using a time-series method.

2 Data

2.1 Weather

We construct daily temperature at county-level, using weather station data from the Global Historical Climatology Network Daily (GHCN-Daily), managed by the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA). The GHCN-Daily database provides daily climate statistics, such as maximum and minimum daily temperature, precipitation, and snowfall, from approximately 15,000 weather stations across the US, offering a comprehensive climatic dataset with the highest frequency, resolution, and quality since the 19th century. We use data from stations with complete annual records during 1950–2019. [3] To aggregate station-level data to each county level, we employ an inverse-distance weighting method (e.g., Barreca et al. (2016)) Specifically, for each county we select the three nearest weather stations to the county's population centroid and aggregate their daily records, weighted by the inverse square of the distance from the centroid. Then, we construct an average daytime temperature for each day d as a weighted average of the maximum and minimum temperature, i.e., $T_d = \omega T_d^{\max} + (1-\omega)T_d^{\min}$. Instead of using $\omega = 0.5$ as is common in the climate literature, we assign $\omega = 0.75$ in light of our focus on regular working hours, 8 am to 6 pm.[4] We find a substantial geographical variation of exposure to climate change across counties even within states.[5]

2.2 Unemployment

To uncover the climate-unemployment mechanism, we combine a series of datasets to measure employment flow.

Local Area Unemployment Statistics (LAUS) The LAUS provides unemployment and employment by counties-by-year-months. The dataset is produced by the Bureau of Labor Statistics (BLS) from the CPS, the Current Employment Statistics (CES) survey, and state unemployment insurance (UI) systems.

[3]The relative humidity is constructed from dew points at another set of station records from NOAA's Global Summary of the Day (GSoD).

[4]This calculation assumes a linear fluctuation of temperature between its minimum at 6 am and its maximum at 1:30 pm.

[5]Other extreme weather or natural disasters caused by climate change would trigger unemployment (hurricanes in Groen and Polivka (2008); Belasen and Polachek (2008), tornados in Riesing (2018).) Although our precipitation proxies partially captures these phenomenon, our analysis is focused on temperature.

Quarterly Workforce Indicators (QWI) The QWI provides local employment flows by county-by-NAICS-by-year-quarter during 2001-2019: job flows (creation and destruction) as well as worker flows (separation and hires). This is constructed from the Longitudinal Employer-Houshold Dynamics (LEHD) by the Census Bureau—employer-employee linked massive longitudinal microdata covering over 95% of US private sector jobs.

The Job Openings and Labor Turnover Survey (JOLTS) The JOLTS provides demand-side indicators of labor shortages at the national level. We use job openings on the last business day of the month, hires and separations (split by layoffs and quits) by state-by-year-month during 2000 December-2019 December across 48 states. This data is constructed from a monthly survey of approximately 21,000 U.S. business establishments in all nonagricultural industries, collected by the BLS.

Mass Layoff Statistics (MLS) The MLS offers mass layoffs reported by the BLS. In particular, we use mass layoff cases for a variety of reasons by state-by-year-quarter during 1995 Q2-2013 Q1 [6]across 48 states and the DC.. The data is constructed from monthly information on all establishments that generate at least 50 initial unemployment insurance (UI) claims for a 5-week period. In contrast to the strong cyclical nature of mass layoff cases from business demands or financial constraints, we find that seasonal layoffs *acyclically* accounts for 20-30% of total mass layoff cases (see Figure A-1).

3 Unemployment Seasonality

To extract seasonal unemployment rate at each county on a monthly basis, we take a difference of non-seasonally-adjusted (NSA) and seasonally-adjusted (SA) unemployment rate from the BLS during 1990-2019. Figure 2 documents the regularity of changing monthly unemployment seasonality, which we codify as three stylized facts.

Fact 1: The unemployment rate in the first quarter is declining. The left of Panel (a) illustrates the seasonal unemployment at monthly level before and after the post-war recessionary peak in 1983. The nationwide unemployment peaks in the first quarter and reaches lowest in the last quarter. [7] Traditionally, the unemployment rate jumps up in January from the last

[6]The data was discontinued in 2013 due to spending cut.

[7]A notable pattern is a spike in unemployment from May to June, the onset of summer, coinciding with start of the summer break and graduation of high schools and colleges when students search for summer jobs.

year's December, presumably reflecting annual contracts (January-December) in fiscal years. [8] However, one can see that unemployment rate in Q1 has declined.

Fact 2: The unemployment in the third quarter is on the rise. Panel (a) shows that unemployment in Q3 (July-September) is gradually on the rise.[9] Intriguingly, the change in unemployment rate in Q1 and Q3 (**Fact 1** and **Fact 2**) corresponds with fewer cold days and more hot days, driven by temperature warming (as observed in the quarterly trend of unemployment rate and temperature shocks in Panel (b)).

Fact 3: Unemployment seasonality has been declining since the 1970s. As a consequence of lower and higher unemployment in Q1 and Q3, unemployment seasonality has declined overtime. Panel (c) illustrates seasonal component of monthly unemployment rates overtime and its within-year variance declined since 1960s, when global warming loomed up. Given the forecast of global warming in the coming century, unemployment in summer (e.g., labor day) is alarming. According to the standard climate forecast in the coming decades, unemployment seasonality may be amplified.

4 Empirical Analysis

4.1 Baseline Results

Model. The baseline model regresses county-level monthly unemployment rates on the number of hot and cold days for each county, controlling for other climatic factors and a rich set of socioeconomic variables. Specifically, for counties (indexed by l) in years (indexed by t, 1950-2019) and month m , we build the following model:

$$\text{UnempRate}_{l,t,m} = \sum_{b \in \{1,\cdots,10,13,\cdots,16\}} \beta^b \text{days}^b_{l,t,m} + \mathbf{\Lambda}\mathbf{C}_{l,t,m} + \delta_{l,t} + \delta_{t,m} + \varepsilon_{l,t,m}, \tag{1}$$

