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Joshua Graff Zivin
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Joshua Graff Zivin
University of California, San Diego and NBER

Anthony Lepinteur
University of Luxembourg and IZA

Matthew Neidell
Columbia University, NBER and IZA

Adrian Nieto
Lund University and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

A Cold Stop: Temperature, Unemployment and Joblessness Dynamics*

We provide new evidence that short-run temperature shocks affect unemployment dynamics. Linking daily weather data with three decades of Current Population Survey microdata, we show that cold, but not hot, temperatures significantly increase unemployment risk. This effect is concentrated in climate-exposed industries and driven by both increased job separations and longer unemployment durations. Separations appear to be driven by a rise in layoffs rather than quits, while the increase in unemployment duration is largely explained by a decline in employer vacancy postings. Taken together, temperature-induced joblessness dynamics are primarily demand-driven, rather than a result of changes in worker behavior.

JEL Classification: J2, Q5, I1

Keywords: temperature, unemployment, joblessness dynamics, layoffs, quits, job absences, job search, vacancies

Corresponding author:
Adrian Nieto
Department of Economics
Lund University
P.O. Box 7080, 22007 Lund
Sweden

E-mail: adrian.nieto castro@nek.lu.se

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1 Introduction

Weather shocks pose a ubiquitous and salient source of economic risk with the potential to disrupt employment dynamics. Since labor markets are characterized by frictions - contracts are lumpy, matching takes time, and separations are costly - adverse weather can not only reduce hours worked and productivity (Garg et al., 2020; Graff Zivin and Neidell, 2014; LoPalo, 2023; Neidell et al., 2021; Somanathan et al., 2021), it can sever employment relationships entirely, increase unemployment duration or discourage job search and hiring. With expected changes in weather due to climate change, understanding the impacts of weather shocks can help economies prepare for and adapt to the ensuing labor market disruptions.

This paper investigates the impact of temperature on unemployment, the workforce dynamics driving this effect, and the underlying mechanisms. We develop a theoretical model of firm and worker decisions and labor market matching to characterize the margins where temperature may impact unemployment. For instance, temperature can influence unemployment through both firms and workers: cold weather may reduce labor demand by making certain activities temporarily infeasible, and may also alter workers' willingness to supply labor when outdoor conditions become unpleasant or unsafe. Using high-frequency weather data linked to three decades of monthly Current Population Survey microdata consisting of over 15 million observations, we estimate the effect of temperature exposure in the past three months on the probability that an individual is unemployed. Following the literature before us, we estimate models with multiple fixed effects to isolate causal impacts of temperature and control for temperature flexibly by using a binned approach. Informed by our theoretical model, we then analyze the effects of weather shocks on various measures of unemployment inflows and outflows, and bring additional data on time use and job postings to analyze the drivers of these workforce dynamics.

Our main finding is that cold, but not hot, temperatures significantly increase unemployment risk. This effect is concentrated among individuals in industries with high risk of climate exposure but is largely non-existent for those with low risk. Our estimates imply that a one standard deviation increase in the share of days below 5°C increases unemployment by approximately 2.7 percent, while the corresponding effect in high-risk industries is roughly 7.3 percent. These impacts are driven by both higher job separation rates (higher unemployment inflows) and slower transitions back to employment (lower unemployment outflows).

On the mechanisms driving the inflow side, we find that cold temperatures increase layoffs but not quits or the end of temporary contracts. Among employed workers, cold temperatures also lead to higher rates of weather-related work absences, consistent with heightened operational disruptions that may be early signals contributing to fragility in the employment relationship, with prior evidence linking absenteeism to the onset of job loss (Grønstad and Bernstrøm, 2025; Ichino and Maggi, 2000). Moreover, our results provide suggestive evidence of a moderating role of unions, perhaps driven by increased bargaining power and employment protection, as the effects are attenuated in areas with more unionized sectors.

We also explore mechanisms behind the decrease in unemployment outflow at the lower end of the temperature distribution by exploring job search effort and hiring activity to better understand demand and supply-side factors. Using the American Time Use Survey, we find that cold weather is not statistically significantly related to job search activities. Using the Job Openings and Labor Turnover Survey, we find, however, that cold temperatures lead to important reductions in employer vacancy postings. These findings imply that the lower unemployment outflows due to cold weather are likely demand-driven: firms reduce hiring activity in response to cold shocks.

Our finding that colder weather increases unemployment while hotter weather does not differs from prior studies that emphasize the negative effect of heat on worker productivity. We believe this contrast arises because much of the existing literature focuses on immediate and intensive-margin labor supply responses, such as daily reductions in hours worked or productivity, typically using same-day temperature exposure. Instead, we examine extensive-margin labor market responses to prolonged temperature exposure over longer periods of time. It is plausible that sustained exposure to cold leads to more severe and persistent employment disruptions than exposure to heat. In fact, the nature of weather-related disruptions differ substantially by weather. Many tasks face hard thresholds in cold weather below which they cannot proceed, such as concrete pouring, asphalt paving, and masonry work that become less feasible below 5°C due to freezing risks. In contrast, high temperatures are less likely to make tasks outright infeasible, at least at levels currently experienced in most of the world, but instead slow productivity. Cold weather also depresses product demand considerably more than heat in climate-exposed industries (Chan and Wichman, 2020, 2022; Kuruc et al., 2025), which may lead firms to scale back hiring or lay off workers. Thus, while heat may reduce productivity, extreme cold may impose both operational constraints and reductions in product demand, helping to explain the observed asymmetric effect on unemployment.

These asymmetric results suggest that the cold-weather burden on the labor market may decline under milder future winters expected under climate change. As a result, there may be a reduced need for labor market intervention, such as seasonal unemployment insurance, in milder winters. However, any full evaluation of climate change's net impact on the economy requires a broader accounting of impacts beyond the channel of unemployment. A large body of work documents that hot temperatures harm population health, impede child development, reduce mental well-being, increase mortality, lower labor productivity, slow long-run economic growth, and raise energy demand.[1] Thus, while our study points to the benefit of

[1]For examples, see Albanese et al. (2025); Aragón et al. (2021); Auffhammer et al. (2017); Barreca et al. (2015, 2016); Baylis (2020); Baylis et al. (2018); Belloc et al. (2025); Bilal and Känzig (2024); Burgess et al. (2014, 2017); Burke and Emerick (2016); Burke et al. (2018, 2015); Carleton and Hsiang (2016); Chen and Yang (2019); Dell et al. (2012, 2014); Deschênes (2014, 2022); Deschênes and Greenstone (2011); Deschênes and Moretti (2009); Evans et al. (2025); Garg et al. (2020, 2024); Graff Zivin and Neidell (2014); Graff Zivin and Shrader (2016); Guirguis et al. (2018); Heutel et al. (2021); Hsiang (2010); Jain et al. (2020); LoPalo (2023); Miller et al. (2021); Mullins and White (2019); Neidell et al. (2021); Noelke et al. (2016); Rode et al.

warming in a specific context, it should not be interpreted as a comprehensive assessment of the overall economic effects of climate change, but instead as providing evidence relevant to understanding the ways in which we might develop adaptation policies in response to warmer temperatures.

This paper also contributes to the broader labor economics literature that studies how shocks shape unemployment dynamics. Much of this literature has focused on policy-induced variation in unemployment insurance (Chodorow-Reich et al., 2019; Farber et al., 2015; Hagedorn et al., 2013; Johnston and Mas, 2018; Karahan et al., 2025), trade or tariff shocks (Furceri et al., 2018; Kim and Vogel, 2021; Yi et al., 2024), or large-scale layoffs. The latter have been studied either as macro shocks (Davis and Von Wachter, 2011), more localized shocks such as mass layoff at the firm-level (Flaaen et al., 2019) or military base closures (Dahlberg et al., 2024). Our work is most closely related to this last strand, which treats the termination of employment contracts as plausibly exogenous but is complicated by the fact that displaced workers simultaneously flood local labor markets. By contrast, our use of temperature as a shock provides a novel and clean source of exogenous variation: weather shocks are sharp, transitory, and arguably orthogonal to underlying labor market conditions, allowing us to isolate their causal impact on both inflows into and outflows from unemployment. In doing so, our study complements prior work that primarily examines worker search behavior or firm responses to changing outside options, by bringing new evidence on how exogenous environmental shocks disrupt labor market matching and alter the incidence and duration of unemployment. Our paper also contributes to the literature on the determinants of unemployment inflows and outflows (Elsby et al., 2019, 2010; Elsby and Michaels, 2013) by introducing weather shocks as a novel driver of these flows.

The remainder of the paper is organized as follows. Section 2 develops a theoretical framework for understanding the effect of temperature on unemployment. Section 3 describes the data sources. Section 4 outlines the empirical strategy. Section 5 presents the main

(2021); Severen et al. (2018); Somanathan et al. (2021); White (2017); Zhang et al. (2018).

results and robustness checks. Section 6 examines the underlying mechanisms. Section 7 concludes.

2 Theoretical Framework

We begin with a conceptual framework to characterize how temperature affects unemployment through its influence on firm decisions, worker behavior, and the efficiency of labor market matching. This framework informs our empirical approach by identifying the margins along which temperature-induced shocks can alter the risk of unemployment.

2.1 Firm Behavior

Firms produce output using labor, and choose employment levels to maximize profits. We assume competitive product and labor markets, so that firms take both the output price p and the wage w as given. Productivity is sensitive to temperature, which affects both worker performance and broader business operations. We denote the firm's static profit function as:

$$\pi(T) = p \cdot A(T) \cdot L - w \cdot L, \tag{1}$$

where L is labor employed, and $A(T)$ is total productivity per workers, which depends on temperature T. We define:

$$A(T) = g(A_W(T), A_B(T)), \tag{2}$$

where $A_W(T)$ captures the effect of temperature on worker-specific productivity (e.g., fatigue, absenteeism, injury risk), and $A_B(T)$ captures the effect of temperature on firm-level productivity beyond worker performance (e.g disruptions to firm operations, demand fluctuations, supply chain instability). We do not impose a functional form to $g(\cdot)$ but assumes that it increases with $A_W(T)$ and $A_B(T)$.

A job is destroyed when the marginal revenue product of labor falls below the wage:

$$p \cdot A(T) < w. \tag{3}$$

The job destruction rate $d(T)$ therefore increases in response to reductions in $A_W(T)$ or $A_B(T)$ induced by temperature changes.

Vacancy posting is similarly responsive to temperature. Let J_t denote the number of vacancies:

$$J_t = h(T), \tag{4}$$

where $h(\cdot)$ reflects the expected profitability of hiring. It may be non-monotonic, accommodating the possibility that extreme cold or heat discourages vacancy creation.

2.2 Worker Behavior and Reservation Wages

Workers derive utility from wages ω and disutility from working under adverse temperature conditions. Utility is given by:

$$V = V(\omega) - F(T), \tag{5}$$

where $V(\omega)$ is increasing and concave, and $F(T)$ captures thermal discomfort, health risks, or other costs of labor supply. We assume $F(T)$ is minimized at an interior optimum and increases on either side, such that $F''(T) > 0$. This allows both extreme heat and cold to reduce the attractiveness of work. Workers compare this to the utility of their outside option b (e.g., unemployment benefits, home production).

