Job searching and the weather: Evidence from time-use data

Jorge González Chapela

Centro Universitario de la Defensa de Zaragoza, Zaragoza, Spain.

Email: jorgegc@unizar.es

ORCID: 0000-0003-3550-6370

Abstract: This paper combines individual-level time-use data for 2003–2017 with daily weather observations for U.S. counties to estimate the effects of precipitation and temperature on the intensity of job searching by the unemployed. Linear and nonlinear effects are investigated, along with heterogeneous responses across different populations. A 1°C increase in maximum (minimum) temperature produces a same-day decrease (increase) in job-search time of close to 0.9 (1.7) minutes. For women, job-search time is 17 minutes shorter on days of heavy rain, whereas men search some 21 (26) minutes more on days of mild (moderate) rain. These changes do not appear to be offset on subsequent days.

Keywords: Job searching, weather, time use, unemployment.

JEL codes: C31, J64.

Acknowledgements: The current version of this paper owes a great deal to the comments and suggestions of several anonymous reviewers. Bryant Korzeniewski and Mark Seiderman (NOAA NCEI) provided diligent assistance with GHCN-Daily data. Financial support by the Centro Universitario de la Defensa de Zaragoza (grant number 2019-07) and the Government of Aragón (grant number S32-20R) is gratefully acknowledged.

1. INTRODUCTION

The availability of large-scale time-use surveys around the world has prompted analyses of how much time job seekers allocate to job searching. Equipped with a reliable measure of the time spent searching for a job, researchers have provided new evidence on the link between this time and unemployment benefits (Krueger and Mueller 2010), and have documented its variability across countries (Krueger and Mueller 2012) and over spells of unemployment (Krueger and Mueller 2011), the life-cycle (Aguiar et al. 2013), and the business cycle (DeLoach and Kurt 2013, Gomme and Lkhagvasuren 2015, Mukoyama et al. 2018). However, job-search time has not been examined in search of evidence on the role of the weather in the intensity of job searching by the unemployed, who are generally free to set their search intensity on a day-to-day basis.

Through its impact on the marginal utility of leisure (Connolly 2008), good weather may encourage the unemployed to substitute leisure for job-search activities.[1] However, good weather may also encourage job searching for at least three reasons: First, although it's rarely conducted outdoors, about 40% of job-search time in the U.S. is spent outside the home, so job seekers are exposed to weather during the related travel. Second, buildings are not perfectly insulated, so even when job-search activities are conducted indoors, individuals may be put off by uncomfortable temperatures (Heal and Park 2016), which may lead them to forsake job searching for more relaxed activities. And third, good weather may lift people's mood (e.g., see Keller et al. 2005), which could lead the

[1] As occurs in the 2003 Spanish nominee for the Academy Award for Best Foreign Language Film *Mondays in the Sun* (Ahn et al. 2005).

unemployed to revise upward their beliefs as to how productive searching for a job may be (Barron and Mellow 1979).[2]

A priori, therefore, the potential influence of the weather on time spent searching for a job is ambiguous, as it involves potentially opposing linkages. However, it is important to measure it, as job-search intensity is a fundamental determinant of unemployment and, by extension, of individual well-being and socio-economic inequality. Furthermore, confirming a link between weather and job-search time would open up the possibility that the job-finding rate may vary over the year and from one climate area to another, inducing seasonal unemployment and geographic gaps in steady-state unemployment rates.[3] Policies designed to promote job-search efforts could be required in periods or climates that discourage such efforts.

---

[2] The possibility that job applications may be judged differently by recruiters depending on weather conditions (Simonsohn 2007 analyzes a parallel phenomenon affecting university admissions), is another way in which weather could influence the productivity of searching.

[3] The job-finding rate results from the two sides of the market (supply and demand), so the potential effects on it of weather via job-search time may be altered by the behavior of employers. Suppose that the intensity of job searching is reduced by good weather. If employers reduce the number of vacancies in periods when the unemployed search less, then the negative effect of good weather on the job-finding rate would be amplified. If the number of vacancies is fixed and employers increase recruiting effort per vacancy (in the sense of Davis et al. 2013), the negative effect of good weather on the job-finding rate would be counteracted.

This paper examines the empirical link between precipitation, maximum and minimum temperature and time spent searching for a job by the unemployed in the U.S. To that end, two sources of publicly available data are combined: Individual-level time-use information from the American Time Use Survey, and county-level daily weather summaries from the National Centers for Environmental Information. The use of daily-level observations enables the dynamics of links to be investigated, as the contemporaneous and delayed effects of the weather can be estimated. Investigating these dynamics is relevant because if reduced job-search effort due to same-day weather is not offset on subsequent days, the chances and speed of reemployment could depend on the weather. The analysis is conducted using a four-activity system (job search, outdoor and indoor leisure, and sleep), so the source of job-search time can be traced, and the plausibility of potential time allocation mechanisms can be investigated.

By documenting a previously unexplored link, this paper contributes to the literature characterizing the intensity of job search (see the references cited above, plus Shimer 2004, Faberman et al. 2017, Potter 2017, Faberman and Kudlyak 2019, and Marinescu and Skandalis 2019) and, more generally, the link between weather and the allocation of time (Connolly 2008, Eisenberg and Okeke 2009, Tam et al. 2013, Graff Zivin and Neidell 2014, Krueger and Neugart 2018). There is great academic and policy interest in identifying ties between weather and socio-economic outcomes, as weather can provide meaningful insights into how projected climate changes may affect societies (Dell et al. 2014, Carleton and Hsiang 2016, Hsiang 2016). The huge size of the U.S. means that the weather varies widely across the country, with hot summers in the southwest (Arguez et al. 2012), so the weather conditions whose impact is assessed here may be informative for the range of changes that may occur in the future.

The paper is organized as follows. Section 2 describes the data and reviews the construction of the sample and the main measures. Section 3 outlines the empirical methodology. Results are presented in Section 4. Section 5 sets out the main conclusions and offers some considerations for interpreting them.

2. DATA

This section describes the data, the construction of the sample, and the main measures. The primary sources of data utilized in this study are the American Time Use Survey (ATUS) of the Bureau of Labor Statistics (BLS) and the Global Historical Climatology Network (GHCN)-Daily database of the National Centers for Environmental Information (NCEI).

2.1. ATUS

The ATUS is a cross-sectional yearly survey that has been collecting information about how Americans spend their time since 2003 by the time-diary method. The ATUS is drawn from a subset of households that have completed the last month of Current Population Survey (CPS) interviews. In each selected household, a randomly chosen person of at least 15 years of age is assigned a 24-h period beginning at 4 AM called the "diary day." This person is called on the day when the diary day ends and asked to report on her/his activities over the diary day, including the activities undertaken, the length of time allocated to each activity, and where and with whom each activity took place. All the usual CPS demographics are available in the ATUS, but since it is conducted two to five months after the final CPS interview, some information (including employment status) is updated in the ATUS.

I pool ATUS data for 2003–2017 and restrict the sample to unemployed workers aged 20–65. Employed workers and nonemployed workers outside the labor force are excluded because they do not spend significant time searching for a job, so their overall responses to weather are practically zero. Furthermore, the small number of observations with positive job-search times for these groups precludes comparing responses over the intensive margin across labor market statuses.

There are 6,744 unemployed workers aged 20–65 in the ATUS for 2003–2017. ATUS response rates were below 60%. Both the CPS and the ATUS ask what kind of search methods the interviewee used in the past month,[4] conditional on her/his being unemployed and not on temporary layoff. Table 1 shows that unemployed individuals selected to participate in the ATUS tend to report more search methods than ATUS respondents. Hence, the results of this paper may not generalize to the complete pool of unemployed workers.

Following Krueger and Mueller (2010) (or KM 2010), job-search time is measured as the total number of minutes spent searching for a job on the diary day plus the associated time spent traveling (ATUS activity codes 0504xx and 180504).[5] Job searching includes activities such as contacting a potential employer or employment agency, reading and replying to job advertisements, and having job interviews. Figure 1 shows that job-search activities are conducted more frequently in the morning.

One major cost of search is the opportunity value of the time required, which could otherwise be allocated to leisure (Mortensen 1977). Following Graff Zivin and Neidell (2014) (or GZN 2014), leisure is measured as total waking time (excluding time allocated to job search) and divided into outdoor and indoor leisure. Activities that take place in ambiguous locations such as "at the home or yard" are classified as indoors, so "Outdoor

[4] This measure of search intensity was first used by Shimer (2004).

[5] Travel related to job searching was not codified in 2003. Nor can it be distinguished in the multi-year ATUS data file. This is why I work with single-year files.

Leisure” here probably understates actual leisure time spent outdoors. Nearly all activities included in outdoor leisure are somewhat physically demanding.

Sleep (which is the remaining broad activity) is also included in the analysis. Atypically high minimum temperatures lead to insufficient sleep, particularly among lower-income persons (Obradovich et al. 2017). Thus, short sleep might release time to job search, but it might also harm the productivity of the search (paralleling the negative effect on market productivity documented by Gibson and Shrader 2018). “Sleep” here is time spent sleeping, lying sleepless, and ‘‘sleeping, not elsewhere classified’’ (ATUS code 0101xx) (Ásgeirsdóttir and Ólafsson 2015).