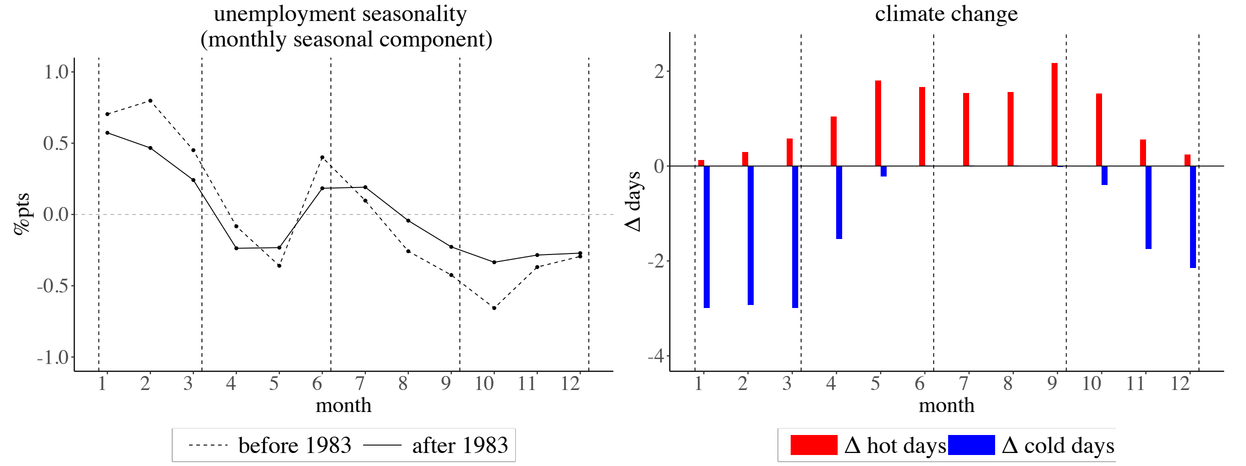
where $\text{UnempRate}_{l,t,m}$ is county l's average unemployment rate at year t and month m. We also control for additional climate covariates $\mathbf{C}_{l,t,m}$, including daily precipitation and the number of days with no precipitation, and those with heavy snowfall. The granularity of the data permits inclusion of county-year fixed effects $\delta_{l,t}$, suggesting that the estimates are within-year impacts at county level. Year-month fixed effects $\delta_{t,m}$, capturing any time-varying nationwide shocks (e.g.,

[8] This annual contract might be aligned with Americans' preference for leisure at festive seasons of the fourth quarter Thanksgiving and Christmas—when few employers would wish to layoff workers.

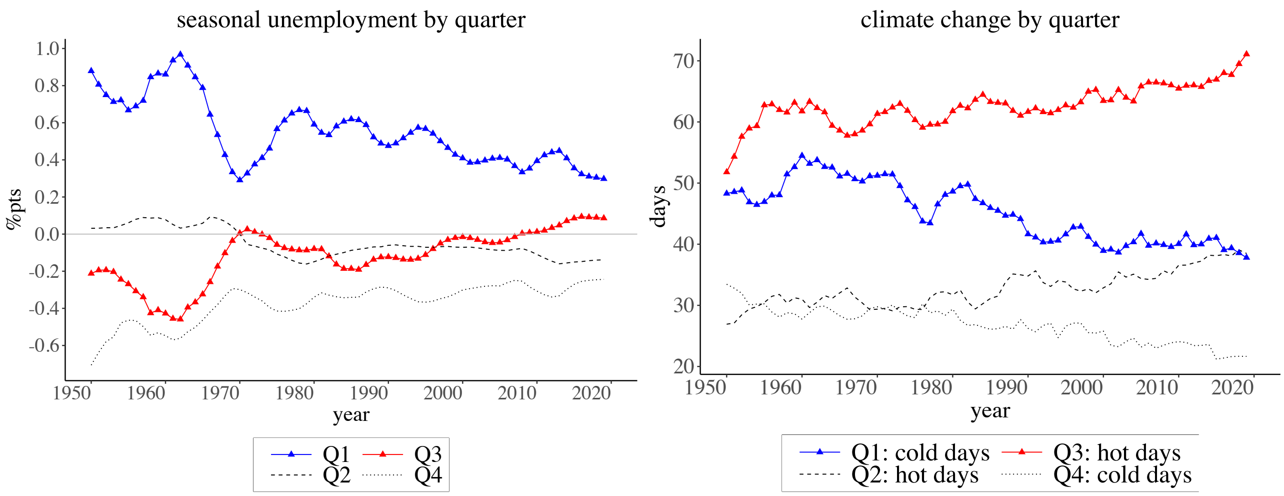
[9] Unemployment rate in June decreased even though hot days in June increased. This is probably due to lagged effects (see Table A-2) from less cold days in Q1 and Q2.

Figure 2: Dynamics of Unemployment Seasonality in the US

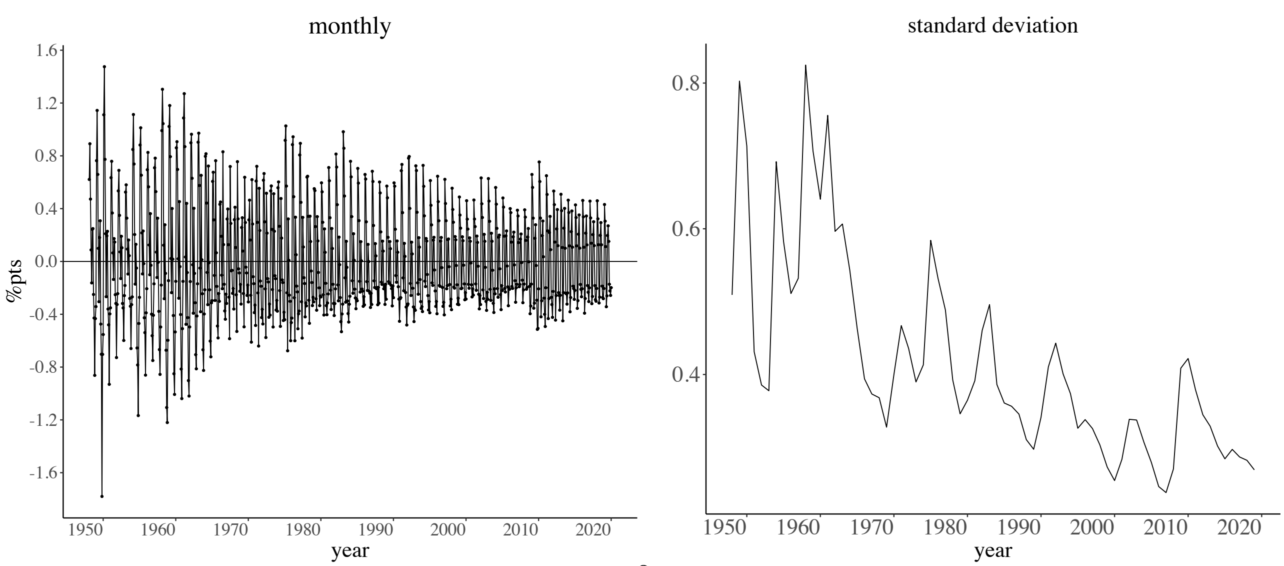
(a) Seasonal Unemployment By Months: Before and After 1983



(b) Seasonal Unemployment By Quarters: 1948–2019



(c) Shrinking Unemployment Fluctuation: 1948–2019



Notes: Seasonal UR is a difference of NSA and SA nationwide unemployment rate computed by the BLS.

business cycles or technological, globalization shocks). $\delta_{t,m}$ also isolate temperature effects from institutional calendar effects (e.g., end of year contracts). As we presume that temperatures shocks are unconditionally random, β^b captures the temperature impact of 10 days in each bin. The regression is weighted by log of labor force of each county and, standard errors are clustered at the county level.