Acceptance occurs when:

$$V(\omega) - F(T) \geq b, \tag{6}$$

which implies a reservation wage:

$$\omega^*(T) = V^{-1}(b + F(T)). \tag{7}$$

The quit rate is similarly temperature-dependent:

$$q(T) = \Pr[\omega < \omega^*(T)]. \tag{8}$$

2.3 Matching Efficiency and Labor Market Flows

Employment transitions occur through a matching process that depends on vacancies, unemployment, and matching efficiency. We define the matching function as:

$$m(U_t, J_t, T) = \mu(T) \cdot f(U_t, J_t), \tag{9}$$

where U_t is unemployment, J_t is vacancies, $f(\cdot)$ is a standard Cobb-Douglas function, and $\mu(T)$ is a temperature-dependent efficiency term. Temperature may reduce $\mu(T)$ by impeding mobility, lowering search effort, or delaying hiring processes.

2.4 Law of Motion for Unemployment

Let $u(t)$ denote the unemployment rate and normalize the size of the labor force to one. The unemployment rate dynamics reflect the difference between inflows (job destruction and quits) and outflows (matches):

$$\dot{u}(t) = d(T) \cdot (1 - u_t) + q(T) \cdot (1 - u_t) - m(U_t, J_t, T). \tag{10}$$

Differentiating with respect to temperature yields:

$$\frac{d\dot{u}}{dT} = \underbrace{\left(\frac{\partial A_W(T)}{\partial T} \cdot \frac{\partial d(T)}{\partial A_W(T)} + \frac{\partial A_B(T)}{\partial T} \cdot \frac{\partial d(T)}{\partial A_B(T)}\right) \cdot (1-u_t)}_{\text{Job destruction}}$$
$$+ \underbrace{\left(\frac{\partial F(T)}{\partial T} \cdot \frac{\partial q(T)}{\partial F(T)}\right) \cdot (1-u_t)}_{\text{Quits}}$$
$$- \underbrace{\left[\frac{\partial \mu(T)}{\partial T} \cdot f(U_t, J_t) + \mu(T) \cdot \frac{\partial f(U_t, J_t)}{\partial J_t} \cdot \frac{\partial J_t}{\partial T}\right]}_{\text{Matching efficiency and vacancies}}.$$

As this equation shows, temperature affects labor market dynamics through its impact on the rate at which workers flow into and out of unemployment through three channels. Job destruction may rise when temperature depresses productivity. Quits may increase as temperature raises the disutility of work and the reservation wage. Temperature may also affect matching efficiency, with firms reducing vacancy postings and the unemployed having less incentives to engage in job search. These forces jointly contribute to higher steady-state unemployment and longer unemployment durations.

Note that we have so far implicitly assumed firms and workers to be homogeneous. However, our framework accommodates heterogeneity (e.g. some firms or workers may be more temperature-sensitive) by simply allowing all components in Equation (10) to vary across groups $g \in \{1, \ldots, G\}$.

The remainder of the paper provides an empirical test of the framework developed above. We begin by assessing whether temperature systematically affects unemployment in the aggregate, then examine heterogeneity across groups with different temperature-sensitiveness, and finally investigate the relative contribution of each modeled mechanisms to the observed responses.

3 Data Sources

3.1 Current Population Survey Data

The main source of labor market information used in this paper is the Current Population Survey (CPS), a monthly household survey conducted jointly by the U.S. Census Bureau and the Bureau of Labor Statistics. The CPS has been administered on a consistent monthly basis since 1948 and remains the primary instrument for producing official labor force statistics in the United States. We use data from 1994 to 2023.

Each month, the CPS collects data from approximately 60,000 eligible households, yielding information on roughly 100,000 individuals. The survey gathers detailed data on employment status, hours worked, occupation, industry, unemployment duration, and reason for job separation. In addition to labor force indicators, the CPS includes rich demographic characteristics such as age, gender, ethnicity, education, and household structure. The CPS also contains information on the county of residence of individuals when they are interviewed, which we use to merge the CPS dataset with our weather dataset on the history of temperature conditions at the county–day level.[2]

Among unemployed respondents, the CPS records the length of the unemployment spell (in weeks) and a categorical indicator for the reason for separation, such as layoff, voluntary quit, or the end of a temporary job. For employed individuals, the CPS tracks whether the respondent was absent from work during the reference week and, if so, the reason for the absence (e.g., illness, family obligations, or weather-related disruptions). These features make the CPS particularly well suited for studying not only the incidence of unemployment, but also the mechanisms underlying labor market transitions.

[2] For 48.47% of the sample, the data only identifies their Metropolitan Statistical Area (MSA) of residence, not their specific county. For these cases, we use the population distribution as a proxy for likely residence, assigning individuals to the most populous county within their MSA.

3.2 American Time Use Survey Data

To further investigate the mechanisms underlying the impact of temperature on unemployment, we use the American Time Use Survey (ATUS) data. The ATUS is administered by the U.S. Census Bureau on behalf of the Bureau of Labor Statistics, which conducts approximately 8,500 interviews annually. Respondents complete a 24-hour time diary referring to the day before the interview, which provides minute-level information on all activities undertaken during the diary day. Activities are classified into 4-digit categories, allowing us to observe in detail how individuals allocate their time. Importantly, this allows us to construct precise measures of time spent searching for a job - our outcome of interest for examining supply-side behaviors.

In addition to activity data, the ATUS contains detailed information on demographic characteristics and geographic identifiers, including the date of the interview and the respondent's county of residence. This enables us to merge the ATUS with National Oceanic and Atmospheric Administration weather data at the county-day level.

3.3 Job Openings and Labor Turnover Survey Data

We use the Job Openings and Labor Turnover Survey (JOLTS) dataset to provide additional evidence on the mechanisms behind the effect of temperature on unemployment. The JOLTS is a monthly survey conducted by the U.S. Bureau of Labor Statistics at the national level. The JOLTS collects data from approximately 21,000 nonagricultural business establishments across all 50 states and the District of Columbia, providing estimates of job openings, hires, and separations. While the JOLTS dataset only provides information at the state-by-month level - providing less granular data than our aforementioned county-level analyses - its rich information on employers and labor shortages makes it a valuable source to analyze demand-side factors contributing to the effect of temperature on unemployment.

3.4 Weather Data

To measure individuals' exposure to temperature, we use weather data from the National Oceanic and Atmospheric Administration (NOAA). NOAA compiles daily meteorological information from more than 9,000 weather stations across the United States, including maximum and minimum temperatures, average temperature, precipitation, and snowfall.

We link these data to each of the above to implement our analyses, aggregating the station-day-level observations at the finest geographic levels available in our other datasets (county–day for CPS and ATUS and state–month for JOLTS). Because the effect of temperature on unemployment may take some time to materialize, we construct weather exposure measures capturing the history of weather conditions over the months preceding each county–day (we provide a more detailed description of our main independent variables when describing our empirical strategy). Given the more than 3,000 counties in the United States, this results in a panel weather dataset containing more than 32 million county-day observations. The high spatial and temporal resolution of this dataset allows us to exploit granular variation in the exposure to temperature conditions.

4 Empirical Strategy

We estimate the following empirical model throughout the analysis:

$$U_{i,c,s,m,y} = \sum_{T=1}^{7} \beta_T Temp_{T,c,s,m,y} + \phi X_i + \delta_c + \delta_y + \delta_{s,m} + \varepsilon_{i,c,s,m,y} \tag{11}$$

where i stands for individual, c for county, s for state, m for the month and y for the year of the interview. $U_{i,c,s,m,y}$ is a binary variable taking a value of one if individual i is unemployed during month m of year y and zero otherwise.

Our independent variables of interest, $Temp_{T,c,s,m,y}$, comprise of continuous variables of the share of days with a maximum temperature falling in interval T over the last three months prior to month m of year t in county c. We measure temperature over the three months prior to the month of the survey interview to allow sufficient time for temperature conditions to affect unemployment. As detailed below, we also explore alternate windows of time before the survey interview (1 month and 6 months). To allow for nonlinear effects, we use seven temperature intervals T (in degrees Celsius): lower or equal to 5°C; 5-10°C; 10-15°C; 15-20°C; 25-30°C; higher or equal to 30°C, with 20-25°C as the reference category. Our main estimates of interest can be interpreted as the effect of an increase of one percentage point in the proportion of days with maximum temperatures within a temperature interval during the three months prior to the survey interview on unemployment relative to being exposed to temperatures within the benchmark temperature range (i.e., between 20 and 25 °C).

We include county fixed effects, δ_c, to absorb time-invariant cross-county differences in unemployment that may be correlated with temperature or economic conditions. Year fixed effects, δ_y, control for time-varying changes in our dependent and independent variables at the national level, such as macroeconomic cycles. Finally, $\delta_{s,m}$ denote state-by-month fixed effects, which allow us to flexibly account for seasonality that may differ systematically across states, for instance, capturing the fact that January in Minnesota differs from January in Florida. Together, this set of fixed effects enables us to identify the relationship between temperature and unemployment from within-county, within-year, and within-season-state fluctuations in weather. Individual covariates are denoted by X_i, which includes pre-determined characteristics of the individual (gender, a quadratic function of the individual's age and a dummy for respondents identifying as 'white').[3] Standard errors are clustered at the county level to account for the grouped nature of temperature exposure and serial correlation in temperature over time.

We estimate Equation 11 using an estimation sample pooling the aforementioned CPS

[3]Race categories in the CPS have changed over time, making it difficult to construct a consistent set of detailed categories across our sample period. To maintain comparability over time, we define race as a binary indicator for respondents identifying as 'white' versus 'non-white.'

monthly microdata from 1994 to 2023. We restrict the sample to individuals under the age of 65 and exclude respondents with missing information on labor force status, age or gender. We also exclude individuals for whom we cannot observe the temperature to which they have been exposed (i.e. for whom there is no information available on their county or Metropolitan Statistical Area of residence). Applying these criteria yields a final sample of 15,227,914 individual-month observations.

Estimating Equation 11 with this final sample yields estimates of the average impact of temperature across all workers. But differences in climate exposure across workers may mask important heterogeneity in impacts. To explore this, we use the classification scheme in Graff Zivin and Neidell (2014) and assign each individual to high- or low-risk of temperature exposure based on their industry. Specifically, we label high-risk of exposure for workers in the agriculture, mining, construction, manufacturing, entertainment or transportation industries, and low-risk to the remainder; and estimate Equation 11 separately for each.[4] We also explore alternative definitions of risk using occupational classification developed by Park and Stainier (2021), with results described in Section 5.2. If extreme weather creates systemic disruptions to labor markets, such as road closures or power outages, we would expect all workers to be impacted by weather, irrespective of their sector or occupation. On the other hand, if the impacts are driven by conditions on the job, then workers in outdoor environments or facilities with limited climate control should experience greater effects from weather shocks than workers in climate-controlled environments, who may experience no impacts at all. As such, our heterogeneity analysis not only reveals how impacts are distributed across workers, but also clarifies the channels through which temperature affects labor outcomes.