In order to assign local weather conditions, I went back to the CPS to get the county or metropolitan area (MA) of residence of individuals in the sample. County and MA data are only released for individuals from locations with over 100,000 residents, so geographic identifiers were only available for 5,562 unemployed workers (82% of the initial sample). Of these, 2,303 reported only MA. Individuals reporting only MA are assigned to the most populated county in the MA (GZN 2014).[6]

2.2. GHCN-Daily

GHCN-Daily (Version 3.24) is a database of daily weather summaries from land stations across the globe whose records have been integrated and subjected to a common suite of quality checks (Menne et al. 2012a). For the U.S., it is both the official archive for daily weather data and the most complete collection of such data available (Menne et al.

[6] County intercensal population estimates are drawn from the Census Bureau’s Population and Housing Unit Estimates datasets CO-EST00INT-TOT (released in September 2011) and CO-EST2017-alldata (released in March 2018). The delineation of MAs is also taken from the Census Bureau.

2012b). The GHCN-Daily weather variables selected for this study are precipitation (ppt) and maximum and minimum temperatures (tmax and tmin, respectively). Ppt and tmax have been the focus of previous research on the allocation of time. Tmin may also be relevant as job searching takes place more frequently in the morning and because insufficient sleep may spill over to job-search activities.

Ppt is the amount of rain-water or melted frozen precipitation measured in mm. Temperature is surface air temperature measured in °C. The county of each weather station is taken from NCEI's Master Station History Report (Enhanced Version), available at https://www.ncdc.noaa.gov/homr/reports. When there is more than one station in a county, the average for the county is taken (GZN 2014).

The quality of a day may also be affected by other weather variables (see, e.g., Steadman 1979 and Neidell 2010). Ancillary humidity and wind speed data (plus some measures of pollution) are taken, respectively, from the PRISM Climate Group's AN81d dataset[7] and the Environmental Protection Agency's Air Quality System (AQS) database. Humidity is measured as dew-point temperature (tdew) in °C (Daly et al. 2015). An increase in tdew means that there is more moisture in the air.

2.3. Merged Data

[7] PRISM Climate Group, Oregon State University, http://prism.oregonstate.edu, created August 29, 2019. The AN81d dataset contains daily gridded data covering the conterminous U.S. with a resolution of approximately 4×4 km. PRISM data are read using the Stata command *ras2dta* (Mueller 2005) and are linked to ATUS using the latitude and longitude of each county's centroid, obtained from the MABLE/Geocorr 2014 application maintained by the Missouri Census Data Center.

When ATUS data are merged with GHCN-Daily and AN81d data by county and date, 155 individuals drop out of the sample. These are persons for whose county-dates of residence there are no weather records. A further 184 individuals are discarded because there are missing data for them in one or more weather variables. Thus, the final sample comprises 5,223 unemployed workers, who are classified into the following four types (KM 2010): Job losers, on temporary layoff, re- or new entrants, and voluntary job leavers.

There are 413 counties and 3,001 days in the final sample (out of a total of 5,479 days in the period 2003–2017). ATUS diary days are distributed evenly across the weeks of the year, but some days are not included in the sample due to survey nonresponse. Following GZN (2014), Table 2 compares the distributions of ppt and temperature for days included and excluded from the sample. Distributions for days excluded comprise observations for the same counties as the final sample, but for days excluded from the sample. The only differences which are significant at 10% or less are that participation is slightly higher (lower) on days with light rainfall (tmax 30°C–35°C).

Descriptive statistics for the full sample and for subsamples stratified by unemployment insurance eligibility status, state-level monthly unemployment rate, and sex are presented in Table 3. In the full sample, average job-search time is 34 minutes per day including weekends. Excluding job interviews reduces this figure slightly to 32.5 minutes. About 19% participate in job-search activities on a given day, and those who participate spend an average of 176 minutes searching.

3. METHODS

To isolate the impact of daily weather conditions on the allocation of time by the unemployed, the following regression model (or a variant of it) is estimated by the method explained below:

$$y_{ij} = \beta_j X_{c(i),t(i)} + \gamma_j Z_i + f\left(c(i),t(i)\right) + \varepsilon_{ij} \tag{1}$$

In equation (1), y_{ij} is the number of minutes allocated by individual i to activity j on the diary day (j = job search, outdoor leisure, indoor leisure, or sleep), $t(i)$ represents the date of the diary day, and $c(i)$ is the county of i. The vector $X_{c(i),t(i)}$ comprises the weather variables plus a control for the hours of daylight, Z_i is a set of demographics and observed temporal factors, $f\left(c(i),t(i)\right)$ is a set of terms controlling for unobserved spatial and temporal factors, and ε_{ij} is an error term.

Through a combination of observations with zero and positive time spent on j, the regressions yield the overall effects of the weather on j. Overall effects are the weighted outcome of effects on the probability of allocating time to j on the diary day (the extensive margin), and effects on the duration of j conditional on time being spent on j (the intensive margin). The focus on overall effects is because the number of observations is too small to identify effects over the intensive margin with any accuracy (as shown below).

Precipitation, temperature, and humidity tend to be correlated (Auffhammer et al. 2013, Daly et al. 2015), so if only some of these variables are included in $X_{c(i),t(i)}$, their coefficients will pick up the effects of those omitted. Likewise, the amount of daylight is correlated with temperature and is also likely to influence individuals' time allocation, making it a potential confounder. The hours of daylight for every day in each county are taken from GZN (2014).

The effects of weather are often nonlinear (Steadman 1979, Dell et al. 2014, Hsiang 2016). Previous studies on the allocation of time have generally used dummy variables to specify the link between the regression and weather variables. But splitting my sample into various subgroups significantly lowers the number of observations and makes the estimates imprecise. Hence, after inspecting the regression relations with dummy variables, simpler approximations to these links are fitted. Humidity alters people's thermal comfort for tdew > 14°C (Steadman 1979), so humidity is modeled as a linear spline function with a knot at tdew = 14°C.

The set $f\left(c(i),t(i)\right)$ comprises county-season fixed effects (FE),[8] year-month dummies, and state-year dummies. These terms account, respectively, for seasonal local conditions (e.g. there might be disruptions in some industries or schools due to local weather conditions, complicating the search for a job at the same time), secular and seasonal changes common to all unemployed, and cross-state variation in the intensity of business cycles or changes to UI laws. Thus, the estimated effects of weather are not confounded by seasonal conditions in a given county, conditions in a given month of a certain year for the whole country, or year-to-year changes in a given state. The specification of $f\left(c(i),t(i)\right)$ explains 39% of the sample variation in ppt, 89% of that in tmax, and 90% of that in tmin.

Including Z_i in equation (1) absorbs residual variation and produces more precise estimates. Following previous studies, Z_i comprises age and age squared, dummy variables for type of unemployed worker, female, married or cohabiting with a partner, working partner, presence of children under age 18, White non-Hispanic, and education level completed, plus dummy variables for the diary day being on a weekend or a holiday. The dummy for a working partner addresses the concern that higher-income unemployed

[8] Seasons are based on the annual temperature cycle: December–February, March–May, June–August, and September–November.

workers are under less pressure to search and are potentially more likely to live in cities with milder weather (within a county).[9]

Model (1) is estimated in Stata activity by activity using the FE method, with heteroskedasticity robust standard errors clustered at county level (Cameron and Miller 2015). After FE are absorbed, ordinary least squares (OLS) applied activity by activity are identical to system feasible generalized least squares, as the same regressors appear in every activity equation (e.g., Wooldridge 2010). OLS activity by activity automatically take into account the adding-up constraints on the allocation of time

$$\sum_j \beta_j = 0 \qquad \sum_j \gamma_j = 0 \tag{2}$$

Standard errors clustered at county level control for potential within-county serial correlation in weather variables. In tables with estimation results, the number of clusters is denoted by *M*.

4. RESULTS

Section 4.1 discusses the contemporaneous (i.e., same-day) effects of the weather and presents several sensitivity analyses. Section 4.2 addresses the dynamics of the link between weather and job-search time. Subsample analyses are dealt with in Section 4.3. Finally, Section 4.4 assesses the importance of acclimatization as an adaptation mechanism.

4.1. Contemporaneous effects of weather

Figure 2 shows the effects on job-search time of indicator variables for precipitation and temperature bins. The linear function may be a satisfactory summary description of the

[9] Household income is missing for 6% of observations. Median household income for unemployed workers with a working partner is twice that of those with no partner or with a partner who is not working ($50,000–$59,999 versus $25,000–$29,999).

links, the main exception being the response at tmin > 25°C, which occurs in 1.3% of the sample. In addition, for every j, Schwarz's (1978) BIC favors linear functions over more complicated polynomials. To model the upsurge at tmin > 25°C, a linear spline function of tmin with a knot at tmin = 25°C is used.[10]

Panel 1 of Table 4 presents the main estimates of equation (1) organized by columns. Column (1) shows a relatively small, statistically not different from zero, effect of ppt on job-search time, but statistically significant effects at 10% or less associated with temperature. Results suggest that time spent in job-search activities is on average 0.89 (S.E. 0.48) minutes lower when tmax increases by 1°C, with the difference being allocated mainly to outdoor leisure (Columns 2–4). In contrast, a 1°C increase in tmin is associated with an increase in job-search time, the extra time being taken mainly from outdoor leisure. This increase is of 1.67 (S.E. 0.67) minutes for tmin < 25°C, and of an additional 28.69 (S.E. 13.53) minutes for tmin > 25°C. At average time allocation values, these responses represent, respectively, -2.6%, 4.9%, and 89.8% of time spent searching for a job.