Results. Panel (a) of Figure 3 illustrates our baseline results. The red line of the top figure plots the response of unemployment rate to each temperature bin of 10 days with 95 % confidence intervals. One can see that 10 day increase of hot days ($\geq$ 75°F) and cold days ($<$ 45°F), approximately increases the unemployment rate by 0.2-0.3 %pts. Panel (b) shows the change of distribution of days from the pre-analysis period (1950-1986) and the analysis period (1990-2019). One can see that mildly hot days of 75-80°F is a mode of the climate distribution. The distributional change is characterized by the increase of hot days (>75°F) and decrease of cold days (<45°F). Recall that since $\mathbf{C}_{l,t,m}$ includes snowfalls, the effect of cold days should be isolated from the effect from snowfall. The second and third figures decompose the unemployment rate into unemployment and employment in log-scales. The loss of employment is larger than the increase of unemployment in magnitude, implying the increase of non-employment, presumably, including discouraged workers.

Two-tail parsimonious models Founded on the U-shaped estimates in Figure4a, we use a parsimonious two-tail model below[10]: replace treatment variables $\sum_{b\in\{1,\cdots,10,13,\cdots,16\}} \text{days}^b_{l,t,m}$ by $\beta^h \text{hd}_{l,t,m} + \beta^c \text{cd}_{l,t,m}$, where $\text{hd}_{l,t,m}, \text{cd}_{l,t,m}$ are hot and cold days in county l during year t, month m, respectively. The coefficients of interest, β^h, β^c, capture the impact of additional 10 hot or cold days on unemployment rates. Each location's exposure to climate change is measured as the changing number of monthly hot and cold days. Specifically, hot and cold days are defined as those with an average working-hour temperature above 75°F (23.4°C) and as below 45°F (7.2°C) respectively.

4.1.1 Robustness checks

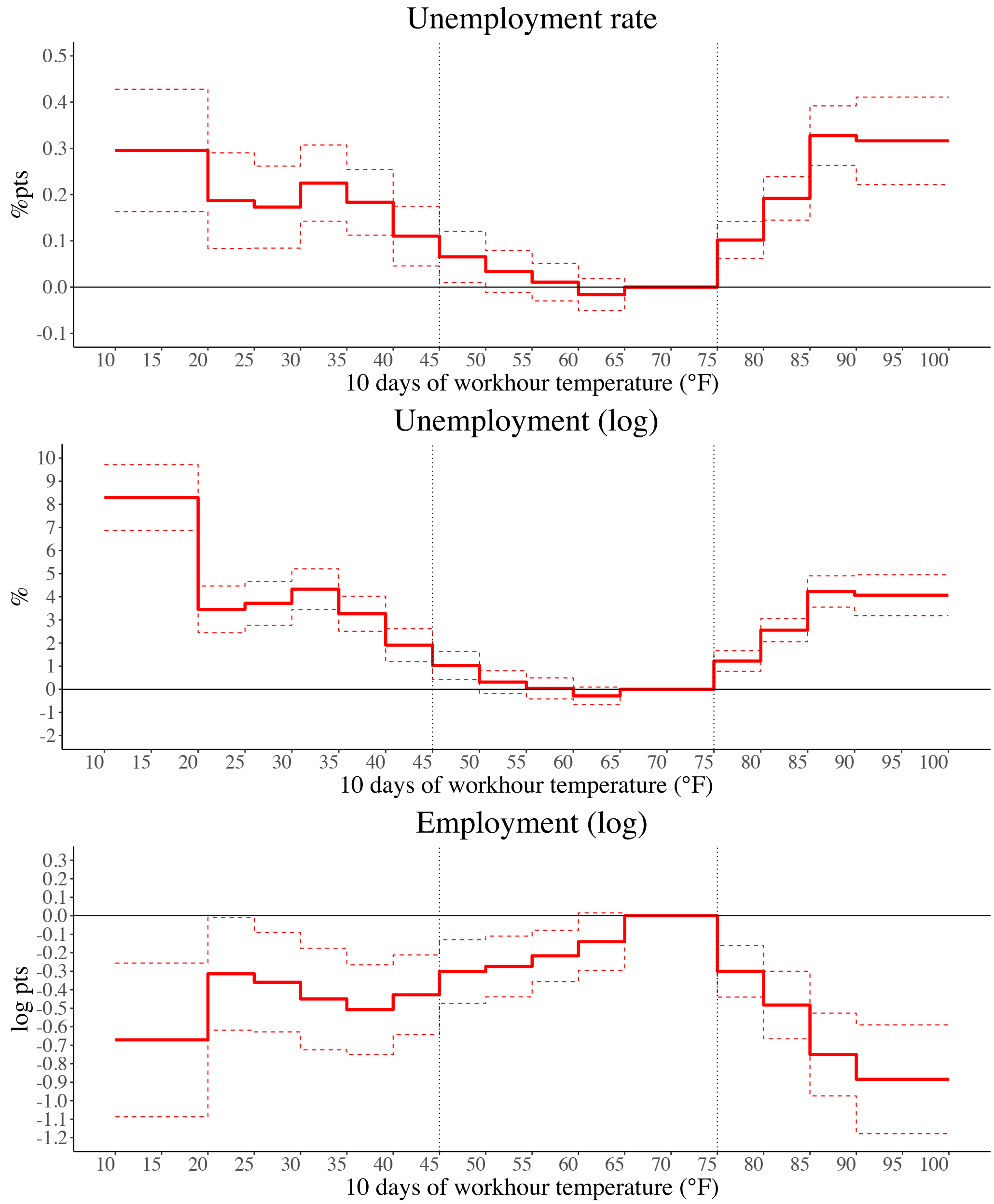
To establish our main findings, we provide a list of robustness checks. All the tables are shown in Appendix.