Table 1 provides descriptive statistics of our main independent and dependent variables for our sample separately for all, low-risk and high-risk workers. The mean unemployment rate is 3.5 percent. The sample is 47.4 percent female, and the average respondent is 40.5

[4]One could argue that some industries, such as entertainment, may fall under either category. While our main definition of temperature-exposure groups assigns ambiguous industries to high-risk industries, we have estimated these models using alternative definitions of temperature-exposure group and find similar results.

years old. High-risk workers make up approximately 27 percent of the sample, have higher unemployment, are less female and slightly older. In terms of weather, on average, 11.7 percent of days during the three months preceding the CPS interviews fall below 5°C, and 9.4 percent fall between 5–10°C, while the warmest category - days exceeding 30°C - accounts for 16.8 percent.

5 Temperature and Unemployment

5.1 Main Results

We begin by estimating the effect of past temperature exposure on the likelihood of being unemployed at the time of the CPS interview for all workers and separately by exposure risk. The analysis leverages the merged CPS-NOAA dataset introduced in Section 4, and employs Equation 11 as the baseline specification. The left panel of Figure 1 plots the estimated coefficients associated with each temperature interval alongside their 95% confidence intervals.

In contrast to the typical U-shaped effects of temperature, the figure shows that recent exposure to cold weather leads to a statistically significant increase in the probability of unemployment, but heat has a smaller and statistically insignificant impact. To place these impacts in context, we first focus on the lowest temperature bin. The coefficient of 0.004 implies that a one standard deviation increase in the share of days with maximum temperatures below 5°C in the three months prior to the CPS interview (corresponding to a 20.9 percentage point rise) leads to a 0.094 percentage point increase in the probability of unemployment. While modest in absolute terms, this effect amounts to approximately a 2.7 percent increase relative to the sample mean unemployment probability of 3.5 percent. A one standard deviation rise in the share of days with maximum temperatures between 5°C and 10°C (an increase of 12.1 percentage points) is also associated with a 0.094 percentage point increase in unemployment probability. By contrast, the estimates for hot weather exposure are closer to zero and statistically insignificant, indicating that heat does not appear to influence contemporaneous unemployment risk. For example, a one–standard–deviation increase in the share of days with maximum temperatures above 30°C leads to a 0.038 percentage point increase in unemployment probability. The pattern in the left panel of Figure 1 thus points to an asymmetric relationship: cold temperatures elevate unemployment risk, while heat has no discernible impact.

Turning to the estimates by risk of temperature exposure in the remaining panels of Figure 1, we find, as expected, the effect of temperature on unemployment is substantially stronger for workers in high-risk exposure industries.[5] A day below 5°C has a four times larger impacts for high-risk workers compared to all. A one standard deviation increase in the share of days below 5°C raises the unemployment probability by 0.359 percentage points, or roughly 7.3 percent relative to a higher baseline unemployment rate of 4.9 percent. By contrast, the estimates for individuals in low-risk exposure industries are smaller in magnitude and generally statistically indistinguishable from zero. This pattern of results provides strong support for our earlier contention that impacts are driven by sector-specific reductions in labor demand and constraints on supply arising from direct exposure to ambient conditions, rather than systemic disruptions that affect employment across the board.[6]

Lastly, it is important to note that the asymmetric effect of cold compared to hot days on unemployment risk may be driven by differences in the duration of daily exposure to the maximum temperature. For example, a day with a maximum temperature of 30°C will

[5]Cold-related increases in unemployment within high-risk exposure industries are more pronounced among men and among workers with lower levels of education (see Appendix Figure A1). This pattern likely reflects differences in job tasks and exposure: higher-educated workers and women in these industries are more often in supervisory or administrative roles (Castañeda-Burciaga et al., 2025), while men and less-educated workers are more frequently engaged in outdoor or physically demanding activities where temperature shocks are most consequential.

[6]In Appendix Figure A2, we show the impacts of temperature on unemployment separately for tradeable and non-tradeable industries. The similarity in the estimates across sectors underscores the importance of supply-side disruptions (presumably driven by lower productivity or disrupted operations and supply chains under extreme cold), as weather-related changes in consumer demand would only manifest for non-tradeables.

include cooler hours in the morning and evening, implying that workers average experienced temperature throughout the workday is less extreme than what is implied by measures of maximum temperature. By contrast, maximum temperature of 0°C implies that the rest of the workday is, if anything, more extreme. Since maximum temperatures generally occur in the middle of the workday (as opposed to minimum temperatures which occur in the early hours of the morning), this also implies a much more limited scope for intraday adjustments to work schedules in order to limit exposure to extreme cold temperatures. This asymmetry in exposure intensity has been identified as a key factor in accounting for the persistent effects of cold, but not hot, temperatures on mortality (Deschênes and Moretti, 2009). Later in the paper, we provide extensive evidence of the mechanisms underlying the relationship between temperature and unemployment risk.

5.2 Sensitivity Analysis

This section assesses the robustness of our baseline estimates along several dimensions. All results are reported in Appendix Figures A3, A4 and A5. First, we examine the potential confounding for individual-level covariates by removing the set of demographic controls to Equation 11. The exclusion of these variables leaves the temperature coefficients virtually unchanged.

Second, we explore the possibility that our baseline estimates conflate the effect of recent temperatures with that of longer exposure, given serial correlation in local weather conditions. To address this concern, we augment Equation 11 by controlling for temperature exposure during the prior three-month window (months -6 to -3 relative to the CPS interview). Specifically, we include as controls the full vector of temperature bin shares from this earlier period, denoted $\sum_{T=1}^{7} Temp36_{T,c,s,m,y}$. The point estimates for all the baseline temperature bins remain essentially unchanged, providing reassurance that serial correlation in temperature is not driving our results. Note that the coefficients for the earlier-period temperature variables are small and almost always not different from zero. Hence, the impact of cold weather on unemployment is short-lived: once recent conditions are accounted for, we find no evidence of persistent or delayed effects from past temperatures.

Then, we assess the sensitivity of our results to the length of the temperature exposure window. While our baseline model considers temperature exposure over the three months preceding the survey interview, this choice is somewhat arbitrary. Appendix Figure A3 shows the estimated coefficients when we instead measure exposure over the single month prior to the survey interview. We focus on short-run temperature exposure because, as shown in the prior sensitivity test, earlier temperature conditions do not have an effect on unemployment. The point estimates using the one-month window are similar in direction, magnitude and statistical significance to the baseline results, suggesting that our findings are robust to variation in the definition of the exposure period.

We also assess whether the relationship between temperature and unemployment could be mediated by other weather conditions. Appendix Figure A3 reports specifications where we control for the share of days with rainfall during the previous three months and for the share of days with snowfall. While the inclusion of these variables leave most temperature coefficients unchanged, controlling for snowfall brings the coefficient of the coldest bin to zero. This finding is consistent with snow mediating part of the effect of cold temperatures. As snowfall is itself a function of temperature, however, it likely constitutes a 'bad control' (Angrist and Pischke, 2009), so we interpret this result with caution.

Lastly, our baseline model includes county, year, and state-by-month fixed effects. This set of controls is designed to absorb time-invariant spatial heterogeneity, temporal changes at the national level, and seasonal variation at the state level. We view this as a credible identification strategy for isolating plausibly exogenous variation in temperature, however, we test the sensitivity of our baseline estimates to using alternative combinations of fixed effects. Appendix Figure A3 presents the results of replicating Equation 11 under alternative fixed effect structures. Across these specifications, the core result - that recent cold exposure increases unemployment risk - holds consistently.

When using less demanding fixed effects than in our baseline model, the coefficients for the highest two temperature bins increase in magnitude and become statistically significant, suggesting that heat may also impact unemployment. Since the hot temperature bins' significance disappears and magnitude decreases with more stringent fixed effects, we view the impacts of heat on unemployment with caution. Regardless, the coefficients for heat are considerably smaller than for cold, supporting the general finding that cold impacts unemployment.

As argued in Park and Stainier (2021), categorizing exposed workers solely on industry classifications may mischaracterize heterogeneity in workplace temperature risks. We complement our industry-based analysis with an occupational classification developed by those authors, which ranks occupations based on average access to air conditioning. Although they only focus on air conditioning exposure, we interpret this as a proxy for exposure to climate-controlled environments more generally. Applying this classification to our data results in a loss of approximately one-third of observations due to incomplete matching between the occupation codes in Park and Stainier (2021) and those available in the CPS. We re-estimate Equation 11 separately for workers in the bottom quartile of AC access and for those in the top three quartiles. The coefficients associated with the temperature bins from these regressions are reported in Appendix Table A1. As expected, we find that the effects of cold temperatures on unemployment are substantially larger among occupations with limited access to climate control. This pattern reinforces the view that physical exposure to ambient conditions is a key determinant of weather-induced labor market vulnerability.

6 Mechanisms

Given that the unemployment effects of temperature are concentrated among individuals with high exposure to ambient conditions (where the theorized mechanisms are most salient), the remainder of the analysis focuses on this subgroup.

6.1 Joblessness Dynamics

The theoretical framework outlined in Section 2 highlights that two non-mutually exclusive mechanisms can account for the observed increase in unemployment following exposure to cold temperatures. First, cold weather may raise job separations (voluntary or involuntary), increasing inflows into unemployment. Second, it may reduce the rate at which unemployed individuals exit unemployment - either by constraining job search or decreasing hiring - thereby prolonging unemployment spells and lowering outflows. In this subsection, we examine the relative contribution of these two channels to the overall effect of temperature on unemployment.

Disentangling unemployment inflow and outflow dynamics is inherently challenging, but the CPS provides a useful proxy in the form of self-reported unemployment duration. Given the results in Figure 1, which established that cold weather in the preceding three months is associated with a higher probability of unemployment but that additional lags in temperature do not, we leverage the reported unemployment durations to gain traction on mechanisms. Specifically, if exposure to cold over the past three months predicts a higher likelihood of unemployment spells exceeding three months, this can only reflect a reduction in unemployment outflows, since those individuals entered unemployment before the relevant temperature window. By contrast, an increase in the share of individuals unemployed for less than three months may reflect either increased inflows, reduced outflows or a combination of both. Thus, long spells provide a lower bound on the contribution of outflows, while short spells provide an upper bound on the contribution of inflows.

To explore this, we re-estimate Equation 11 separately for the probability of being unemployed for less than three months and for more than three months (relative to being employed). The corresponding estimates are plotted in Figure 2.

We begin with the right panel of the Figure, which shows a clear positive relationship between cold temperatures in the preceding three months and the likelihood of reporting an unemployment duration longer than three months. This pattern provides direct evidence that cold weather reduces unemployment outflows by extending the duration of joblessness.

The left panel shows that cold weather also predicts a higher likelihood of having become unemployed during the last three months. While this result is consistent with increased unemployment inflows, it cannot be interpreted as definitive evidence of that channel. Some of the individuals with recent job separations may have exited employment for reasons unrelated to weather, but remain unemployed longer due to cold conditions hindering job search or hiring.