While increasing tmax may reasonably raise the opportunity value of outdoor leisure and thus progressively reduce job-search time, the rationale behind the direct link with tmin could be that job-search activities tend to be conducted in the morning, so less cold mornings might reduce the disutility of searching. The upsurge at tmin > 25°C does not appear to be the result of short sleep, but of reduced outdoor leisure. This impression does not change if time lying sleepless (ATUS code 010102) is excluded from sleep.

[10] The linear spline is favored by the *J* test (e.g. Davidson and MacKinnon 2004) when compared to a function preserving the slope over the range of tmin, but allowing a break in the function's level at tmin = 25°C.

Since the time diary starts and ends at 4 AM, short sleep in the morning due to nighttime heat could be offset by going to bed earlier in the evening. Yet, the coefficient at tmin > 25°C in a regression for sleep time between 4 AM and noon is positive (11 minutes).

The results of some sensitivity analyses are presented in Panel 2 of Table 4. The inclusion of job interviews (ATUS code 050403) among job-search activities may be biasing the estimated responses downward as job interviews may be more difficult to reallocate. Column (1) shows that the exclusion of job interviews makes the estimated responses to tmax and tmin a little larger, so that they become significant at 5%. Estimates suggest that the average time spent in job-search activities other than job interviews is 0.96 (S.E. 0.47) (1.84, S.E. 0.66) minutes lower (higher) when tmax (tmin, for tmin < 25°C) increases by 1°C. These responses represent -3.0% and 5.7% respectively of the average time spent searching for a job, excluding interviews.

Other environmental variables that can affect the quality of a day are wind speed and pollution (Neidell 2010). The results of incorporating daily summaries of wind speed, fine particulate matter (PM2.5), and ground-level ozone are shown in Column (2). Not every county has an AQS monitor, so the sample becomes much smaller. The effects of tmax and tmin (for tmin < 25°C) are substantially larger in this subsample. Wind speed and pollution appear to be individually and jointly insignificant for time spent searching for a job (*p*-values > 0.26).

Columns (3) and (4), respectively, show responses along the extensive and intensive margins of job searching. The effects on the probability of searching on the diary day have the same sign as the corresponding overall effects. A 1°C increase in tmax reduces the probability of searching by 0.11 (S.E. 0.23) percentage points. If the time spent by the additional individuals not searching is the average job-search time conditional on searching, the extensive margin would account for 0.19 minutes (or 21%)

of the overall effect of tmax. The response to tmin at the extensive margin becomes significant at 5%, and suggests that the likelihood of searching is 0.62 (S.E. 0.29) percentage points higher when tmin rises by 1°C. This effect represents 3.2% of the average probability of searching, and accounts for 1.09 minutes (65%) of the overall effect of tmin if the time spent by the additional individuals searching is the average job-search time conditional on searching. Estimates for the intensive margin may be unreliable as a result of the much smaller sample.

Coming back to Panel 1, the hypothesis that the coefficient on tmax in the regression for job-search time is equal to the negative coefficient on tmin for tmin < 25°C is not rejected at standard levels (*p*-value 0.15). Thus, the effects of tmax and tmin can be summarized by calculating the response to a 1°C variation in diurnal temperature range (DTR; DTR = tmax – tmin). Re-estimating the regression in Column (1) to use DTR in place of tmax and tmin and excluding observations with tmin > 25°C returns an estimated coefficient of -0.96 (S.E. 0.47), which is statistically significant at 5%. Extrapolating the scale of this estimate to Willcox, Arizona, where DTR drops from approximately 24°C at the beginning of July to about 16°C over a 3-week period (Leathers et al. 1998), would result in approximately 7.7 minutes more per day of job-search time, a 23% increase at average time allocation values.

The results in Columns (2) and (3) suggest that a 1°C increase in tmax produces an increase of 1.61 (S.E. 0.56) minutes in outdoor leisure and a decrease of 0.96 (S.E. 1.16) minutes in indoor leisure over the range of tmax. However, GZN (2014) have shown that the nonemployed protect themselves from the heat by spending more time inside as from around 32°C. Re-estimating the regressions for leisure with indicator variables for ppt and temperature bins yields the results shown in Figure 3. These results suggest that among unemployed workers the growing trend for outdoor leisure as tmax increases reverses slightly at 30°C–35°C and resumes at the highest bin.

Eisenberg and Okeke (2009) find that for low-income persons the direct link between outdoor physical activity and tmax for tmax < 15°C is almost absent. Re-estimating the equation for outdoor leisure using the linear spline function of tmax employed by Eisenberg and Okeke (with knots at approximately 15°C and 27°C), but specifying ppt and tmin using dummy variables, yields a positive though small response for tmax < 15°C: a 1°C increase in tmax raises outdoor leisure by 0.53 minutes (S.E. 0.73). Interacting tmax with the working partner indicator yields a smaller response among individuals without a working partner (0.43 minutes, S.E. 0.81).

The slightness of the influence of ppt detected so far may be due to individuals' greater adaptation to precipitation, perhaps because it is easier to shift job-search activities to non-raining parts of a rainy day or because of the availability of more efficient technologies to cope with rain. The humidity variables have the same sign as tmax in Columns (1) and (2), and the effect of humidity increases when tdew > 14°C. However, they are individually insignificant in all activity equations, and when their joint significance is tested the hypothesis of no effect cannot be rejected in any activity equation (*p*-values > 0.21).

As for the impact of the controls included in Z_i, there are few surprises in general: See e.g. KM (2010), Aguiar et al. (2013), and Ásgeirsdóttir and Ólafsson (2015). As a difference with KM (2010), the correlation between job-search time and education appears to be positive, which is probably reflecting the fact that the more educated receive, on average, higher wage offers and hence have more incentives to search for a job.[11] The negative correlation of education and working partner with sleep duration echoes the generally negative association between sleep time and income.

4.2. Total effects of weather

Unemployed workers may make up for decreased job-search effort on a given day by searching harder on subsequent days. To investigate this possibility, I follow previous studies and include lagged ppt and lagged temperature among the regressors. Lagged weather values are the maximum of the previous 6 days (GZN 2014). To maintain consistency with the specification employed so far, a linear spline of lagged tmin with a knot at 25°C is used. The sum of the contemporaneous and delayed effects yields the total effect of a weather variable.[12]

The main results of re-estimating equation (1) to include lagged weather variables are presented in Table 5. In Column (1), the estimated coefficients on lagged variables show the opposite sign to their same-day counterparts, except for lagged tmin, but are small and statistically insignificant. This suggests that same-day effects are offset only a little or not at all on subsequent days. However, the hypothesis of zero total effect for each weather variable cannot be rejected at 5%. For tmin, the null of zero total effect has a *p*-value of 0.05, and it is rejected at 5% when job interviews are excluded. For tmin > 25°C, the null of zero total effect has a *p*-value of 0.05, which rises to 0.06 if job interviews are excluded. In Column (2), the coefficients on lagged variables are relatively

[11] KM (2010) employ individual characteristics and state fixed effects to identify the influence of expected wages on job-search time. Their approach is not feasible in this study.

[12] For tmin > 25°C, the total effect is the sum of the coefficients on tmin, $1(\text{tmin} \geq 25)*(\text{tmin} - 25)$, lagged tmin, and $1(\text{lagged tmin} \geq 25)*(\text{lagged tmin} - 25)$.

small, but only the hypothesis of zero total effect of tmin for tmin > 25°C is marginally questioned (p-value 0.05). Further evidence on total effects is provided in the sections below.

4.3. Subsample analyses

Insights from labor and psychological research suggest that the weather may induce different responses among unemployed persons eligible for unemployment insurance (UI) benefits from those among the unemployed not eligible for benefits. As explained below, the predicted moderation effect of UI eligibility status differs in the two literatures.

Barron and Mellow (1981) find that the unemployed are more likely to drop out of the labor market when they are not receiving UI benefits. Consistent with this result, Young (2012) argues and provides some evidence that the joint processes of UI program requirements and tangible liquidity raise the labor market attachment of the unemployed by inducing persistence in job-search effort (see also Wanberg et al. 2005). Increasing the extent to which search effort continues over the unemployment spell could make the UI-eligible less sensitive to the weather.

However, paralleling results in (among others) Schmittmann et al. (2015), a happier mood could make the unemployed more optimistic about the productivity of job searching. Experimental results in Keller et al. (2005) suggest that temperature becomes more positively associated with mood as time spent outside increases. Since the UI-eligible allocate some 10 minutes more per day to outdoor leisure activities than the UI-ineligible (Table 3), the happier mood effect could be stronger for the former, making them search harder on warmer days.

Since the ATUS lacks information on UI receipt, unemployed workers are classified into eligible and ineligible for benefits following KM (2010). Job losers and temporarily laid-off workers are considered eligible, whereas re- and new entrants and voluntary job leavers are considered ineligible. In states where part-time job seekers do not qualify for UI, those who worked part-time are considered ineligible.[13] This classification is of course imperfect, so observed behavioral differences are likely to underestimate true differences. Of the 5,223 individuals in the sample, 2,933 appear as eligible for UI. On average these individuals search for 19 minutes longer per day than the UI-ineligible (Table 3).

The results of regressing job-search time separately for UI-eligible and ineligible individuals are presented in Columns (1) and (2) of Table 6, respectively. Among the contemporaneous variables, the effects of the weather appear greater among the UI-ineligible (except for tmin, when tmin > 25°C), as the unequal labor attachment view predicts. The response to tmax appears to be slightly positive among the UI- eligible, so it is the response to tmax among the UI-ineligible that drives the behavior observed in the full sample. A test for equal contemporaneous responses between UI-eligible and ineligible individuals does not reject the null of equality for any weather variable (*p*-values > 0.24).[14] This conclusion is maintained if tests are conducted for responses relative to average job-search time (*p*-values > 0.17).