Temperature thresholds The baseline model used 75°F and 45°F as cutoffs for hot and cold days.

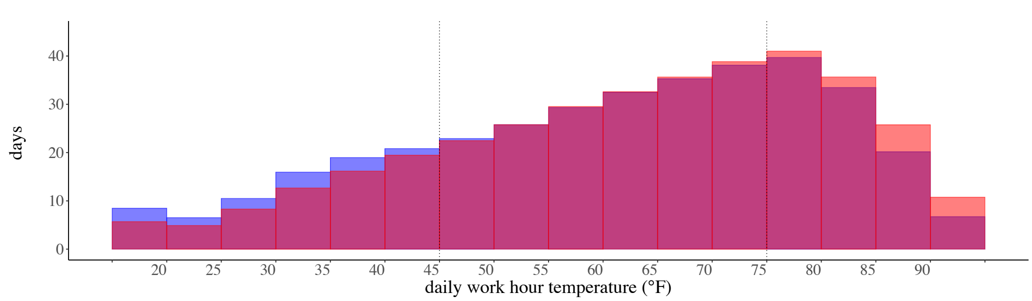
[10] A similar two-tail specification has been a standard in the climate literature, for example, Barreca et al. (2016) and Somanathan et al. (2021).

Figure 3: Temperature Shocks and Unemployment (by county-by-month, 1990–2019)

(a) Semi-parametric Estimates (65-75°F as baseline)



(b) Climate change (1950-1986 vs. 1990-2019)



Notes: Panel (a): Unit of analysis: outcome years (1950-2019) × months × counties. The daily temperature is averaged during business hours (8 am to 6 pm). The regressions are weighted by log of labor force. Dotted lines are 95% confidence intervals, constructed from standard errors clustered at the county level.

Alternatively, we reasonable pairs of temperature cutoffs of 73, 75, 77, 80°F for hot days, and 35, 40, 45, 50°F for cold days. Consistent with the U-shape estimates at Figure 1, all models exhibit significantly positive estimates (see Table A-1).

Fixed effects Under the baseline, we incorporate state-by-year and monthly fixed effects. We tried out alternative constellation of fixed effects. The estimates are broadly stable. Instead of $\delta_{t,m}$, the inclusion of state-by-year-month fixed effects $\delta_{s,t,m}$ preserves the effect, suggesting that any time-varying statewide change of business cycles, unemployment insurance and other institutions (e.g., minimum wage; unionization) does not confound the estimate (see Table A-3).

Other climatic variables It is well known that humidity affects the human discomfort, interacted with temperature. Consistently, using heat index, interacting temperature and humidity, increases the magnitude and precision of the estimate. We also find significant effects of precipitation or snowfall on unemployment in both extensive and intensive margins (see Table A-4).[11]

Treatment windows The baseline model takes one month as treatment of temperature. However, businesses might take a lag to adjust monthly labor demand in response to temperature shocks. To account for temperature adjustment, we expand the treatment window to 6 months in a lagged treatment model. The effects of hot and cold days is larger for 5-6 months after the shock, suggesting the cumulative impact of temperature (see Table A-2).

5 Mechanism

Job Creation and destruction across sectors Having established the main findings, we turn to explore the mechanism of temperature-induced unemployment. We track the change of unemployment by job flows (destruction and creation) and by worker flows (separation and hires). [12] Using QWI, we estimate responses of county-by-NAICS level employment flows by quarters during 2001-2019. We build and estimate the following model at county l, year t, and quarter $q \in \{1, \cdots, 4\}$.

$$\frac{\Delta \mathrm{E}_{l,i,t,q}}{\mathrm{E}_{l,i,t,q}} = \beta^h \mathrm{hd}_{l,t,q} + \beta^c \mathrm{cd}_{l,t,q} + \mathbf{\Lambda C}_{l,t,q} + \delta_{l,i,t} + \delta_{i,t,q} + \varepsilon_{l,i,t,q}, \tag{2}$$

[11] Since our dataset does not include natural disasters (e.g., hurricanes; floods; wildfires), the paper limits our analysis to conventional proxies.

[12] A caveat is that these job flows include J2J flow and transition to non-employment, which does not affect unemployment.

where $\frac{\Delta E_{l,i,t,q}}{E_{l,i,t,q}}$ is employment change from the start-of-quarter employment. [13] $\delta_{i,t,q}$ captures time-variant sector specific shocks (ICT, robot shocks and business cycles), the estimates are interpretably free from sectoral business cycles. Guided by Figure 4a, Panel A tracks the

Table 1: Temperature Shocks and Job Creation/Destruction

	Panel A: Employment						
	level (%)	**Job Flow (%pts)**				**Worker Flow (%pts)**	
	End-quarter Emp.	**Job creation**	**Job destruction**	**Net Job. growth** (1)-(2)	**Job Turnover** ((1)+(2)) /start-of-quarter emp.	**Hires**	**Separation**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
10 hot days per quarter	−0.149*** (0.040)	−0.276*** (0.046)	0.052*** (0.006)	−0.327*** (0.046)	−0.224*** (0.046)	−0.210** (0.083)	0.118** (0.049)
10 cold days per quarter	−0.375*** (0.043)	−0.167*** (0.042)	−0.035*** (0.005)	−0.132*** (0.043)	−0.202*** (0.042)	−0.411*** (0.083)	−0.279*** (0.054)
Observations				378,579			
Adjusted R^2	0.998	0.554	0.577	0.498	0.601	0.611	0.602
	Panel B: By Sectors						
	Agriculture	**Cons- truction**	**Manu- facturing**	**Trans- portation**	**Retail**	**Low-skill service**	**High-skill service**
	Panel B-1: Job Creation Rate (%pts)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
10 hot days per quarter	0.002 (0.397)	−0.627*** (0.063)	−0.094*** (0.029)	0.057 (0.045)	0.077*** (0.028)	−0.315*** (0.063)	−0.232*** (0.037)
10 cold days per quarter	−1.461*** (0.453)	−0.315*** (0.076)	0.008 (0.032)	−0.090* (0.048)	−0.123*** (0.028)	−0.186*** (0.053)	−0.076** (0.038)
Observations	41,398	57,447	47,860	44,736	52,609	59,130	58,103
Adjusted R^2	0.480	0.459	0.647	0.328	0.461	0.550	0.584
	Panel B-2: Job Destruction Rate (%pts)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
10 hot days per quarter	0.078* (0.041)	0.126*** (0.013)	0.033*** (0.007)	0.051*** (0.011)	0.020** (0.008)	0.026*** (0.009)	0.043*** (0.008)
10 cold days per quarter	−0.235*** (0.047)	−0.039*** (0.014)	0.001 (0.006)	0.003 (0.011)	−0.016** (0.008)	0.009 (0.009)	−0.038*** (0.008)
Observations	41,398	57,447	47,860	44,736	52,609	59,130	58,103
Adjusted R^2	0.479	0.459	0.647	0.328	0.461	0.550	0.584
county × sector × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year× quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Unit of analysis: counties × sectors × quarters × years, 2001–2019. Employment flows are from Quarterly Workplace Indicators from the Census Bureau.