The sum of the estimated effects in the left and right panels of Figure 2 equals the total temperature effect on unemployment reported in the right panel of Figure 1, allowing us to bound the relative contribution of inflows and outflows. The coefficient on long unemployment spells (right panel) provides a lower bound on the contribution of reduced outflows, since these individuals entered unemployment before the relevant temperature window. The coefficient on short spells (left panel) provides an upper bound on the contribution of inflows, as it may also include some slower re-employment among recent job losers. Taken together, this decomposition suggests that at least 72 percent of the total effect of the coldest temperature bin on unemployment arises from reduced outflows (0.0126 out of 0.0175), with at most 28 percent attributable to higher inflows into unemployment (0.0049 out of 0.0175).

6.2 On temperature and job separation

As discussed above, the fact that past cold temperatures predict recent unemployment is not, by itself, sufficient to establish a direct effect of temperature on job separations. To more credibly test this channel, we turn to self-reported reasons for unemployment, which are available in the CPS. Among the unemployed, respondents report whether they are jobless due to a layoff, voluntary quit, or the end of a temporary contract (three of the most common categories). We re-estimate Equation 11 and use as dependent variables each of these three reasons for job separation. Figure 3 displays the estimates by temperature for each reason.

The left panel shows that the likelihood of recent unemployment due to the expiration of a temporary contract is not statistically significantly related to past cold temperatures, suggesting this margin is unrelated to weather. The middle panel reveals no evidence that cold weather increases the likelihood of voluntary quits, ruling out voluntary inflows posited by the model. By contrast, the right panel shows a statistically significant increase in the probability of reporting a layoff as the reason for unemployment following recent exposure to cold weather. This pattern suggests that a rise in temperature-related recent unemployment inflows is driven by layoffs, not quits or the scheduled end of contracts.

Our theoretical model further predicts that cold-induced layoffs should reflect disruptions to worker productivity and/or firm operations. While the CPS does not include direct measures of these mechanisms, employed respondents are asked whether they were absent from work in the past week and, if so, why. We exploit this feature to construct proxies for temperature-sensitive labor supply and firm demand disruptions. Specifically, we use responses indicating absence due to illness or family obligations as a proxy for reductions in worker productivity, as the CPS does not include a direct measure of productivity, and responses indicating absence due to weather as a proxy for disruptions to production that are more likely to be firm-driven.

While the "weather" category could, in principle, reflect either supply or demand factors

- for instance, a worker choosing not to commute due to snow or a firm suspending operations - the wording of the CPS response option lends support to the latter interpretation. Among the listed reasons for absence, respondents can select "weather affected job," which frames the disruption as originating from the nature or availability of the job itself. This phrasing implies that the absence is more likely due to firm-side constraints, such as halted operations or unsafe working conditions, rather than a discretionary decision by the worker. As such, we interpret absences due to weather as the setting in which firm-side disruptions are most salient, even though some supply-side response cannot be ruled out.

Although not all absences lead to job separations, prior work suggests that absenteeism can act both as a precursor to job loss and as a consequence of deteriorating organizational conditions, such as downsizing (Grønstad and Bernstrøm, 2025; Ichino and Maggi, 2000). We therefore interpret temperature-induced absences as indicative of both exposure to operational risk and greater vulnerability in the employment relationship.

We then re-estimate Equation 11 within the sample of employed individuals, using each reason-specific absence indicator as the dependent variable. Because the absence question refers to the week prior to the interview, we construct temperature exposure based on the distribution of daily maximum temperatures over the preceding month, which is better suited to capture the salience and timing of potential disruptions.[7] The results from these regressions are presented in Figure 4. The left and middle panels show no systematic relationship between cold temperatures and absences due to illness or family responsibilities, suggesting that recent weather shocks do not impair worker productivity through these channels. In contrast, the right panel reveals a strong and statistically significant increase in the probability of being absent from work due to weather-related reasons following exposure to cold temperatures. Taken together, this evidence points to cold weather as a source of operational disruption for firms, with weather-induced absences acting as a potential precursor to

[7] Results using the three-month temperature window yield smaller but directionally consistent point estimates.

unemployment.

While our theoretical framework allows for both voluntary and involuntary job separations - potentially arising from either labor supply or labor demand factors - the set of results we have presented so far points toward the latter: the absence of a relationship between cold temperatures and job quits, combined with the significant estimates of the effect of cold temperatures on both layoffs and weather-related absences, suggests that the observed increase in unemployment appears primarily involuntary and driven by firm-side constraints.

To further probe this interpretation, we ask: what would happen if workers held greater bargaining power? If cold-induced separations are indeed involuntary and demand-driven, their incidence should be lower in labor markets with stronger employment protection. To test this, we stratify the analysis by industry-level union coverage. Specifically, we re-estimate the model from the left panel of Figure 3 - where the dependent variable is a dummy for reporting a layoff as the reason for unemployment - separately for industries with low and high unionization rates. Union coverage is measured at the industry-by-year level, and industries are classified as "high union coverage" if their coverage rate exceeds the top quartile of the distribution in a given year (and "low union coverage" otherwise).

Figure 5 plots the temperature estimates separately for each group. In the low-coverage group (left panel), we replicate the earlier result: cold temperatures significantly increase the probability of layoff. In contrast, no such pattern is observed in high union coverage industries (right panel), where the temperature coefficients are smaller and not statistically distinguishable from zero. While the coldest-bin estimates are not significantly different across groups, the pattern is suggestive of some moderating role for worker protections. Greater bargaining power may impose a floor on weather-induced separations, though even in unionized settings, some layoffs likely remain unavoidable when firms face binding operational disruptions during cold spells.

6.3 On temperature and longer unemployment spells

As with temperature-induced job separations, the observed reduction in unemployment exit - reflected in longer unemployment durations - may be driven by either labor supply or labor demand forces, or a combination of both. On the supply side, cold weather may increase the costs of job search, reducing the intensity with which unemployed workers pursue re-employment. On the demand side, firms may respond to adverse weather by decreasing hiring, leading to a contraction in vacancies and fewer available job matches.

Since the CPS does not measure these variables, we turn to two datasets that provide richer information on job search and labor market dynamics to assess the relative importance of supply- versus demand-side frictions: the American Time Use Survey (ATUS) and the Job Openings and Labor Turnover Survey (JOLTS) .

6.3.1 Temperature and job search intensity

We begin by investigating whether cold temperatures impact job search effort among the unemployed. To do so, we merge our NOAA temperature data with the ATUS dataset, which records detailed information on how individuals allocate their time on a given day (using a 4-digit level classification), including time spent looking for work and interviewing. We provided a detailed description of this dataset in Section 3.

We re-estimate our baseline model using indicators for whether individuals spent any time on job search as the dependent variable. The ATUS dataset provides detailed information on the county of residence of individuals, which allows us to exploit granular variation in the exposure to temperature conditions as we did in the CPS. Our estimation sample includes all unemployed respondents between 2004 and 2023, yielding a total sample size of 5,679 observations. Descriptive statistics are reported in Appendix Table A2. Half of our ATUS sample is female, and is on average about 40 years old. Moreover, 17.6% of unemployed individuals search for a job on the diary date.

Columns (1) to (2) of Table 2 report the estimated effects of temperature, using exposure windows of one and three months. Using a window of three months allows for better comparability with our estimates based on CPS data. Adopting a window of one month allows us to test whether the impact of temperature on job search effort might manifest more rapidly than the effect of temperature on unemployment duration. Across both specifications, we do not find a statistically significant relationship between temperature and the likelihood of engaging in job search. However, the direction of the point estimates indicate a decrease in search activity as temperature cools, and the magnitudes of the estimates are not trivial. Our estimates imply that a one standard deviation increase in exposure to cold weather predicts a reduction in job search probability of approximately 1.3 to 2.4 percentage points in the three-month window, and 0.7 to 2.0 percentage points in the one-month window. Relative to the baseline prevalence of job search in our sample (17.6 percent), these implied effects correspond to reductions of roughly 4 to 14 percent. While not statistically significant, the direction of these estimates suggest that cold-induced reductions in job search effort may contribute to the slowdown in unemployment outflows observed in colder periods.[8]

6.3.2 Temperature and job openings

We next turn to the role of labor demand in explaining the observed reduction in unemployment outflows during colder periods. If cold weather leads firms to decrease hiring or scale back recruitment efforts, we should observe a decline in job openings, thereby limiting the ability of unemployed individuals to re-enter the labor market, regardless of their search effort.

To test this hypothesis, we merge our NOAA temperature data with the JOLTS dataset.

[8] We also examine time spent on job interviewing as a secondary outcome. While potentially informative, interviewing is an equilibrium outcome shaped by both supply and demand forces, which complicates interpretation. As with job search, we find no statistically significant effect of cold temperatures on the likelihood of interviewing. However, the point estimates are consistently negative and of similar magnitude, suggesting that cold-related slowdowns in labor demand may extend to the later stages of the job matching process. Results are available upon request.

As explained in Section 3, the JOLTS dataset provides detailed information on the number of job openings, hires, and separations. While the JOLTS only provides this information at the state-by-month level - limiting the granularity of the analysis and reducing statistical power - it remains a valuable data source for directly assessing the responsiveness of labor demand to temperature variation. We have information on the number of job openings in each state and month between 2000 and 2023 and use a sample of a total of 13,517 observations to conduct our empirical analysis. Descriptive statistics are reported in Appendix Table A2.

We estimate Equation 11 using the logarithm of the number of job openings in each state and month as the dependent variable to reduce the influence of outliers. Temperature exposure is defined over the past one and three months, in the same way as we did in our analysis based on individual-level ATUS data. The last two columns of Table 2 report the results. In both specifications, we find that colder conditions lead to significant declines in job postings: a one standard deviation increase in exposure to cold weather predicts a 1 to 2 percent reduction in job openings.[9] In line with the evidence linking cold weather to increased layoffs and weather-related work absences, these findings point to the demand side of the labor market as a key driver of the slowdown in unemployment exit during colder periods.

7 Conclusion

This paper provides novel evidence of the relationship between temperature exposure and unemployment risk in the United States. Using individual-level data from the CPS merged with high-resolution weather data, we find that colder-than-usual conditions in the months preceding the survey interview increase the probability of individuals reporting being unemployed. The impact is economically meaningful and concentrated among workers in industries

[9]Some of the results suggest that hot temperatures also reduce job postings, which is consistent with the results of some of the specifications of our sensitivity analysis suggesting that heat may increase unemployment risk.

highly exposed to ambient conditions.

Our evidence reveals that cold temperatures increase unemployment inflows and slows down transitions back to employment. On the unemployment inflow side, cold exposure increases the likelihood of layoffs, but has no discernible effect on quits or the expiration of temporary contracts, suggesting that involuntary separations are the key margin of adjustment. The rise in layoffs is mirrored by an increase in weather-related absences from work, a common precursor to job loss. Our results also provide suggestive evidence that the incidence of cold-induced layoffs is muted in more unionized sectors, consistent with the idea that greater worker bargaining power offers a buffer against weather-driven separations.

We turn to two additional datasets providing rich information on time use and labor market dynamics to explore the mechanisms driving the reduced unemployment outflow due to cold temperatures. Using American Time Use Survey data, we show that that while job search effort could be a contributing factor of the reduced unemployment outflows, it is unlikely to be the dominant mechanism. Using data from the Job Openings and Labor Turnover Survey, we show that cold weather considerably depresses the number of job openings, pointing to labor demand as the binding constraint. Taken together, our results suggest that cold weather reduces employment primarily through demand-driven, involuntary separations and hiring slowdowns — rather than changes in worker behavior.