As to lagged weather, and contrary to the results obtained for the full sample, some relatively large responses are observed. Being UI-eligible adds 2.09 (S.E. 1.39) minutes to job-search time when the six previous days' highest tmin is 1°C higher. The UI-ineligible respond differently to the same circumstance, with a reduction of 1.66 (S.E. 1.31) minutes. For the UI-eligible, the hypothesis of zero total effect of tmin for tmin <

[13] The information on nonmonetary eligibility in each state is taken from https://oui.doleta.gov/unemploy/statelaws.asp#Statelaw.

[14] Equality of effects is tested with the help of the Stata command *suest*.

25°C is not questioned (p-value 0.10), but it is rejected at 5% for tmin > 25°C. Thus, it appears that the UI-eligible search harder on days with tmin > 25°C (the extra time being taken mostly from outdoor leisure), and that this additional effort is not offset on subsequent days.

The impact of the weather could vary as search effort changes over the business cycle. If they increase search effort during recessions (e.g., Mukoyama et al. 2018) the unemployed could become less sensitive to the weather. To investigate this possibility, the sample is split into two subsamples according to whether the state monthly unemployment rate is above or below the national average for 2003–2017 (6.37%).[15] Results for individuals in state-months with above and below average unemployment rates are presented in Columns (3) and (4) of Table 6, respectively. With the exception of ppt, contemporaneous responses to the weather for job-search time appear larger during good economic conditions. However, none of the differences is significant at conventional levels (p-values > 0.10). If equality is assessed relative to average job-search time, the hypothesis of equal response to tmin for tmin < 25°C is marginally questioned (p-value 0.08). Responses to lagged weather appear relatively small. In good economic conditions, the hypothesis of zero total effect of tmin for tmin < 25°C is rejected at 5%.

Being female has been associated with being more likely to drop out of the labor market in the case of unemployed workers and with reduced persistence of job-search effort (Barron and Mellow 1981, Wanberg et al. 2005). Thus, time allocation by women could be more sensitive to the weather. In a related vein, a review of the literature on the effect of gender on indoor thermal comfort concludes that females are more sensitive to

[15] Unemployment rates are taken from the BLS National Unemployment Rate and Local Area Unemployment Statistics.

deviations from optimal thermal conditions (Karjalainen 2012). To investigate this view, job-search time is regressed separately for males and females. The results are presented in Columns (5) and (6) of Table 6, respectively.

The response to contemporaneous tmax (tmin) appears as larger among females (males). However, the null of equality of effects across genders cannot be rejected (*p*-values > 0.30), in the case of tmax even if equality is assessed relative to average job-search time (*p*-value 0.32). Lagged effects appear to be relatively small except for the effect of tmin on males, which adds 2.17 (S.E. 1.80) minutes to job-search time when the six previous days' highest tmin is 1°C higher. The hypothesis of zero total effect of tmax or tmin cannot be rejected for men or women (*p*-values > 0.10). Excluding job interviews marginally questions that null for tmax among women (*p*-value 0.099).

The small contemporaneous response to ppt observed in the full sample shows a striking disparity between men and women. For men the estimated response is positive but statistically insignificant (0.26, S.E. 0.52), but for women it is negative, larger, and statistically significant at 5%. Accordingly, women's job-search time decreases by 0.60 (S.E. 0.27) minutes when rainfall increases by 1mm. A test for equal response across genders does not reject equality (*p*-value 0.10), but equality is rejected at 5% when the response is assessed relative to average job-search time.

Re-estimating the regression for job-search time with indicators for ppt and temperature bins yields the results shown in Figure 4. The negative linear response among women is due to the 17.2-min (S.E. 8.8) drop on days with ppt > 15mm, a reduction that becomes significant at 6% and represents 69% of women's average job-search time. (The drop is of 14.9, S.E. 9.0, minutes excluding job interviews.) This amount of rainfall occurs on approximately 5.5% of days (Table 2), but for 25% of the counties included in sample the figure is above (below) 7.0% (4.5%). The probability of searching on the diary day declines by 4.9 (S.E. 5.2) percentage points when ppt > 15mm. Thus, if the additional women not searching spend the average job-search time conditional on searching, the extensive margin would account for 7.8 minutes (45%) of the overall reduction.

Interestingly, Figure 4 also reveals significant responses to ppt among men. Job-search time is 21.4 (S.E. 8.4) minutes longer on days with ppt in the range 0mm–1mm, and 26.5 (S.E. 13.8) minutes higher on days with ppt in the range 5mm–15mm than on days with no rain. (Excluding job interviews, the increases are 21.4, S.E. 8.3, and 25.9, S.E. 13.7, respectively.) These responses are significantly different from zero at 5% and 6%, respectively, and represent 47% and 58% of men's average job-search time. For 25% of the counties included in the sample the proportion of days with 0mm–1mm of rainfall is above (below) 24.1% (16.0%); for the 5mm–15mm interval, the corresponding figures are 12.5% and 9.1%. The probability of searching on the diary day rises by 1.3 (S.E. 3.4) (3.6, S.E. 6.7) percentage points when ppt is in the 0mm–1mm (5mm–15mm) range, accounting for 2.5 (6.8) minutes and 12% (26%) of the increase if the time spent by the extra men searching is the average job-search time conditional on searching.

Re-estimating the regressions for the other activities with indicators for contemporaneous ppt and temperature bins yields the results shown in Figure 5. Among women, sleep is the only activity that takes up more time on days of heavy rain. However, the response of indoor leisure at the highest ppt bin becomes positive (about 15 minutes) when caring activities (ATUS codes 03xxxx, 04xxxx, 1803xx, and 1804xx) are disaggregated from leisure. Increases in job-search time among men on days of mild and moderate rainfall are taken primarily from indoor leisure. This behavior of male unemployed workers echoes that found by Connolly (2008) in hourly workers, for whom a rainy day means substantially more time at work and less time at leisure. Reduced social and religious activities may be responsible for these increases. Time spent socializing by men is 26.2 (S.E. 18.9) (10.8, S.E. 34.2) minutes lower on days with 0mm–1mm (5mm–15mm) of rainfall than on days with no rain.[16] Men's religious and spiritual activities (ATUS codes 14xxxx and 1814xx) decrease by 13.8 (S.E. 9.2) minutes on days with 5mm–15mm of rainfall.

Time added to/subtracted from job-search activities on rainy days might not be made up on subsequent days. Re-estimating the regressions in Columns (5) and (6) with indicator variables for contemporaneous ppt and temperature and lagged ppt bins yields coefficients on lagged ppt bins which are small or of the same sign as the corresponding contemporaneous ones. For women a test of zero total effect of ppt > 15mm does not question the null (p-value 0.12). For men, a test of zero total effect of 0mm–1mm (5mm–15mm) of rainfall rejects the null at 5% (it does not question the null: p-value 0.21). If variations in job-search effort caused by same-day ppt are not offset on subsequent days, days of rain could alter the time taken by unemployed workers to find jobs. Investigating this issue calls for detailed longitudinal geolocated data on the search process combined with some measure of search success, plus sufficient weather variation over time within spatial entities.

4.4. Acclimatization

Physiological and psychological acclimatization can occur in a few weeks (Keller et al. 2005, GZN 2014). Hence, it may be reasonable to suppose that responses to warmer temperatures are greater in the coolest months (when individuals are deprived of such weather) than in the warmest months (when pleasant temperatures are less of a novelty).

[16] Time spent socializing is defined as time spent in any activity in which the respondent reported being with people living outside the household.

Behavioral acclimatization may take more time, though. To assess longer-run adjustments, I focus on the responses of unemployed individuals who live in the counties with the warmer half of average summer temperatures (GZN 2014), and of those living in counties with the wetter half of average annual precipitation.[17] The former group's responses may provide information on the potential implications of global warming for job-search time. The results for counties in the coldest (driest) half are not presented because there were very few observations in the highest temperature (ppt) bin.

Columns (1) and (2) of Table 7 present the estimates pertaining to short-run acclimatization. The effects of contemporaneous tmax and tmin on job-search time are greater in the coolest months, suggesting that it is mainly behavior in September–February that underlies the responses to tmax and tmin observed in the full sample. However, none of the responses differs significantly from one time of the year to another (p-values > 0.10). For the coolest months, the hypothesis of zero total effect of tmin for tmin < 25°C is marginally questioned (p-value 0.09).

Turning to behavioral acclimatization (Columns 3 and 4 of Table 7), relatively large responses to tmax (ppt) can be seen in counties in the warmer (wetter) half (cf. Column 1 of Table 5). Thus, there appears to be little evidence of behavioral acclimatization. Although job-search time reacts strongly to same-day tmax in counties in the warmer half, the sum of its contemporaneous and delayed effects may be zero (p-value 0.24). In both subsamples, individuals search some 36 minutes more when tmin, for tmin > 25°C, is 1°C higher (the extra time being taken mostly from outdoor leisure in counties in the warmer half, and from outdoor and indoor leisure in counties in the wetter

[17] Climate normals for 1981–2010 are from the PRISM Climate Group.

half). The hypothesis that this additional effort is made up on subsequent days is rejected at 5% in both subsamples.