level and flow of sector employment. Column 1 shows within-sector impact of end-quarter employment. Columns 2-3 show that hot days significantly reduce job creation and increase

[13] We use a job (or worker flow) /beginning-of-quarter employment. The results are robust to log of end-of-period employment level, $log(E_{l,t,q})$ after dropping zero samples.

job destruction. Cold days reduce both job creation and destruction, economically freezing economic activity. The response of job creation is 4-time larger than job destruction in magnitude. Consequently, net job growth and job turnover are both negative for hot and cold days. Corresponding with job creation and destruction, Columns 6-7 address worker flows, suggesting fewer hires and more separations, respectively.[14] Panel B investigates the job flow by sectors. Panel B-1 shows job creation is inhibited in construction and manufacturing, but also service sectors. This might suggest that some service demand (e.g., tourism; restaurants) is hampered by temperature. This is also consistent with observations that service sectors include a decent share of outdoor jobs (Yoshida (2025)) and evidence that even indoor businesses suffer from productivity loss (Cook and Heyes (2020) for cognitive ability, and Cachon et al. (2012) for automobile plants). As a notable exception, retail sector shows *increased* job creation. Panel B-2 shows that job destruction is facilitated by hot days in near all sectors, especially in construction, which motivates the inquiry into layoff below. For cold days, job destruction is mitigated, especially in agriculture, construction and high-skill service.

Layoffs vs. Quits Previous analysis showed that the increase in unemployment from hot days is driven by fewer jobs creation and more job destruction. To see whether this is driven by the labor demand side, we further limit separations to layoffs and explore the response of job openings, which are direct proxies for labor demand. Use the JOLTS during 2000 Dec.-2019 Dec. across 48 states and DC., we estimate a variant of the model at state s, year t, and month m:

$$\log \mathrm{E}_{s,t,m} = \beta^h \mathrm{hd}_{s,t,m} + \beta^c \mathrm{cd}_{s,t,m} + \mathbf{\Lambda C}_{s,t,m} + \delta_{s,t} + \delta_m + \varepsilon_{s,t,m}, \tag{3}$$

Table 2, Panel A shows the temperature effect on outflows and inflows of employment. Extreme temperature days increase layoffs (Column 2), not quits (Column 3). Moreover, within hiring, job openings, as a more direct proxy of labor demand, significantly shrinks. Combined, the results suggest that the temperature impact is primarily on the labor demand side. Unlike quitters, laid-off workers face a very high probability, close to 90 percent, of entering unemployment (Elsby et al., 2011). This motivates the reasons of mass layoff evens in Panel B. Using Mass Layoff Statistics from BLS. 1995 Q2-2013 Q1 by 48 states and DC., Panel B estimates a model at state s, year t, and quarter q:

$$\log(\text{mass layoffs}_{s,t,q}) = \beta^h \mathrm{hd}_{s,t,q} + \beta^c \mathrm{cd}_{s,t,q} + \mathbf{\Lambda C}_{s,t,q} + \delta_{s,t} + \delta_q + \varepsilon_{s,t,q}, \tag{4}$$

Column 1-5 show the sensitivity of mass layoff cases by reasons: seasonal layoffs increase most as well as other reasons (i.e., demand, finance, and organizational reasons).

[14]For hires, return hiring accounts for most of the effects, suggesting that delayed recall of temporarily laid-off workers would lead to unemployment.

Table 2: Temperature Shocks and Separations and Hires across States

	Panel A: Employment Flow (percent (log scales × 100))				
	outflow			**inflow**	
	Separation	**Layoff**	**Quits**	**Hiring**	**Job openings**
	(1)	(2)	(3)	(4)	(5)
10 hot days	1.216***	1.580***	0.320	−1.980***	−1.122***
	(0.360)	(0.567)	(0.353)	(0.312)	(0.314)
10 cold days	0.631**	2.632***	−1.496***	−4.268***	−2.332***
	(0.296)	(0.469)	(0.327)	(0.309)	(0.322)
state × year FE	Yes	Yes	Yes	Yes	Yes
month FE	Yes	Yes	Yes	Yes	Yes
Observations	11,221	11,221	11,221	11,221	11,221
Adjusted R^2	0.983	0.954	0.982	0.984	0.986
	Panel B: Mass Layoff Events by Reasons (log of mass layoff events)				
	Season	**Demand**	**Finance**	**Organization**	**Production**
	(1)	(2)	(3)	(4)	(5)
10 hot days	0.089***	0.030**	0.028*	0.027***	−0.099
	(0.028)	(0.011)	(0.016)	(0.009)	(0.097)
10 cold days	0.054	−0.020*	−0.014	−0.015	−0.052
	(0.037)	(0.011)	(0.010)	(0.012)	(0.087)
state × year FE	Yes	Yes	Yes	Yes	Yes
quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	1,116	1,346	564	665	101
Adjusted R^2	0.650	0.843	0.692	0.792	0.207

Notes: Panel A: Unit of analysis: years × months × 48 states and DC.. Weighted by log(population). Panel B: Unit of analysis: years × quarters × 48 states and DC.. Weighted by log(employment).