More broadly, our findings shed light on an unexplored dimension of labor market vulnerability: short-run cold weather shocks increase unemployment. By showing the frictional channels driving this impact - colder-than-usual conditions disrupt hiring and increase involuntary separations - this paper also highlights the role of weather variability in shaping labor market flows. Our paper underscores the importance of incorporating transitory climatic shocks into models of unemployment dynamics, and provides evidence of the importance of accounting for climatic conditions in the design of optimal labor market policies. Since climate change will lessen the frequency of cold temperatures in the future, this may reduce unemployment rates in weather-exposed industries, and require adjustments in terms of employment protection legislation and optimal unemployment insurance. Whether this translates into tangible welfare gains, however, depends on a range of general equilibrium macro-level adjustments whose investigation is beyond the scope of this paper.

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Tables and Figures

Table 1: Descriptive Statistics

	Full sample N=15,227,914		Low-risk exposure N=11,046,123		High-risk exposure N=4,181,791	
	Mean	SD	Mean	SD	Mean	SD
Unemployment outcomes:						
Unemployed	0.035	0.184	0.030	0.171	0.049	0.215
Unemployed for less than three months	0.020	0.141	0.017	0.130	0.028	0.166
Unemployed for less than three months - Reasons:						
Layoff	0.013	0.115	0.011	0.104	0.020	0.141
Quit	0.004	0.060	0.004	0.061	0.003	0.054
End of temporary contract	0.003	0.057	0.004	0.051	0.005	0.070
Unemployed for three months or more	0.015	0.121	0.013	0.113	0.020	0.141
Reasons for not working last week:						
Illness†	0.007	0.084	0.007	0.081	0.009	0.092
Family responsibilities†	0.002	0.045	0.002	0.045	0.002	0.044
Weather affected job†	0.001	0.027	0.000	0.017	0.002	0.044
Sociodemographic characteristics:						
Female	0.474	0.499	0.555	0.497	0.259	0.438
Age	40.46	12.39	40.22	12.46	41.09	11.95
White	0.813	0.390	0.803	0.398	0.841	0.366
Maximum temperature (share of days):						
$\leq$ 5°C	0.117	0.209	0.117	0.208	0.118	0.211
5-10°C	0.094	0.121	0.094	0.121	0.093	0.120
10-15°C	0.116	0.115	0.116	0.115	0.116	0.116
15-20°C	0.139	0.121	0.139	0.121	0.140	0.121
20-25°C	0.161	0.128	0.161	0.128	0.163	0.129
25-30°C	0.204	0.199	0.205	0.200	0.202	0.194
$\geq$ 30°C	0.168	0.253	0.168	0.253	0.168	0.253

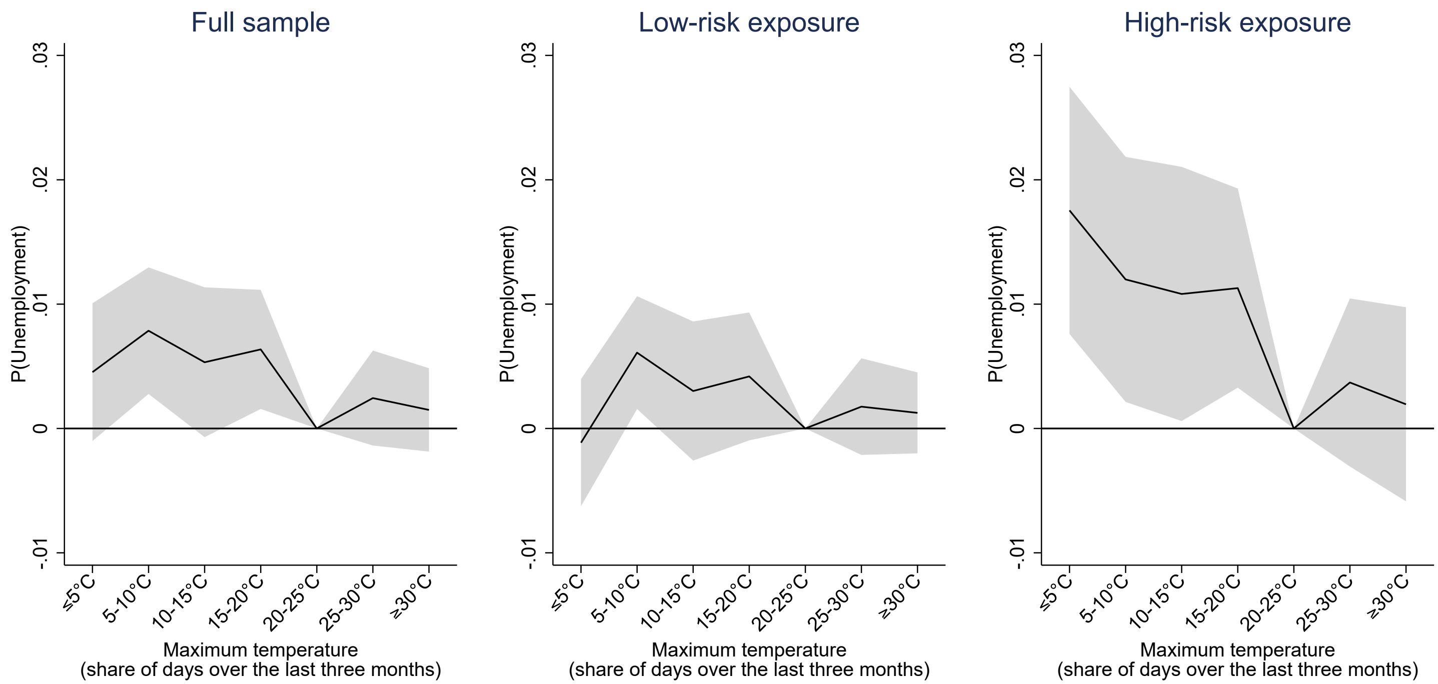
Notes: These statistics refer to the 1994–2023 CPS respondents included in the estimation samples used throughout the analysis. Statistics for the variables marked with † are calculated on the subsample of CPS jobholders. The number of counties for which there is weather information is 508.

Table 2: Temperature and mechanisms of unemployment outflows

	ATUS		JOLTS	
	Job search activities		Job openings	
	(1)	(2)	(3)	(4)
Maximum temperature (share of days):				
$\leq$ 5°C	-0.188	-0.068	-0.087	-0.046*
	(0.135)	(0.091)	(0.054)	(0.024)
5-10°C	-0.161	-0.138	-0.216***	-0.063**
	(0.161)	(0.088)	(0.070)	(0.027)
10-15°C	-0.152	-0.107	0.011	0.005
	(0.108)	(0.081)	(0.038)	(0.025)
15-20°C	-0.196*	0.041	-0.284***	-0.063**
	(0.115)	(0.067)	(0.066)	(0.028)
20-25°C	Ref.	Ref.	Ref.	Ref.
	.	.	.	.
25-30°C	0.010	0.014	-0.254**	-0.060*
	(0.105)	(0.061)	(0.096)	(0.030)
$\geq$ 30°C	0.005	0.008	-0.214**	-0.041*
	(0.095)	(0.060)	(0.085)	(0.021)
Observations	5,679	5,679	13,517	13,517
Temperature window (in months)	Three	One	Three	One

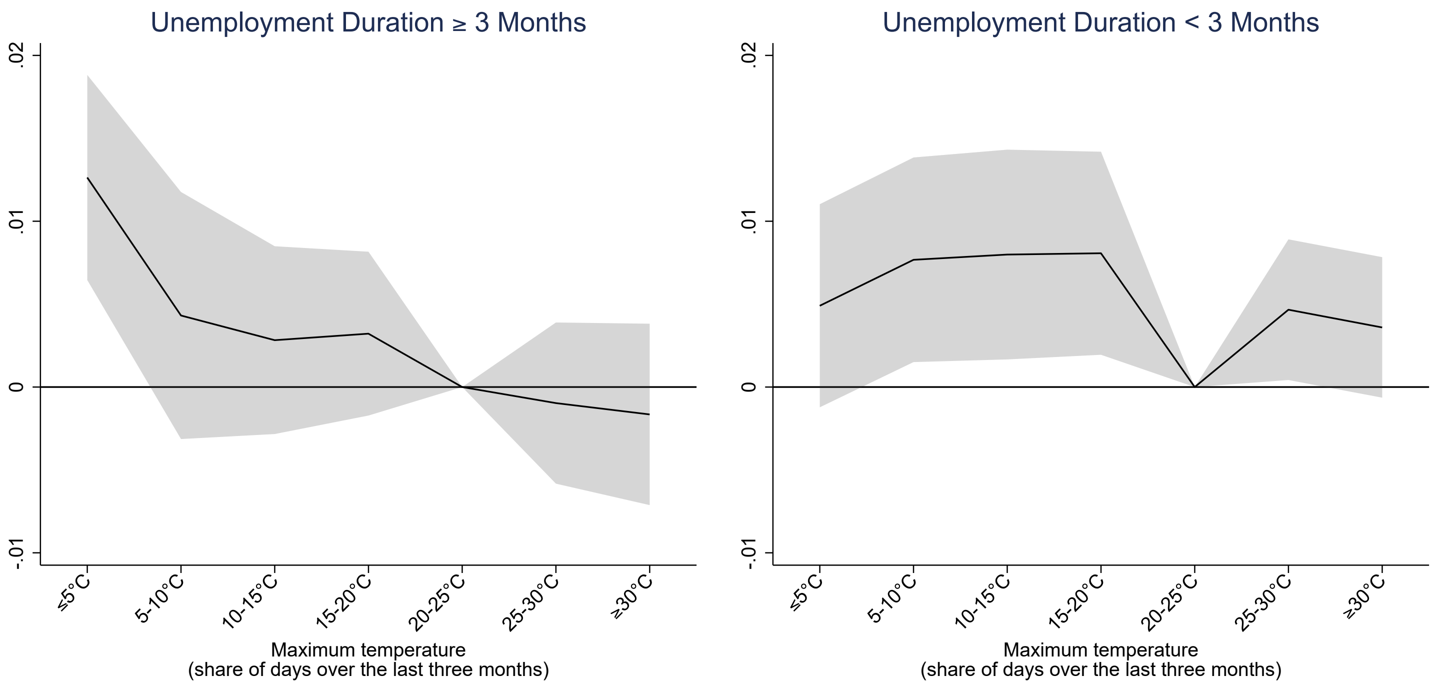
Notes: Columns (1) and (2) report estimates from linear probability models using the ATUS estimation sample restricted to respondents who report being unemployed. The dependent variable is a binary indicator equal to one if the respondent spent any time on the diary day in job search activities. Standard errors are clustered at the county level. ATUS regressions control for a female indicator, age and age squared, county fixed effects, year-of-interview fixed effects, and state-by-month-of-interview fixed effects. Columns (3) and (4) report estimates from OLS regressions based on the JOLTS firm-level sample, where the dependent variable is the logarithm of the number of job openings at the state-year-month level. Standard errors are clustered at the state level. JOLTS specifications include year-of-interview fixed effects and state-by-month-of-interview fixed effects. Statistical significance is denoted as follows: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Figure 1: Temperature and unemployment by risk of temperature exposure