5. CONCLUSION

An analysis of individual-level time-use data for 2003–2017 combined with daily weather records for U.S. counties with a population of more than 100,000 reveals several influences of the weather on unemployed workers' job-search time. A 1°C increase in maximum (minimum) temperature produces a same-day decrease (increase) in job-search time of close to 0.9 (1.7) minutes. The effect of minimum temperature is some 30 minutes greater when that temperature is above 25°C, but this behavior does not appear to be caused by sleep loss. The influence of same-day temperature appears to be greater among unemployed individuals not eligible for UI benefits, during good economic conditions, in the coolest months of the year (suggesting short-run acclimatization), and in counties in the top half of the summer temperature distribution (suggesting no behavioral acclimatization). Significant effects associated with precipitation are also observed. On days of heavy rain women's job-search time is 17 minutes shorter, whereas men search some 21 (26) minutes more on days of mild (moderate) rain. There is little evidence that all these changes are offset on subsequent days, so unemployed workers' chances of reemployment and the time taken to find work could depend on the weather. It also appears that time allocated to outdoor leisure by the unemployed continues to increase with same-day maximum temperature when that temperature is above 35°C.

These results are from an analysis of a few thousand time diaries. Larger sets of time-use data might reveal weather-induced behaviors that have gone undetected here. Weather effects are often dependent on context. One repeated form of heterogeneity is that poor countries appear much more sensitive to weather shocks for many outcomes (Dell et al. 2014), so assessing the link between weather and job-search time in other countries may reveal previously unnoticed effects. The weather actually experienced by respondents and the weather recorded at weather stations might also differ, as ATUS respondents are geolocated at county or metropolitan area level, which may introduce measurement error and thus possibly attenuate the estimates. Also, since geographic identifiers are only available for individuals from locations with over 100,000 residents, and participation in the ATUS may be inversely related to job-search effort, the results of this paper may not generalize to the complete pool of unemployed workers.

REFERENCES

Aguiar, M., E. Hurst, and L. Karabarbounis. 2013. The life-cycle profile of time spent on job search. *American Economic Review* 103(3): 111–116.

Ahn, N., J.F. Jimeno, and A. Ugidos. 2005. Mondays in the sun. In *The Economics of Time Use*, ed. D. Hamermesh and G. Pfann, 237–259. Amsterdam: Elsevier.

Arguez, A., I. Durre, S. Applequist, R.S. Vose, M.F. Squires, X. Yin, R.R. Heim Jr., and T.W. Owen. 2012. NOAA's 1981–2010 U.S. climate normals: An overview. *Bulletin of the American Meteorological Society* 93(11): 1687–1697.

Ásgeirsdóttir, T.L., and S.P. Ólafsson. 2015. An empirical analysis of the demand for sleep: Evidence from the American Time Use Survey. *Economics and Human Biology* 19: 265–274.

Auffhammer, M., S.M. Hsiang, W. Schlenker, and A. Sobel. 2013. Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy* 7(2): 181–198.

Barron, J.M., and W. Mellow. 1979. Search effort in the labor market. *Journal of Human Resources* 14(3): 389–404.

Barron, J.M., and W. Mellow. 1981. Changes in labor force status among the unemployed. *Journal of Human Resources* 16(3): 427–441.

Cameron, A.C., and D.L. Miller. 2015. A practitioner's guide to cluster-robust inference. *Journal of Human Resources* 50(2): 317–372.

Carleton, T.A., and S.M. Hsiang. 2016. Social and economic impacts of climate. *Science* 353(6304): aad9837.

Connolly, M. 2008. Here comes the rain again: Weather and the intertemporal substitution of leisure. *Journal of Labor Economics* 26(1): 73–100.

Daly, C., J.I. Smith, and K.V. Olson. 2015. Mapping atmospheric moisture climatologies across the conterminous United States. *PLoS ONE* 10(10): e0141140.

Davidson, R., and J.G. MacKinnon. 2004. *Econometric Theory and Methods*. New York, NY: OUP.

Davis, S.J., R.J. Faberman, and J.C. Haltiwanger. 2013. The establishment-level behavior of vacancies and hiring. *Quarterly Journal of Economics* 128(2): 581–622.

Dell, M., B.F. Jones, and B.A. Olken. 2014. What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature* 52(3): 740–798.

DeLoach, S.B., and M. Kurt. 2013. Discouraging workers: Estimating the impacts of macroeconomic shocks on the search intensity of the unemployed. *Journal of Labor Research* 34: 433–454.

Eisenberg, D., and E. Okeke. 2009. Too cold for a jog? Weather, exercise, and socioeconomic status. *B.E. Journal of Economic Analysis and Policy* 9(1): Article 28.

Faberman, R.J., and M. Kudlyak. 2019. The intensity of job search and search duration. *American Economic Journal: Macroeconomics* 11(3): 327–357.

Faberman, R.J., A.I. Mueller, A. Sahin, and G. Topa. 2017. Job search behavior among the employed and non-employed. NBER Working Paper No. 23731.

Gibson, M., and J. Shrader. 2018. Time use and labor productivity: The returns to sleep. *Review of Economics and Statistics* 100(5): 783–798.

Gomme, P., and D. Lkhagvasuren. 2015. Worker search effort as an amplification mechanism. *Journal of Monetary Economics* 75: 106–122.

Graff Zivin, J., and M. Neidell. 2014. Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics* 32(1): 1–26.

Heal, G., and J. Park. 2016. Temperature stress and the direct impact of climate change: A review of an emerging literature. *Review of Environmental Economics and Policy* 10(2): 347–362.

Hsiang, S.M. 2016. Climate econometrics. *Annual Review of Resource Economics* 8: 43–75.

Karjalainen, S. 2012. Thermal comfort and gender: a literature review. *Indoor Air* 22: 96–109.

Keller, M.C., B.L. Fredrickson, O. Ybarra, S. Côté, K. Johnson, J. Mikels, A. Conway, and T. Wager. 2005. A warm heart and a clear head. The contingent effects of weather on mood and cognition. *Psychological Science* 16(9): 724–731.

Krueger, A.B., and A. Mueller. 2010. Job search and unemployment insurance: New evidence from time use data. *Journal of Public Economics* 94: 298–307.

Krueger, A.B., and A. Mueller. 2011. Job search, emotional well-being, and job finding in a period of mass unemployment: Evidence from high-frequency longitudinal data. *Brookings Papers on Economic Activity* Spring: 1–81.

Krueger, A.B., and A.I. Mueller. 2012. The lot of the unemployed: A time use perspective. *Journal of the European Economic Association* 10(4): 765–794.

Krueger, J.J., and M. Neugart. 2018. Weather and intertemporal labor supply: Results from German time-use data. *Labour* 32(1): 112–140.

Leathers, D.J., M.A. Palecki, D.A. Robinson, and K.F. Dewey. 1998. Climatology of the daily temperature range annual cycle in the United States. *Climate Research* 9: 197–211.

Marinescu, I., and D. Skandalis. 2019. Unemployment insurance and job search behavior. Available at SSRN: https://ssrn.com/abstract=3303367.

Menne, M.J., I. Durre, B. Korzeniewski, S. McNeal, K. Thomas, X. Yin, S. Anthony, R. Ray, R.S. Vose, B.E. Gleason, and T.G. Houston. 2012a. Global Historical Climatology Network-Daily, Version 3.24. NOAA National Climatic Data Center. http://doi.org/10.7289/V5D21VHZ (accessed: December 12, 2018).

Menne, M.J., I. Durre, R.S. Vose, B.E. Gleason, and T.G. Houston. 2012b. An overview of the Global Historical Climatology Network-Daily Database. *Journal of Atmospheric and Oceanic Technology* 29: 897–910.

Mortensen, D.T. 1977. Unemployment insurance and job search decisions. *Industrial and Labor Relations Review* 30(4): 505–517.

Mueller, D. 2005. Stata in space: Econometric analysis of spatially explicit raster data. *Stata Journal* 5(2): 224–238.

Mukoyama, T., C. Patterson, and A. Sahin. 2018. Job search behavior over the business cycle. *American Economic Journal: Macroeconomics* 10(1): 190–215.

Neidell, M. 2010. Air quality warnings and outdoor activities: evidence from Southern California using a regression discontinuity design. *Journal of Epidemiology and Community Health* 64(10): 921–926.

Obradovich, N., R. Migliorini, S.C. Mednick, and J.H. Fowler. 2017. Nighttime temperature and human sleep loss in a changing climate. *Science Advances* 3(5): e1601555.

Potter, T. 2017. Learning and job search dynamics during the Great Recession. School of Economics Working Paper Series 2017-6, LeBow College of Business, Drexel University.

Schmittmann, J.M., J. Pirschel, S. Meyer, and A. Hackethal. 2015. The impact of weather on German retail investors. *Review of Finance* 19: 1143–1183.

Schwarz, G. 1978. Estimating the dimension of a model. *Annals of Statistics* 6(2): 461–464.

Shimer, R. 2004. Search intensity. Manuscript, available at https://sites.google.com/site/robertshimer/research/workingpapers.

Simonsohn, U. 2007. Clouds make nerds look good: Field evidence of the impact of incidental factors on decision making. *Journal of Behavioral Decision Making* 20(2): 143–152.

Steadman, R.G. 1979. The assessment of sultriness. Part I: A Temperature-Humidity Index based on human physiology and clothing science. *Journal of Applied Meteorology* 18(7): 861–873.

Tam, B.Y., W.A. Gough, V. Edwards, and L.J.S. Tsuji. 2013. Seasonal and weather-related behavioral effects among urban Aboriginal, urban non-Aboriginal, and remote Aboriginal participants in Canada. *Population and Environment* 35(1): 45–67.