6 Unemployment Insurance

Temperature-induced layoffs should expectedly induce insurance claims and recipients, leading to fiscal expenditure. We use the state-level UI initial claimants and continuing recipients, sourced from Employment and Training Administration at the Department of Labor. UI is eligible for laid-off workers with minimum wages earned during a reasonable period under various generosity across states. We find analogous flattening of seasonality pattern of UI recipients (see Figure A-2), suggesting the tight link between unemployment and insurance take-ups. We estimate the following model with UI related variable, $UI_{s,t,m}$ across state s, year t, month m:

$$\mathrm{UI}_{s,t,m} = \beta^h \mathrm{hd}_{s,t,m} + \beta^c \mathrm{cd}_{s,t,m} + \mathbf{\Lambda C}_{s,t,m} + \delta_{s,t} + \delta_m + \varepsilon_{s,t,m}. \tag{5}$$

Table 3 reports the estimates. Columns 1-2 show that 10 hot or cold days per month increase

Table 3: Temperature Shocks and Unemployment Insurance across states (1990–2019)

	Statewide UI Receipts			
	(1)	(2)	(3)	(4)
	UI new claims (%)	**UI recipients** (%)	**share of recipients in unemployment** (%pts)	**share of recipients in covered emp.** (%pts)
10 hot days per month	4.357***	4.402***	0.034***	0.153***
	(0.417)	(0.352)	(0.003)	(0.008)
10 cold days per month	13.049***	8.582***	0.064***	0.147***
	(0.468)	(0.511)	(0.003)	(0.010)
state × year FE	Yes	Yes	Yes	Yes
month FE	Yes	Yes	Yes	Yes
Observations	17,640	17,640	17,640	17,640
Adjusted R^2	0.973	0.980	0.766	0.918

Notes: Unit of analysis: states × years × months. Thresholds for hot and cold days are set at 75°F and 45°F, respectively, based on average temperature during business hours (8 am to 6 pm).

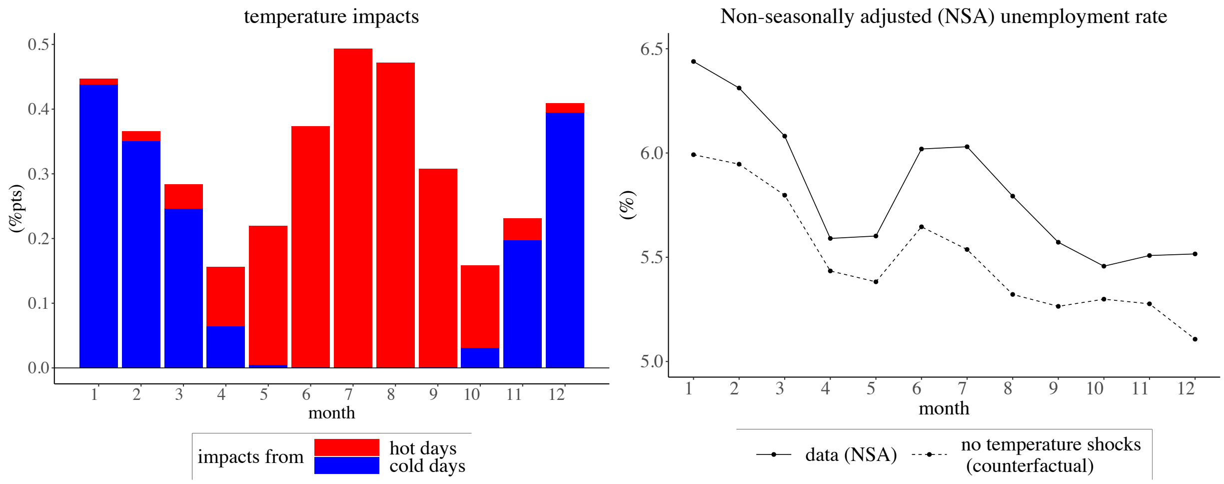
UI new claims and recipients. Columns 3-4 show that the effects are observed for a share of UI recipients in either unemployment or UI-covered employment. Although this paper remains silent on political adjustment of UI generosity, the findings suggest that temperature shocks would expand public expenditure, especially in the summer.

7 Accounting: The Decline of Unemployment Seasonality

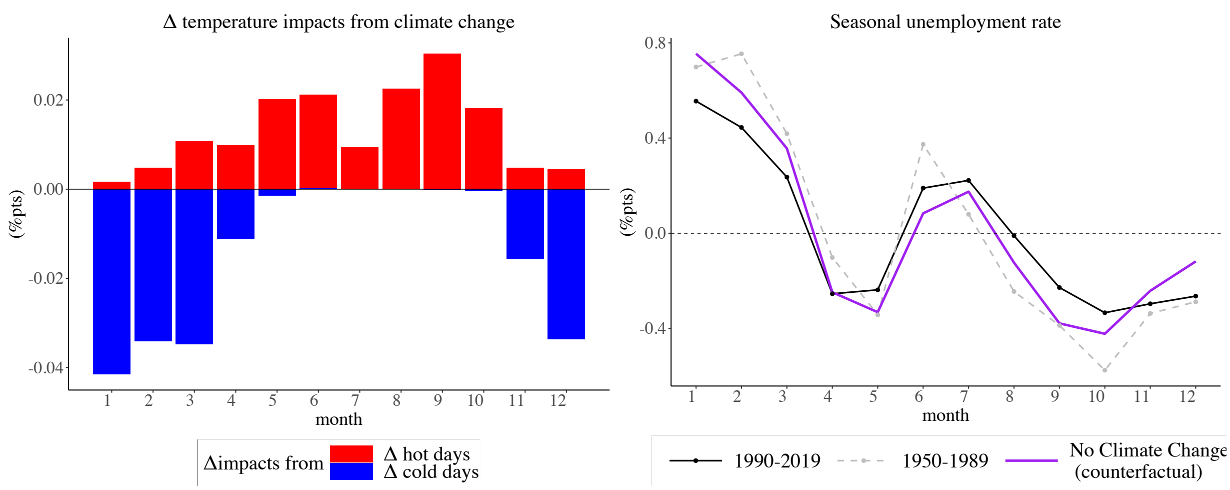
We assess how much contemporaneous temperature shocks account for unemployment seasonality in both unadjusted (NSA) and seasonal unemployment rate in 1990-2019. Panel (a) in Figure4a illustrates the impacts from temperature shocks using the semi-parametric bin model at Figure 4a.

Figure 4: Quantitative Assessment on Unemployment Seasonality

(a) Impacts from Temperature Shocks (1990–2019)



(b) Impacts from Climate Change (1950-1989 vs. 1990-2019)



Notes: Impacts from the level and change of hot days ($\geq$ 75°F) and cold days (< 45°F) are simulated, using bin estimates in Figure 4a. Seasonal unemployment rate is a difference of NSA (non-seasonally adjusted) and SA (seasonally adjusted) unemployment rate from the BLS.