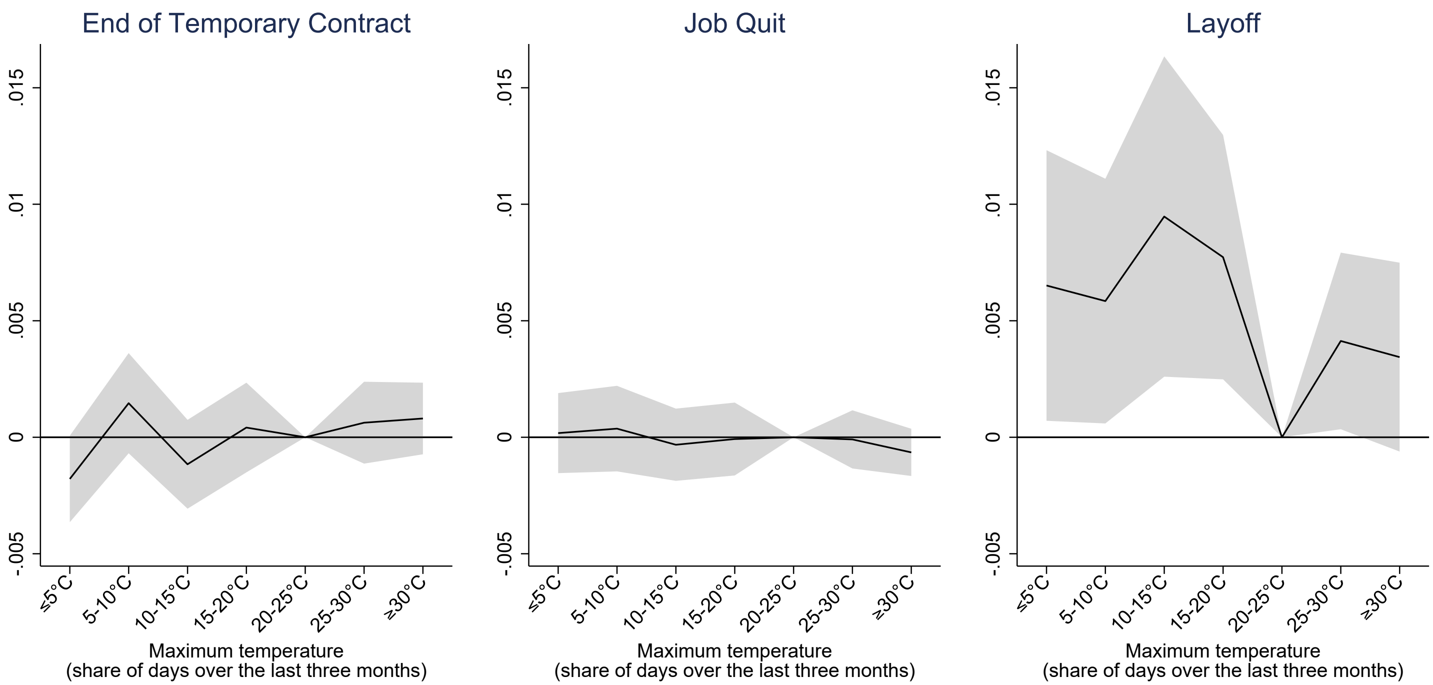
Notes: The figure plots the point estimates of the temperature intervals from the linear probability model described in Equation 11. The dependent variable is a dummy variable taking a value of one if the individual is unemployed at the time of the survey interview and zero otherwise. The estimation samples (from the the left to the right panel, respectively) include the 15,227,914, 11,046,123 and 4,181,791 CPS respondents described in Table 1. Controls include a female indicator, age and age squared, a dummy variable for CPS respondent identifying as ‘white’, county fixed effects, year-of-interview fixed effects, and state-by-month-of-interview fixed effects. Standard errors are clustered at the county level, and 95% confidence intervals are reported.

Figure 2: Temperature and unemployment by duration, high-risk sample



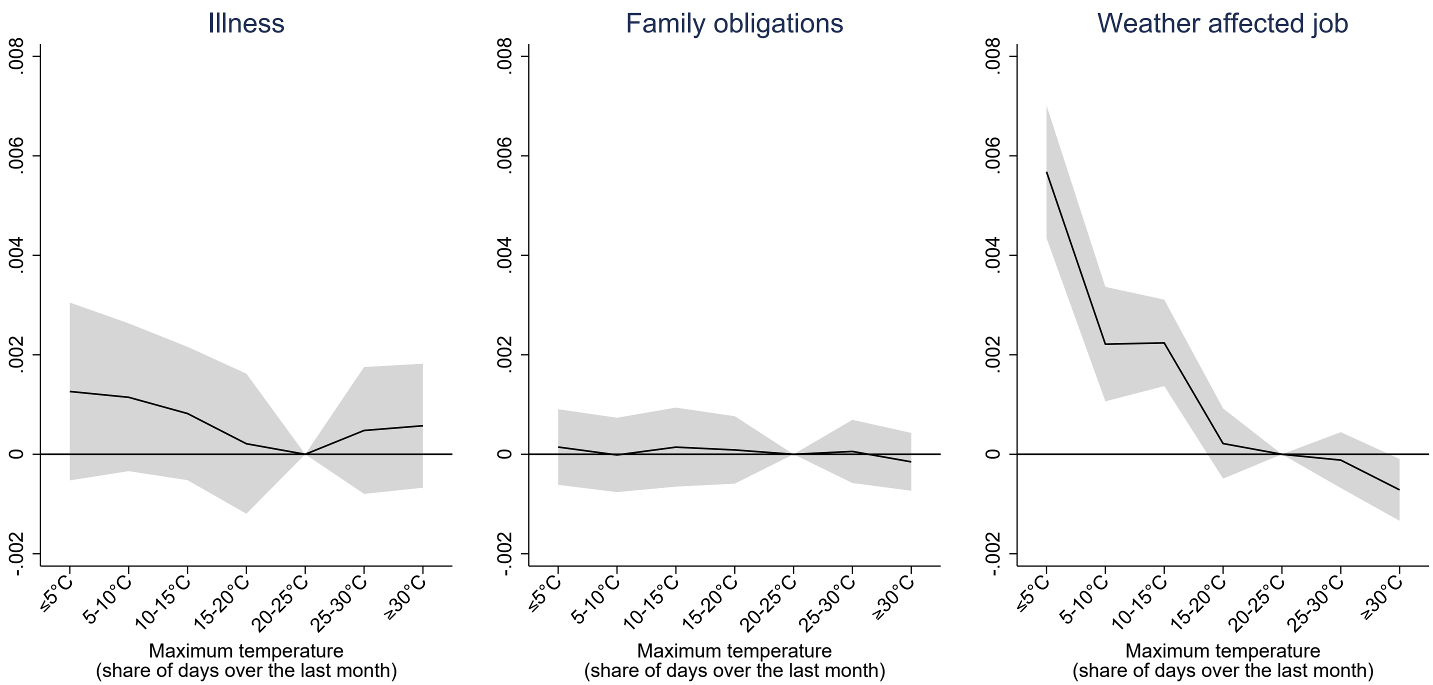
Notes: The figure plots the point estimates of the temperature intervals from the linear probability model described in Equation 11. The dependent variables used in the left and right panel of the figure are dummies taking a value of one if the individual has been unemployed for more and less than three months at the time of the survey interview, and zero otherwise. The estimation sample includes the 4,181,791 high-risk exposure CPS respondents described in Table 1. Controls include a female indicator, age and age squared, a dummy variable for CPS respondent identifying as 'white', county fixed effects, year-of-interview fixed effects, and state-by-month-of-interview fixed effects. Standard errors are clustered at the county level, and 95% confidence intervals are reported.

Figure 3: Temperature and unemployment by reason for unemployment, high-risk sample



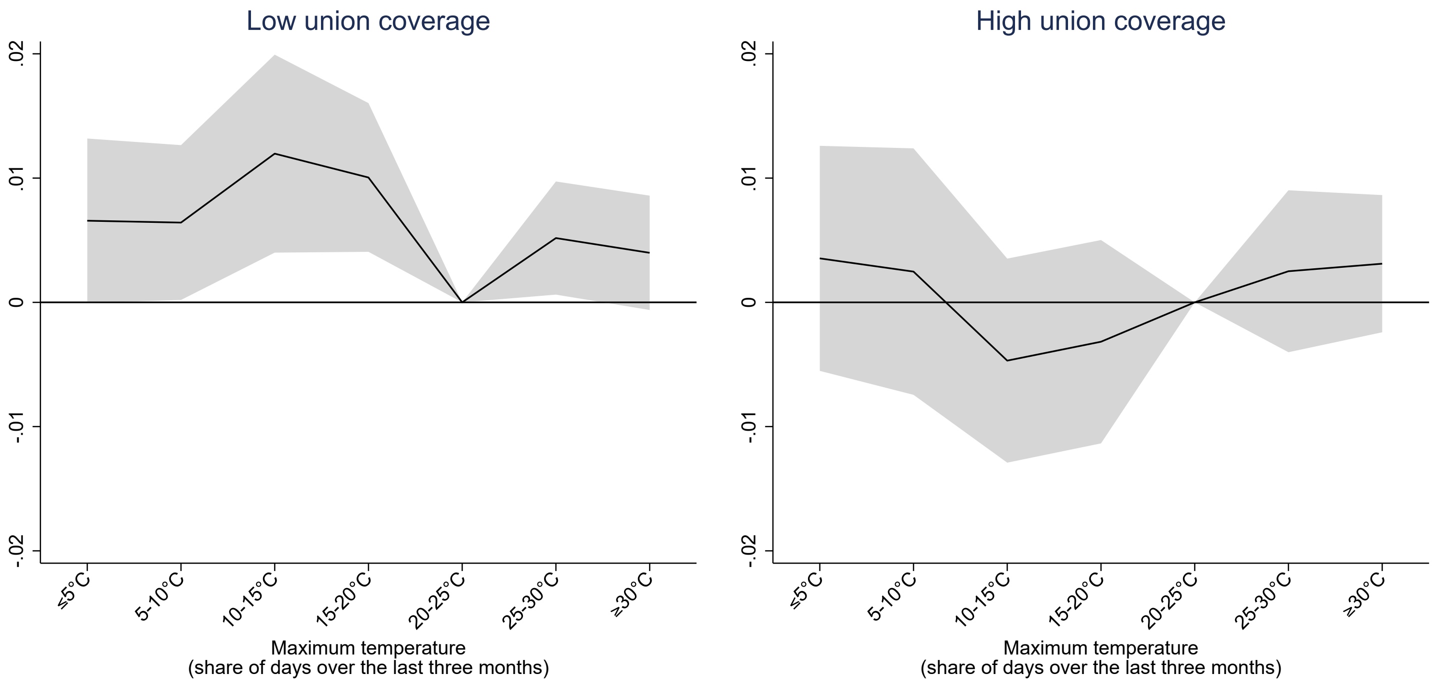
Notes: The figure plots the point estimates of the temperature intervals from the linear probability model described in Equation 11. The dependent variables used in the left, middle, and right panel of the figure are dummies taking a value of one if the individual is unemployed at the time of the survey interview due to (i) the end of their temporary contract, (ii) quitting, and (iii) due to a layoff, and zero otherwise, respectively. The estimation sample includes the 4,181,791 high-risk exposure CPS respondents described in Table 1. Controls include a female indicator, age and age squared, a dummy variable for CPS respondent identifying as 'white', county fixed effects, year-of-interview fixed effects, and state-by-month-of-interview fixed effects. Standard errors are clustered at the county level, and 95% confidence intervals are reported.