Wanberg, C.R., T.M. Glomb, Z. Song, and S. Sorenson. 2005. Job-search persistence during unemployment: A 10-wave longitudinal study. *Journal of Applied Psychology* 90(3): 411–430.

Wooldridge, J.M. 2010. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, MA: MIT Press.

Young, C. 2012. Unemployment insurance and job search activity: Evidence from random audits. Manuscript, Stanford University.

TABLES AND FIGURES

Table 1. Average number of job-search methods reported using in the previous month, by year.

	Selected for ATUS			ATUS respondents			Difference in means
	Mean	S.E.	*N*	Mean	S.E.	*N*	
2003	2.31	0.04	984	2.26	0.06	556	0.05
2004	2.39	0.05	712	2.20	0.08	376	0.19**
2005	2.26	0.05	583	2.45	0.10	296	-0.19*
2006	2.27	0.05	544	2.15	0.08	310	0.12
2007	2.32	0.06	497	2.00	0.09	289	0.31***
2008	2.41	0.05	582	2.51	0.09	351	-0.09
2009	2.58	0.05	963	2.34	0.06	587	0.23***
2010	2.45	0.04	1199	2.32	0.06	653	0.12*
2011	2.42	0.04	1075	2.40	0.07	568	0.02
2012	2.39	0.04	1002	2.23	0.08	457	0.16*
2013	2.34	0.04	893	2.20	0.08	409	0.14
2014	2.40	0.05	721	2.02	0.07	337	0.38***
2015	2.27	0.06	606	2.02	0.08	267	0.25***
2016	2.29	0.06	531	2.00	0.08	226	0.29***
2017	2.38	0.06	546	1.92	0.09	208	0.46***

Notes: Unemployed workers aged 20–65 not temporarily laid-off. Interviewees are allowed to select from twelve search methods. Observations are weighted by individual final weights. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.

Table 2. Distribution of observations for included and excluded days, by weather variable.

	ATUS		ATUS non response
	Mean	S.E.	Mean
Ppt (mm)			
0	0.476	0.010	0.488
0–1	0.224***	0.007	0.203
1–5	0.145	0.005	0.150
5–15	0.103	0.005	0.104
>15	0.052	0.003	0.055
Tmax (°C)			
≤5	0.119	0.013	0.107
5–10	0.084	0.006	0.085
10–15	0.120	0.007	0.111
15–20	0.136	0.008	0.139
20–25	0.168	0.008	0.168
25–30	0.197	0.010	0.208
30–35	0.134*	0.010	0.151
>35	0.042	0.007	0.031
Tmin (°C)			
≤-5	0.097	0.011	0.094
-5–0	0.113	0.007	0.120
0–5	0.150	0.008	0.152
5–10	0.173	0.011	0.166
10–15	0.175	0.009	0.181
15–20	0.162	0.011	0.163
20–25	0.117	0.010	0.114
>25	0.013	0.003	0.009

Notes: ATUS is the final sample used in the analysis. ATUS non response comprises observations for the same counties as the final sample, but for days excluded from the sample. Standard errors are clustered at county-season level. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.

Table 3. Descriptive statistics.

	All (N = 5,223)	UI eligible (N = 2,933)	UI ineligible (N = 2,290)	High U (N = 2,933)	Low U (N = 2,290)	Males (N = 2,291)	Females (N = 2,932)
Time allocation (minutes per day):							
Job search	33.8	42.2	23.1	35.7	31.5	45.4	24.8
Excluding interviews	32.5	40.5	22.4	34.5	30.0	43.8	23.8
Percent minutes > 0	19.2	22.6	14.9	20.5	17.6	24.0	15.6
Minutes | minutes > 0	175.9	186.7	154.9	173.7	179.1	189.6	159.3
Outdoor leisure	51.0	55.3	45.4	49.5	52.9	70.1	36.1
Indoor leisure	808.0	796.5	822.8	807.7	808.5	782.7	827.8
Sleep	547.2	546.0	548.7	547.2	547.2	541.8	551.3
Covariates:							
Precipitation (mm)	2.8 (7.8) [0, 170.5]	2.8 (7.6)	2.9 (8.0)	2.9 (8.3)	2.8 (7.1)	2.7 (7.0)	2.9 (8.4)
Maximum temperature (°C)	19.7 (10.8) [-19.0, 46.3]	19.4 (10.9)	20.1 (10.8)	19.4 (11.1)	20.0 (10.6)	18.8 (11.2)	20.4 (10.6)
Minimum temperature (°C)	8.5 (10.0) [-27.2, 29.9]	8.3 (10.0)	8.7 (9.9)	8.3 (10.1)	8.7 (9.8)	7.8 (10.1)	9.0 (9.8)
Dew point (°C)	6.6 (10.1) [-29.4, 25.6]	6.5 (10.2)	6.7 (10.1)	6.3 (10.0)	6.7 (10.3)	5.8 (10.3)	7.2 (10.0)
Hours of daylight	12.1 (1.8)	12.1 (1.8)	12.1 (1.8)	12.1 (1.8)	12.1 (1.8)	12.1 (1.8)	12.2 (1.8)
Age	40.0 (12.4)	41.7 (11.7)	37.9 (12.9)	40.0 (12.3)	40.1 (12.6)	41.0 (12.7)	39.3 (12.1)
Job loser	47.1	80.5	4.2	49.3	44.2	53.8	41.8
On layoff	11.6	19.5	1.5	10.6	12.9	14.7	9.2
Re- or new entrant	39.0	0	89.0	38.2	40.1	28.9	46.9
Job leaver	2.3	0	5.3	1.9	2.8	2.6	2.1
Female	56.1	47.9	66.7	54.9	57.7	0	100
Spouse/partner present	46.7	47.7	45.5	46.5	47.0	46.6	46.8
Spouse/partner working	34.7	34.2	35.4	33.8	35.9	29.7	38.6
Children < 18 present	53.6	50.3	57.8	52.8	54.5	41.0	63.4
White non-Hispanic	50.4	54.9	44.6	49.2	51.8	52.6	48.6
Some college or associate degree	32.6	31.4	34.3	33.2	31.9	32.6	32.6
College degree	23.3	26.2	19.6	22.8	23.9	22.6	23.9
Diary day a weekend day	49.9	48.8	51.4	49.2	50.9	50.2	49.7
Diary day a holiday	1.6	1.9	1.2	1.3	1.9	1.5	1.6

Notes: Standard deviations are in parentheses and observed ranges in brackets. High U (Low U) denotes observations in state-months whose unemployment rate was above (below) the national average for 2003–2017.

Table 4. Contemporaneous effects of weather on unemployed workers' allocation of time.

Panel 1: Baseline results

	Dependent variables (N = 5,223; M = 413)							
	(1) Job search		(2) Outdoor leisure		(3) Indoor leisure		(4) Sleep	
Independent variables	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Ppt (mm)	-0.16	0.17	-0.10	0.22	0.27	0.46	-0.02	0.39
Tmax (°C)	-0.89*	0.48	1.61***	0.56	-0.96	1.16	0.24	0.84
Tmin (°C)	1.67**	0.67	-1.64*	0.86	-0.81	1.59	0.78	1.12
$1(\text{tmin} \geq 25) * (\text{tmin} - 25)$	28.69**	13.53	-28.27***	10.71	-12.75	26.89	12.33	10.56
Tdew (°C)	-0.77	0.49	0.59	0.50	0.38	0.99	-0.20	0.77
$1(\text{tdew} \geq 14) * (\text{tdew} - 14)$	-0.72	1.48	0.94	1.49	2.66	2.89	-2.88	2.14
Hours of daylight	1.52	5.22	7.43	5.55	-14.81	10.09	5.86	7.37
Age	2.81***	0.86	2.48***	0.73	-1.85	1.80	-3.44**	1.71
Age^2	-0.03***	0.01	-0.02**	0.01	0.03	0.02	0.02	0.02
On layoff	-38.81***	5.36	14.87**	6.27	14.09	10.47	9.85	7.31
Re- or new entrant	-21.07***	3.80	2.44	3.10	25.81***	6.80	-7.17	5.20
Job leaver	-2.40	11.24	20.94*	11.45	4.04	20.50	-22.58	15.15
Female	-19.37***	4.18	-29.40***	3.46	41.17***	7.23	7.59	4.82
Spouse/partner present	-5.20	6.38	7.38	5.31	-2.78	9.58	0.60	6.16
Spouse/partner working	-2.18	6.79	-6.44	5.54	17.11	11.04	-8.49	6.69
Children < 18 present	-4.55	3.49	-0.50	3.81	9.20	7.22	-4.14	5.96
White non-Hispanic	7.35*	3.85	9.10**	3.63	-6.58	6.93	-9.86*	5.13
Some college	8.91**	3.72	-11.11***	4.23	19.37**	8.03	-17.17***	6.51
College degree	18.87***	4.26	-12.72**	5.09	23.78**	9.32	-29.94***	6.72
Weekend day	-39.60***	3.75	7.60**	3.73	1.76	7.20	30.24***	4.58
Holiday	-31.12***	8.62	-5.61	11.58	53.28**	26.89	-16.55	22.87
Intercept	5.79	67.81	-250.08***	73.43	1090.14***	166.21	531.43***	113.84

Panel 2: Robustness to sensitivity analyses

	Dependent variables							
	(1) Job search excluding interviews (N = 5,223; M = 413)		(2) Job search (N = 1,586; M = 135)		(3) Participation in job search (N = 5,223; M = 413)		(4) Job search | job search >0 (N = 1,005; M = 259)	
Independent variables	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Ppt	-0.14	0.17	-0.09	0.38	-0.0007	0.0010	-0.46	1.95
Tmax	-0.96**	0.47	-2.51**	1.20	-0.0011	0.0023	-5.39	6.78
Tmin	1.84***	0.66	3.38**	1.45	0.0062**	0.0029	-4.70	9.36
$1(\text{tmin} \geq 25) * (\text{tmin} - 25)$	28.74**	14.13	12.38	19.85	0.0205	0.0212	280.7***	75.71
Wind speed[a] (km/h)			-0.52	0.57				
PM2.5[a] ($\mu g/m^3$)			0.31	0.54				
Ozone 8-hour[a] (ppm)			-628.2	485.9				

Notes: Dependent variables measured in minutes except Column (3) of Panel 2 (dummy variable = 1 if searching for a job on the diary day). All estimations include county-season fixed effects plus year-month and state-year dummies. Estimations in Panel 2 include the controls listed in Panel 1. Standard errors are clustered at county level. $1(\cdot)$ is the indicator function. [a]: Available for AQS sites. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.