If all days have normal temperature days (45-75°F), the NSA unemployment rate is lower by the range from 0.156 *pp* (2.8% in April) to 0.493 *pp* (8.2% in July). Comparison with this counterfactual scenario suggests that monthly extreme temperature explains 28% of unemployment seasonality (i.e., within-year variance of NSA unemployment rate). This suggests that the residual of 72% stems from the institutional calendar effect. Next, we assess how much *climate change* accounts for the documented moderation of monthly NSA unemployment fluctuation and unemployment seasonality. Panel (b) illustrates the average shifting climate impacts from the previous period (1950-1989) to the study period (1990-2019), using the estimates from the bin model. The left shows that while impacts from more hot days raise unemployment in all months, impacts from less cold days are limited in last November to May; the right shows counterfactual unemployment seasonality in addition to shrinkage of unemployment seasonality shown at Panel (a) in Figure 2. If temperature distribution stayed in the average of 1950-1989, the seasonality should have been more volatile. Using the model with a six-month treatment window, climate change accounted for about 40% of the decline in unemployment seasonality (i.e., the variance in the seasonal unemployment rate within a year) and about 13% of the moderation in the overall NSA unemployment fluctuations (i.e., the variance in the NSA unemployment rate).[15]

Policy Implication: Summer Programs Unemployment might induce serious mental health disasters, such as crimes (Raphael and Winter-Ebmer (2001)) and suicides (Milner et al. (2013)).[16] Given the forecast of accelerated warming, our findings create policy implications of job security, especially in the summer. Overall findings suggest that the forecast of unemployment may be interacted with weather forecasting technology with a long established history, and call for countermeasures of job security at federal or state level: UI extension, Continuation of Health Coverage (COBRA), and retraining program (e.g., Summer Youth Employment Program (SYEP)), targeted in the summer.

8 Concluding Remarks

Since the pre-industrial era, economic activity has been hampered by seasonality of Mother Nature, including drought, floods, hurricanes and the pandemic.[17] Using a newly created county-level panel data, this paper demonstrates the effect of temperature shocks on seasonal unemployment, most presumably via labor demand adjustment. Our paper provides one explanation for shrinking uncertainty of macro outcomes after 1980s, called Great Moderation. Imminent global warming in the next decades would expand the summer unemployment and may propagate the unemployment seasonality.

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[15] Our temperature analysis speak to the Great Moderation since 1980s, which has been often treated by ad hoc shrinkage of TFP shocks.

[16] This is consistent with prior work connecting extreme hot days and suicides (Burke et al., 2018) or violent crimes (Ranson, 2014).

[17] In ancient Egypt, the summer flooding of the Nile River created an abundance of unemployed workers. The kingdom provided pyramid construction as job security.

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APPENDICES FOR ONLINE PUBLICATION

Temperature Shocks and Unemployment Dynamics

Similan Rujiwattanapong and Masahiro Yoshida

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I Mass Layoff Statistics

Figure A-1 illustrates the composition and change of mass layoff events by reasons. Seasonal layoffs acyclically accounts for 20-30% of mass layoffs, which generates 50+ UI claims. The cases from a disaster/safety reason spiked in 2005 due to Hurricane Katrina.

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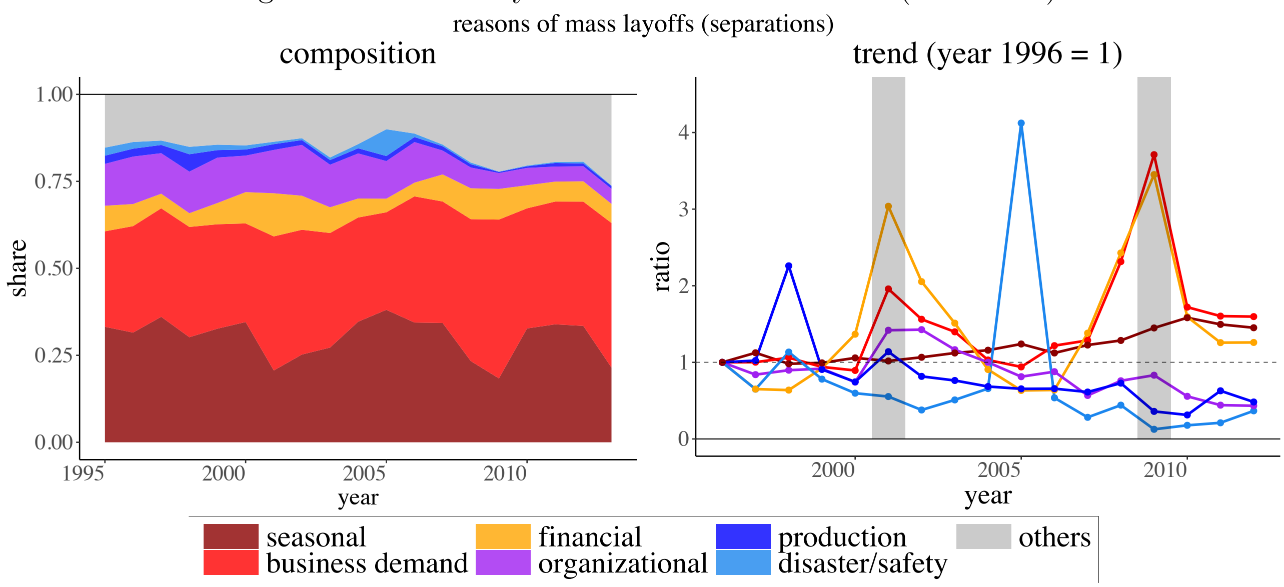
Figure A-1: Mass Layoff Events and its Reasons (1995-2013)

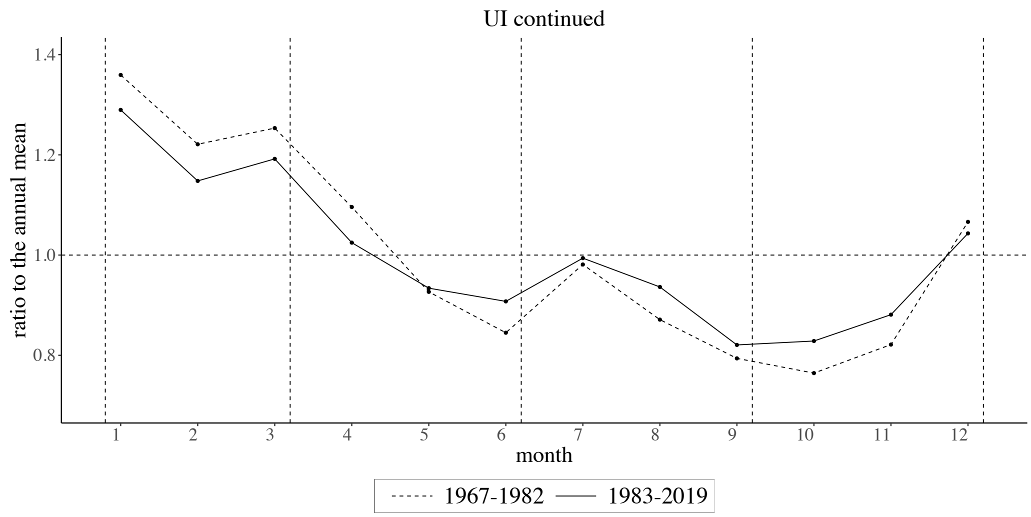


Notes: Computed from Mass Layoff Statistics from the BLS.