Figure 4: Temperature and absences from work, high-risk sample



Notes: The figure plots the point estimates of the temperature intervals from the linear probability model described in Equation 11. The dependent variables used in the left, middle, and right panel of the figure are dummies taking a value of one if the individual has been absent from work in the week preceding the survey interview due to (i) illness, (ii) family responsibilities, and (iii) weather disruptions, and zero otherwise, respectively. The estimation sample includes only the CPS respondents with a job among the 4,181,791 high-risk exposure CPS respondents described in Table 1. Controls include a female indicator, age and age squared, a dummy variable for CPS respondent identifying as 'white', county fixed effects, year-of-interview fixed effects, and state-by-month-of-interview fixed effects. Standard errors are clustered at the county level, and 95% confidence intervals are reported.

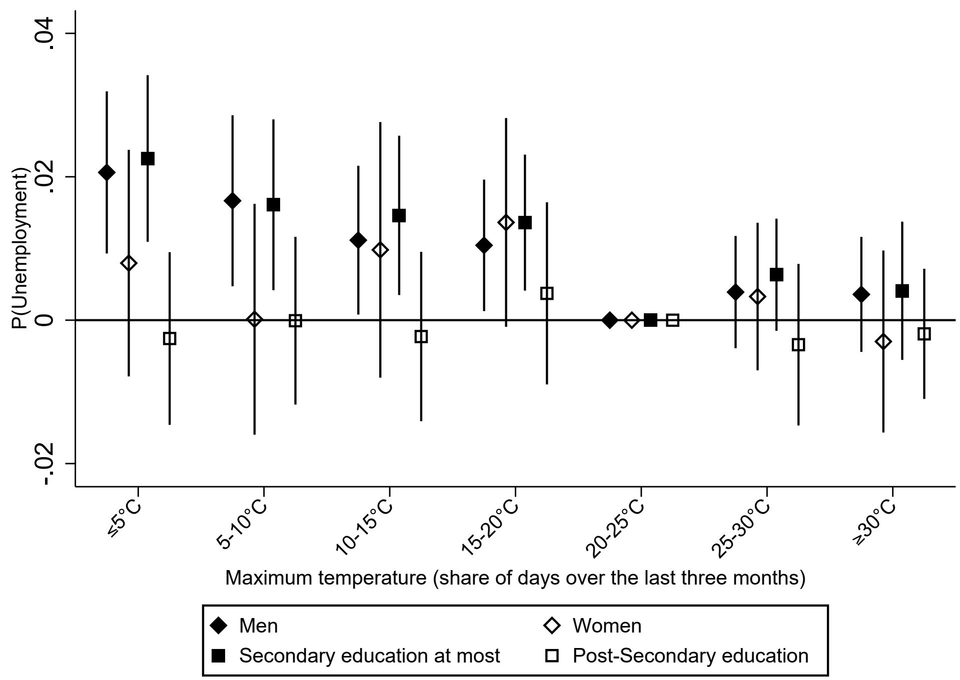
Figure 5: Temperature and unemployment by union coverage, high-risk sample



Notes: The figure plots the point estimates of the temperature intervals from the linear probability model described in Equation 11. The dependent variable is a dummy variable taking a value of one if the individual has been laid off at the time of the survey interview and zero otherwise. The estimation sample includes the 4,181,791 high-risk exposure CPS respondents described in Table 1. We estimate our model separately for individuals working in industries with an union coverage rate above and below the top quartile of the distribution in a given year, respectively. Controls include a female indicator, age and age squared, a dummy variable for CPS respondent identifying as 'white', county fixed effects, year-of-interview fixed effects, and state-by-month-of-interview fixed effects. Standard errors are clustered at the county level, and 95% confidence intervals are reported.

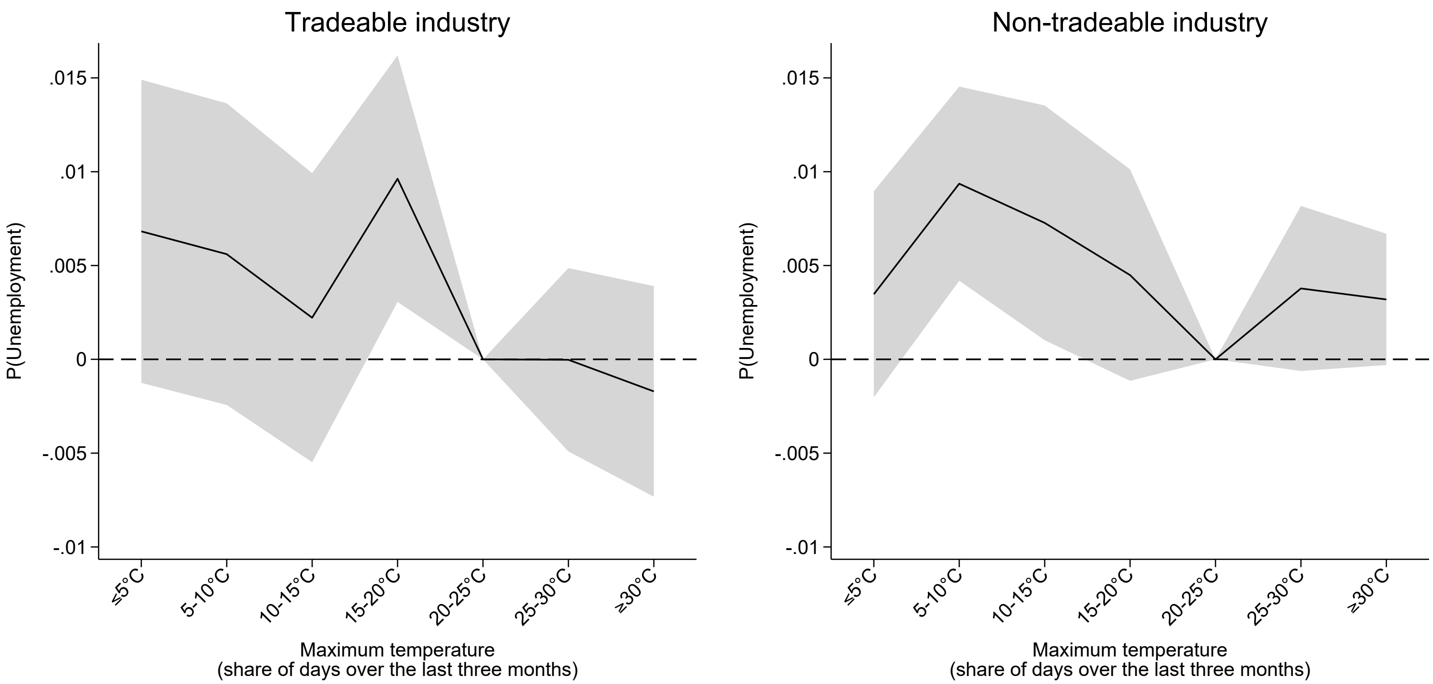
Online Appendix

Figure A1: Temperature and unemployment by groups of workers - High-risk sample



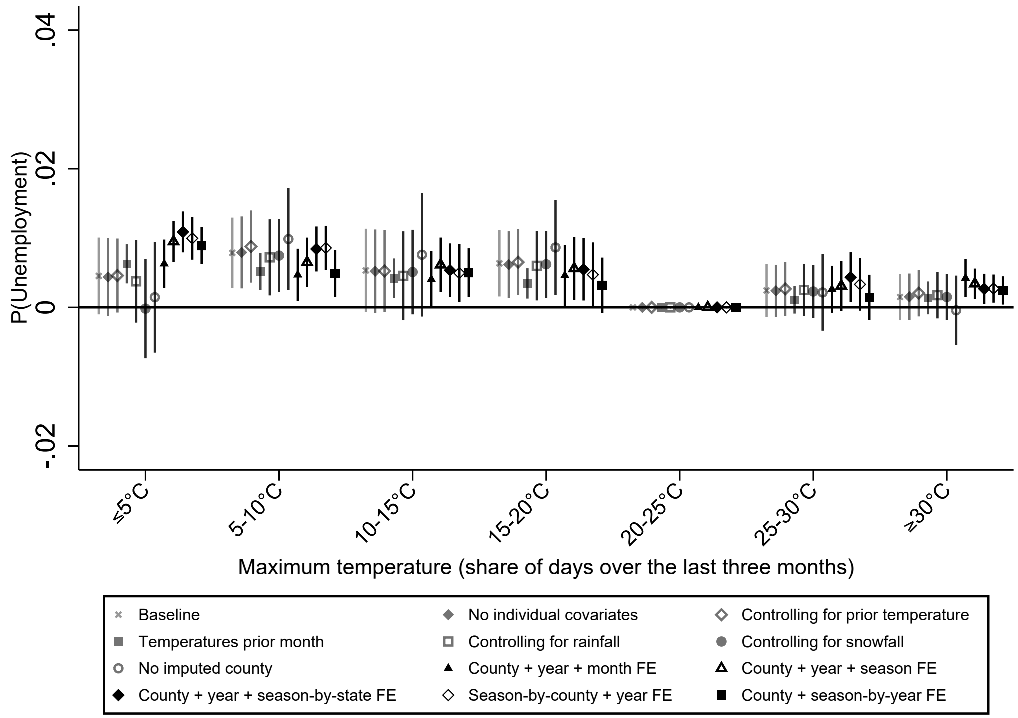
Notes: The figure plots the point estimates of the temperature intervals from the linear probability model described in Equation 11. The dependent variable is a dummy variable taking a value of one if the individual is unemployed at the time of the survey interview and zero otherwise. The estimation sample includes the 4,181,791 high-risk exposure CPS respondents described in Table 1. Controls include a female indicator, age and age squared, a dummy variable for CPS respondent identifying as 'white', county fixed effects, year-of-interview fixed effects, and state-by-month-of-interview fixed effects. Standard errors are clustered at the county level, and 95% confidence intervals are reported.