Table 5. Contemporaneous and delayed effects of precipitation and temperature on unemployed workers' allocation of time.

	Dependent variables (minutes) (N = 5,223; M = 413)							
	(1) Job search		(2) Outdoor leisure		(3) Indoor leisure		(4) Sleep	
Independent variables	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Ppt (mm)	-0.17	0.17	-0.08	0.23	0.33	0.46	-0.09	0.39
Lagged ppt	0.06	0.12	-0.05	0.13	-0.30	0.24	0.29	0.21
Tmax (°C)	-0.89*	0.51	1.62***	0.57	-1.26	1.16	0.53	0.88
Lagged tmax	0.14	0.64	-0.22	0.75	1.12	1.19	-1.04	1.02
Tmin (°C)	1.57**	0.65	-1.55*	0.85	-1.00	1.62	0.97	1.11
Lagged tmin	0.41	0.81	-0.08	0.85	-0.49	1.49	0.15	1.27
$1(\text{tmin} \geq 25) * (\text{tmin} - 25)$	32.55**	13.97	-41.03***	13.32	-0.79	30.81	9.27	12.30
$1(\text{lagged tmin} \geq 25) * (\text{lagged tmin} - 25)$	-7.11	7.54	22.57**	10.74	-21.27	13.68	5.80	9.10

Notes: All estimations include county-season fixed effects, year-month and state-year dummies, and the controls listed in Panel 1 of Table 4. Lagged weather values are the maximum of the previous six days. Standard errors are clustered at county level. $1(\cdot)$ is the indicator function. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.

Table 6. Subsample analyses.

	Dependent variable: Job-search time (minutes)					
	(1)	(2)	(3)	(4)	(5)	(6)
	UI eligible	UI ineligible	High U	Low U	Males	Females
Independent variables	(N = 2,933; M = 368)	(N = 2,290; M = 364)	(N = 2,933; M = 339)	(N = 2,290; M = 379)	(N = 2,291; M = 365)	(N = 2,932; M = 376)
Ppt (mm)	0.07	-0.30	-0.20	-0.14	0.26	-0.60**
	(0.33)	(0.39)	(0.23)	(0.44)	(0.52)	(0.27)
Lagged ppt	-0.20	-0.08	0.06	0.20	-0.02	-0.01
	(0.18)	(0.17)	(0.20)	(0.20)	(0.30)	(0.14)
Tmax (°C)	0.15	-1.49	-0.90	-1.59	-0.54	-1.24
	(1.02)	(1.18)	(0.84)	(1.21)	(1.25)	(0.78)
Lagged tmax	-0.81	1.81*	0.79	-0.16	0.34	-0.42
	(1.19)	(1.05)	(1.18)	(1.44)	(1.65)	(0.91)
Tmin (°C)	1.56	1.72	0.65	3.99**	1.49	0.83
	(1.59)	(1.51)	(1.12)	(1.73)	(1.79)	(1.08)
Lagged tmin	2.09	-1.66	0.87	1.21	2.17	1.37
	(1.39)	(1.31)	(1.22)	(1.56)	(1.80)	(1.10)
$1(\text{tmin} \geq 25)*(\text{tmin}-25)$	52.03**	28.81	29.49	57.98*	47.88	10.04
	(21.40)	(21.51)	(21.24)	(32.40)	(32.12)	(20.50)
$1(\text{lagged tmin} \geq 25)$ $*(\text{lagged tmin}-25)$	4.90	-19.15	-5.10	-17.40	8.12	-4.13
	(13.67)	(13.65)	(15.90)	(13.57)	(19.78)	(8.06)

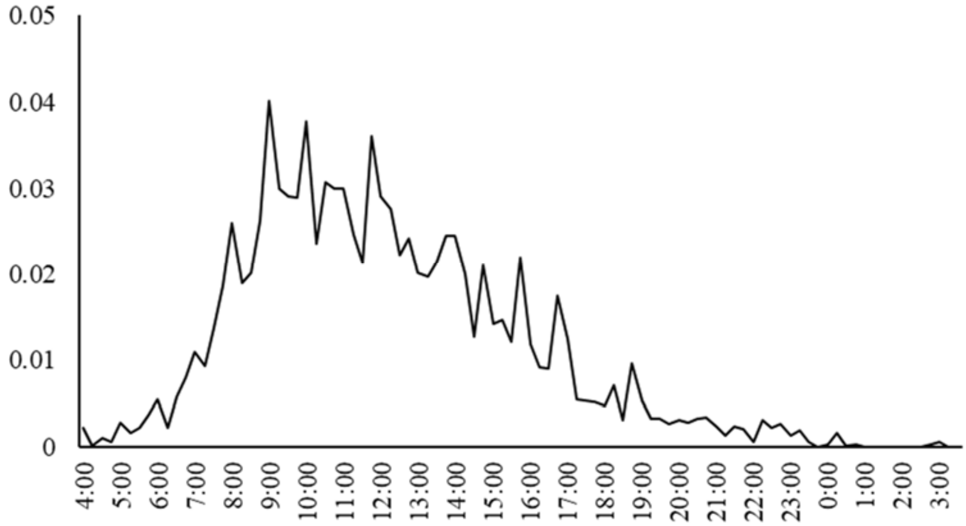
Notes: All estimations include county-season fixed effects, year-month and state-year dummies, and the controls listed in Panel 1 of Table 4. Lagged weather values are the maximum of the previous six days. High U (Low U) denotes observations in state-months whose unemployment rate was above (below) the national average for 2003–2017. Standard errors clustered at county level are in parentheses. $1(\cdot)$ is the indicator function. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.

Table 7. Assessing short- and long-run acclimatization.

	Dependent variable: Job-search time (minutes)			
	Short-run acclimatization		Long-run acclimatization	
	(1)	(2)	(3)	(4)
	Cool	Warm	Warm	Wet
Independent variables	(N = 2,621; M = 369)	(N = 2,602; M = 374)	(N = 2,790; M = 225)	(N = 3,948; M = 342)
Ppt (mm)	0.22	-0.28	-0.13	-0.27
	(0.39)	(0.24)	(0.23)	(0.18)
Lagged ppt	0.32	-0.19	0.14	0.09
	(0.24)	(0.14)	(0.17)	(0.13)
Tmax (°C)	-1.28	-0.23	-1.74**	-0.71
	(0.79)	(0.77)	(0.68)	(0.61)
Lagged tmax	0.70	-0.45	0.40	-0.06
	(0.93)	(1.11)	(1.05)	(0.75)
Tmin (°C)	2.28**	0.10	2.31**	1.16
	(1.05)	(1.12)	(1.03)	(0.75)
Lagged tmin	0.01	1.27	0.95	0.88
	(1.09)	(1.24)	(1.38)	(0.95)
$1(\text{tmin} \geq 25) * (\text{tmin} - 25)$	107.25	30.97**	34.14**	35.39**
	(97.07)	(14.86)	(14.53)	(16.87)
$1(\text{lagged tmin} \geq 25)$ $*(\text{lagged tmin} - 25)$	-29.70*	-3.59	-4.70	-5.25
	(18.00)	(10.13)	(9.25)	(9.72)

Notes: All estimations include county-season fixed-effects, year-month and state-year dummies, and the controls listed in Panel 1 of Table 4. Lagged weather values are the maximum of the previous six days. In assessing short-run acclimatization, observations are stratified by month: Cool (Warm) denotes the period September–February (March–August). In assessing long-run acclimatization, observations are stratified by historical climate: Warm (Wet) denotes counties in the top half of the 1981–2010 summer temperature (annual precipitation) distribution. Standard errors clustered at county level are in parentheses. $1(\cdot)$ is the indicator function. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.

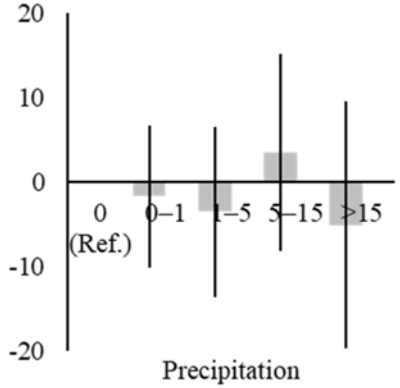
Figure 1. Proportion of unemployed workers searching for a job, by time of day (weekdays).