II Seasonality of UI recipients

Mirroring the unemployment seasonality, UI recipients also exhibit similar seasonality.

Figure A-2: UI recipients by months (1950-1982 vs. 1983-2019)



Notes: Department of Labor. Seasonality is computed as a ratio to the annual mean.

III Robustness checks

Temperature thresholds We consider a variety of temperature thresholds for hot days and cold days in the two-tailed baseline model.

Table A-1: Two-tailed Model

	dependent variable: **Unemployment Rate** (in % pts)					
	Thresholds for hot days					
		Baseline				
	73°F	75°F	77°F	80°F	85°F	90°F
	(1)	(2)	(3)	(4)	(5)	(6)
10 hot days	0.139***	0.195***	0.236***	0.256***	0.230***	0.179***
	(0.024)	(0.023)	(0.021)	(0.019)	(0.020)	(0.037)
10 cold days	0.296***	0.254***	0.216***	0.193***	0.246***	0.327***
(< 45°F)	(0.031)	(0.031)	(0.030)	(0.029)	(0.029)	(0.029)
Observations	1,111,045	1,111,045	1,111,045	1,111,045	1,111,045	1,111,045
Adjusted R^2	0.904	0.904	0.905	0.905	0.904	0.904
	Thresholds for cold days					
		Baseline				
	50 °F	45°F	40 °F	35°F	30°F	25°F
	(1)	(2)	(3)	(4)	(5)	(6)
10 hot days	0.208***	0.195***	0.217***	0.252***	0.282***	0.300***
(> 75°F)	(0.025)	(0.023)	(0.021)	(0.021)	(0.021)	(0.022)
10 cold days	0.240***	0.254***	0.238***	0.210***	0.187***	0.186***
	(0.029)	(0.031)	(0.031)	(0.032)	(0.034)	(0.039)
Observations	1,111,045	1,111,045	1,111,045	1,111,045	1,111,045	1,111,045
Adjusted R^2	0.904	0.904	0.904	0.904	0.904	0.904

Notes: Unit of analysis: by counties × years × months, 2001–2019

Treatment windows We consider a variety of treatment windows for hot days and cold days in the two-tailed baseline model.

Table A-2: Robustness by Treatment Windows

	dependent variable: Unemployment Rate (in % pts)					
	Baseline	2 months	3 months	4 months	5 months	6 months
	(1)	(2)	(3)	(4)	(5)	(6)
10 hot days	0.195***	0.275***	0.368***	0.452***	0.495***	0.488***
	(0.023)	(0.037)	(0.052)	(0.064)	(0.069)	(0.067)
10 cold days	0.254***	0.335***	0.353***	0.337***	0.320***	0.309***
	(0.031)	(0.041)	(0.049)	(0.055)	(0.058)	(0.057)
Observations	1,111,045	1,111,045	1,111,045	1,111,045	1,111,045	1,111,045
Adjusted R^2	0.904	0.906	0.907	0.907	0.906	0.905

Notes: Unit of analysis: by counties × years × months, 2001–2019

Fixed effects We consider a variety of fixed effects in the two-tailed baseline model.

Table A-3: Robustness by Fixed Effects

	dependent variable: Unemployment Rate (in % pts)					
	Baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
10 hot days	0.195***	0.135***	0.204***	0.131***	0.228***	0.208***
	(0.023)	(0.037)	(0.020)	(0.033)	(0.023)	(0.020)
10 cold days	0.254***	0.195***	0.221***	0.192***	0.244***	0.223***
	(0.031)	(0.051)	(0.026)	(0.049)	(0.030)	(0.025)
			Fixed effects			
county-year FE	Yes	Yes	Yes	-	-	-
county FE	-	-	-	Yes	Yes	Yes
year-month FE	Yes	Yes	-	-	Yes	-
state-year-month FE	-	Yes	-	Yes	-	-
state-year FE	-	-	-	-	-	Yes
state FE	-	-	Yes	-	-	-
month FE	-	-	Yes	-	-	Yes
Observations	1,111,045	1,111,045	1,111,045	1,111,045	1,111,045	1,111,045
Adjusted R^2	0.904	0.918	0.895	0.796	0.714	0.776

Notes: Unit of analysis: by counties × years × months, 2001–2019

Other climate proxies We use a meteorological formula of heat 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 heat 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

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

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. Heat Index$_d$ is a function of a temperature T_d and a daily relative humidity H_d such that Heat Index$_d = 0.81T + H_d(0.99T_d - 14.3) + 46.3$.

Table A-4: Other climate proxies

	dependent variable: **Unemployment Rate** (in % pts)			
	Baseline			
	(1)	(2)	(3)	(4)
10 hot days	0.195***		0.172***	0.177***
	(0.023)		(0.023)	(0.022)
10 uncomfortable days		0.244***		
		(0.020)		
10 cold days	0.254***	0.212***	0.180***	0.178***
	(0.031)	(0.029)	(0.032)	(0.029)
light rainy days	0.119***			
	(0.019)			
medium rainy days	0.144***			
	(0.028)			
heavy rainy days	0.125***			
	(0.037)			
light snow days	0.124***			
	(0.017)			
medium snow days	0.181***			
	(0.030)			
heavy snow days	0.266***			
	(0.047)			
no rainy days		−0.126***		
		(0.022)		
daily precipitation		0.020**		
		(0.010)		
no snowy days		−0.139***		
		(0.021)		
daily snowfall		0.0001***		
		(0.00002)		
humidity	0.004	0.003		
	(0.003)	(0.003)		
Observations	1,111,045	1,111,045	1,117,982	1,111,045
Adjusted R^2	0.904	0.905	0.905	0.905

Notes: Unit of analysis: by counties × years × months, 2001–2019