Figure A2: Temperature and unemployment by industry tradeability



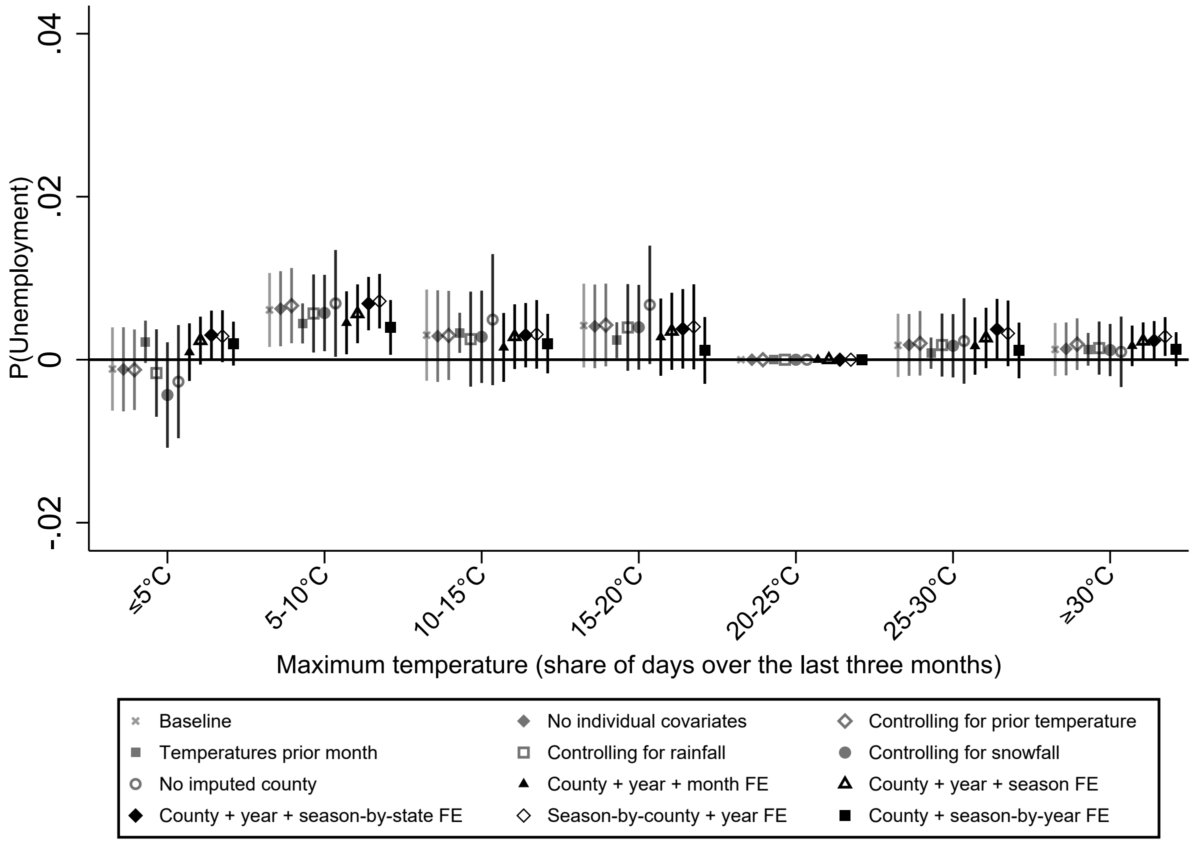
Notes: The figure plots the point estimates of the temperature intervals from the linear probability model described in Equation 11. The dependent variable is a dummy variable taking a value of one if the individual is unemployed at the time of the survey interview and zero otherwise. The estimation samples (from the the left to the right panel, respectively) include the 5,579,310 and 9,648,604 CPS respondents in tradeable and non-tradeable industries. Controls include a female indicator, age and age squared, a dummy variable for CPS respondent identifying as 'white', county fixed effects, year-of-interview fixed effects, and state-by-month-of-interview fixed effects. Standard errors are clustered at the county level, and 95% confidence intervals are reported.

Figure A3: Temperature and unemployment: Robustness checks - Full sample



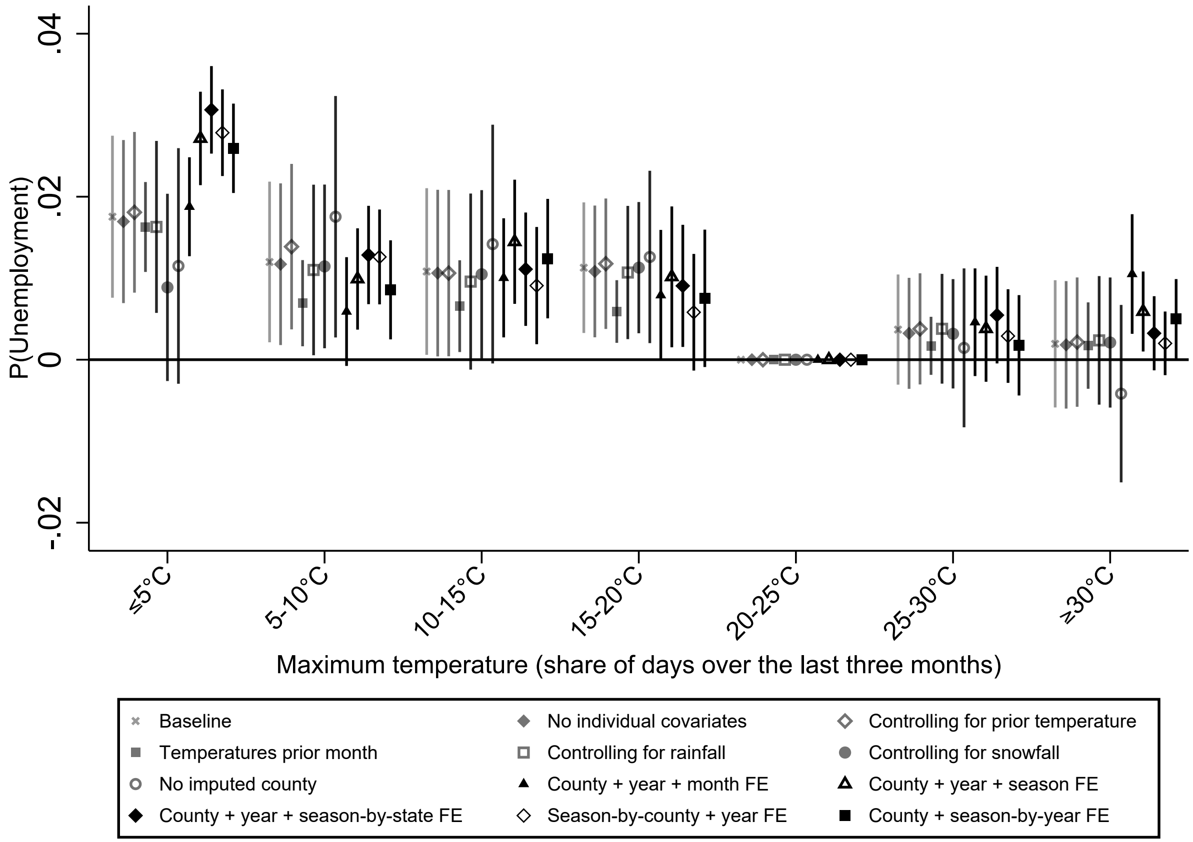
Notes: The figure plots the point estimates of the baseline temperature intervals using different specifications described in detail in Section 5.2. The dependent variable is a dummy variable taking a value of one if the individual is unemployed at the time of the survey interview and zero otherwise. The estimation sample includes the 15,227,914 CPS respondents described in Table 1. Standard errors are clustered at the county level, and 95% confidence intervals are reported.

Figure A4: Temperature and unemployment: Robustness checks - Low-risk sample



Notes: The figure plots the point estimates of the baseline temperature intervals using different specifications described in detail in Section 5.2. The dependent variable is a dummy variable taking a value of one if the individual is unemployed at the time of the survey interview and zero otherwise. The estimation sample includes the 11,046,123 low-risk exposure CPS respondents described in Table 1. Standard errors are clustered at the county level, and 95% confidence intervals are reported.

Figure A5: Temperature and unemployment: Robustness checks - High-risk sample



Notes: The figure plots the point estimates of the baseline temperature intervals using different specifications described in detail in Section 5.2. The dependent variable is a dummy variable taking a value of one if the individual is unemployed at the time of the survey interview and zero otherwise. The estimation sample includes the 4,181,791 high-risk exposure CPS respondents described in Table 1. Standard errors are clustered at the county level, and 95% confidence intervals are reported.

Table A1: Temperature and unemployment using alternative risk classifications

	P(Unemployment)		
	AC-exposure by occupation Park and Stainier (2021)		
	Full sample	Low exposure	High exposure
	(1)	(2)	(3)
Maximum temperature (share of days):			
$\leq$ 5°C	0.006*	-0.000	0.024***
	(0.004)	(0.003)	(0.007)
5-10°C	0.010***	0.008***	0.016**
	(0.003)	(0.003)	(0.007)
10-15°C	0.009**	0.007*	0.013**
	(0.004)	(0.004)	(0.006)
15-20°C	0.009**	0.005	0.020***
	(0.003)	(0.003)	(0.006)
20-25°C	Ref.	Ref.	Ref.
	.	.	.
25-30°C	0.002	0.000	0.007
	(0.003)	(0.003)	(0.005)
$\geq$ 30°C	0.002	0.001	0.006
	(0.002)	(0.002)	(0.005)
Observations	9,698,650	7,255,508	2,443,142
Adjusted R^2	0.011	0.008	0.018

Notes: The table presents the point estimates of the temperature intervals independent variables from the linear probability model described in Equation 11. The dependent variable is a dummy taking a value of one if the individual is unemployed at the time of the survey interview and zero otherwise. Controls include a female indicator, age and age squared, a dummy for CPS respondent identifying as 'white', county fixed effects, year-of-interview fixed effects, and state-by-month-of-interview fixed effects. The estimation sample of column (1) consists of the 9,698,650 CPS respondents with non-missing AC-exposure measure (Park and Stainier, 2021). Columns (2)–(3) split this sample into workers in the top three quartiles of AC access and in the bottom quartile. Statistical significance is denoted as follows: $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

Table A2: Descriptive Statistics

	ATUS N=5,679		JOLTS N=13,517	
	Mean	SD	Mean	SD
Maximum temperature (share of days):				
Three months prior interview				
$\leq$ 5°C	0.103	0.201	0.105	0.199
5-10°C	0.085	0.116	0.086	0.112
10-15°C	0.116	0.119	0.115	0.109
15-20°C	0.142	0.123	0.143	0.115
20-25°C	0.167	0.130	0.167	0.114
25-30°C	0.199	0.182	0.205	0.180
$\geq$ 30°C	0.188	0.272	0.179	0.248
One month prior interview				
$\leq$ 5°C	0.109	0.241	0.105	0.229
5-10°C	0.086	0.145	0.086	0.135
10-15°C	0.115	0.154	0.115	0.140
15-20°C	0.139	0.162	0.143	0.149
20-25°C	0.162	0.175	0.167	0.153
25-30°C	0.196	0.228	0.205	0.215
$\geq$ 30°C	0.192	0.313	0.179	0.279
Outcomes:				
Job search activities	0.176	.	.	.
Job openings (in log)	.	.	11.94	1.018
Sociodemographic characteristics:				
Female	0.549	.	.	.
Age	39.21	13.43	.	.

Notes: These statistics refer to the 2004–2023 ATUS respondents and 2000-2023 JOLTS observations included in the estimation samples used in Table 2.