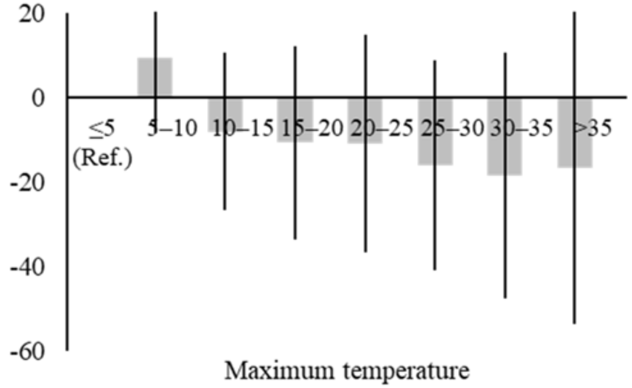
Notes: ATUS 2003–2017. Observations are weighted by individual final weights.

Figure 2. Contemporaneous effects of precipitation and temperature on unemployed workers' job-search time (minutes).

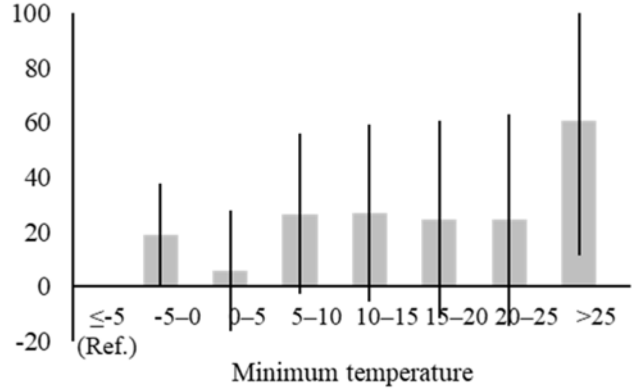
Precipitation (mm)



Maximum temperature (°C)



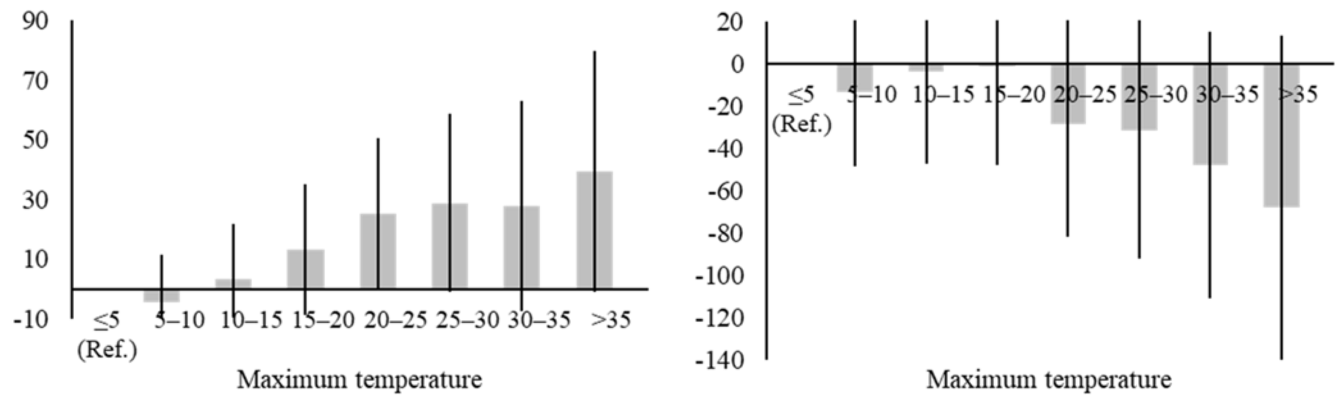
Minimum temperature (°C)



Notes: Error bars show 95% confidence intervals robust to clustering at county level.

Figure 3. Contemporaneous effect of maximum temperature (°C) on unemployed workers' leisure time (minutes).

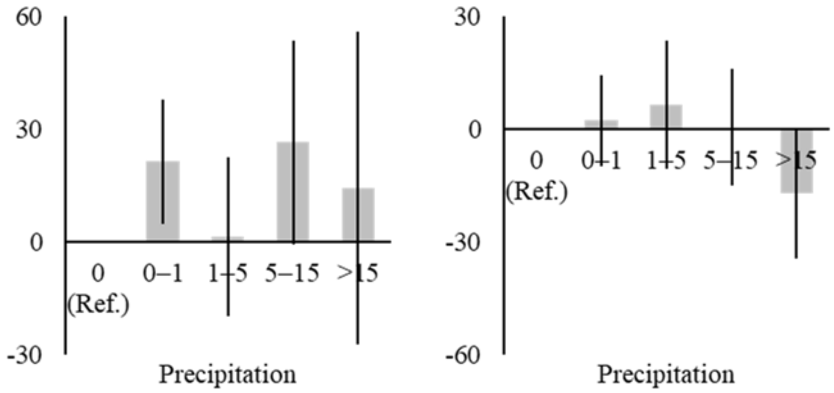
Outdoor	Indoor



Notes: Estimates pertain to the regressions shown in Columns (2) and (3) of Panel 1 of Table 4, but specifying precipitation and temperature with dummy variables. Error bars show 95% confidence intervals robust to clustering at county level.

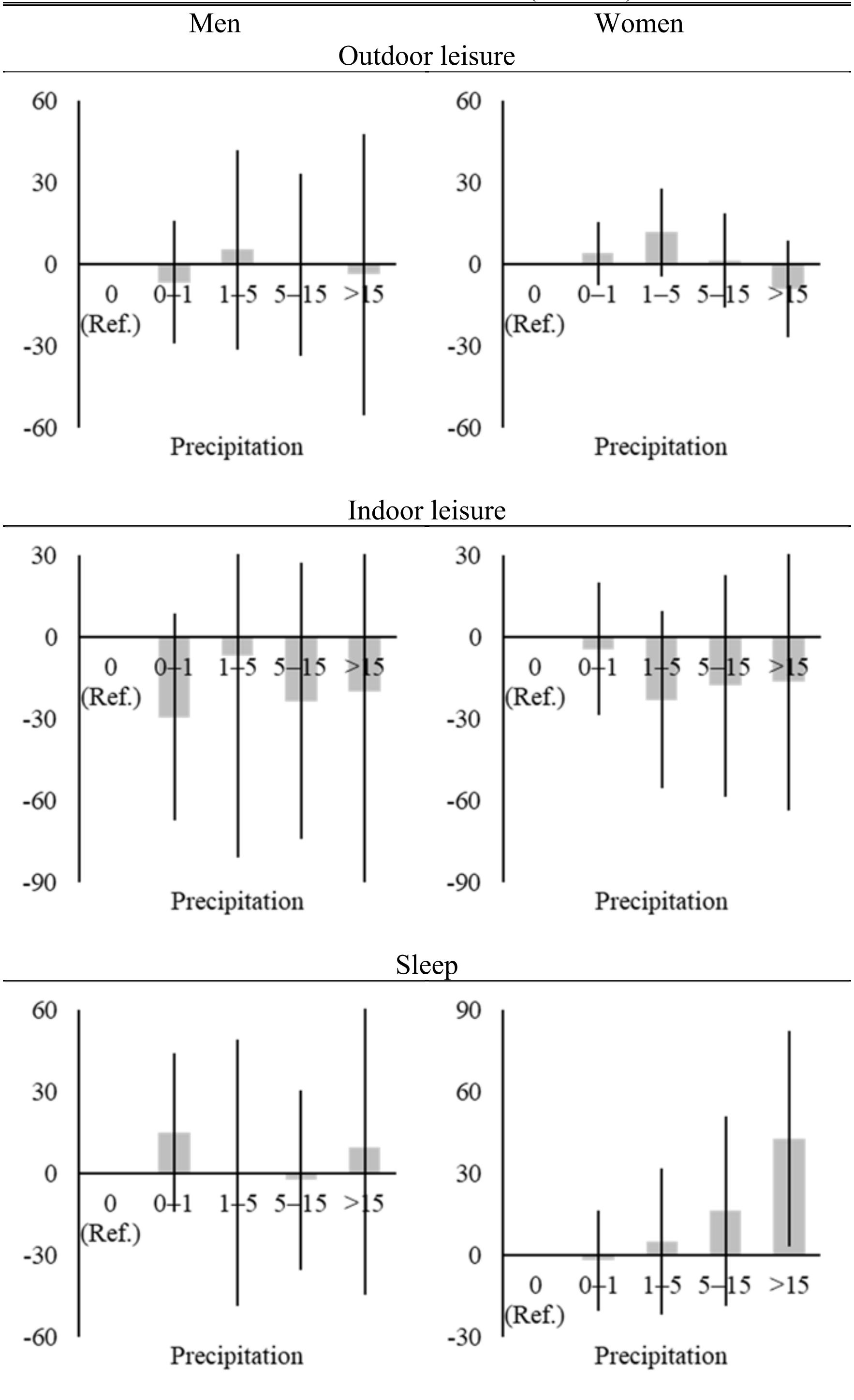
Figure 4. Contemporaneous effect of precipitation (mm) on unemployed workers' job-search time (minutes).

Men	Women



Notes: Estimates pertain to the regressions shown in Columns (5) and (6) of Table 6, but specifying contemporaneous precipitation and temperature with dummy variables. Error bars show 95% confidence intervals robust to clustering at county level.

Figure 5. Contemporaneous effect of precipitation (mm) on unemployed workers' allocation of time (minutes).



Notes: Error bars show 95% confidence intervals robust to clustering at county level.