Heat and Productivity: Evidence From Flight On-Time Performance

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Abstract

We investigate the impact of high temperatures on productivity using microdata from the U.S. airline industry. By linking high-frequency on-time flight performance measures with meteorological data, we show that higher temperatures significantly reduce airline productivity by increasing cancellation and delay rates and lengthening delay times. Using the American Time-Use Survey (ATUS), our complementary analyses suggest that the impact of higher temperatures operate in part through decreased labor supply (fewer hours worked and greater worker absenteeism) as well as reduced sleep quality and well-being, which may affect on-the-job productivity.

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1 Introduction

Extreme temperature events are increasing in frequency, duration, and magnitude across the globe (World Health Organization 2018). Their prevalence amidst a warming planet has spurred research on the economic consequences of rising temperatures. There is mounting evidence based on cross-country and subnational data that higher temperatures reduce economic growth and per capita income (Deryugina and Hsiang 2014; Dell, Jones, and Olken 2012), as well as industrial and agricultural production (Hsiang 2010; Schlenker, Hanemann, and Fisher 2006; Fisher et al. 2012). Understanding the economic consequences of rising temperatures has gained increasing importance for simulating the economic implications of future climate change and for informing policy-making processes in response to global warming (Dell, Jones, and Olken 2014). However, relatively less is known about the causal impact of heat on productivity across workplace contexts.

This paper examines the consequences of higher temperatures for productivity in the United States using novel microdata from the airline industry. This industry, alongside the broader transportation and logistics sector, is relatively climate-exposed, making it an opportune setting for exploring how rising temperatures shape productivity.

We build a 15-year longitudinal panel of high-frequency weather data linked to productivity as measured by on-time flight performance. These measures allow us to identify the role of heat stress by leveraging variation in temperatures over time and using a model augmented with a rich set of fixed effects. We find that flights operating during days where temperatures are greater than 35C are 24% more likely to be cancelled, 7% more likely to involve a late departure, and experience 18% longer delay time conditional on late departure. The adverse impact of high temperatures extends beyond immediate exposure and persists throughout later periods of the same day. When controlling for contemporaneous temperatures, an additional hour of heat exposure (at temperatures above 35C) during the day (5am to 6pm) is estimated to increase the departure delay rate and delay time later in the same day when the temperature is cooler. These effects are estimated to be about 2% for the departure delay rate and 1% for the delay time, relative to the corresponding sample average. Given that time is a limited yet exceedingly valuable resource, the welfare implications linked to heat-induced time losses (resulting from flight cancellations and delays) are likely to be significant

(Graff Zivin and Neidell 2014). Our study also shows that small-hub and non-hub airports are especially vulnerable to the shock of rising temperatures. Compared to hotter and colder areas, regions experiencing milder climates show greater vulnerability to heat exposure. These findings highlight how climate change disproportionately affects certain regions and undermines equitable development.

We provide suggestive evidence on the mechanisms behind these estimates. Higher temperatures can affect airline productivity by reducing workers' labor supply, changing their on-the-job performance, or altering productivity via non-labor means. We use data from the American Time Use Survey (ATUS) linked to daily weather measures to first show that heat reduces hours worked and increases absenteeism. Climate-exposed workers who perform their jobs largely outdoors spend 39 fewer minutes at work and are 0.7 p.p. more likely to be absent on hotter days. Additionally, we find that daily maximum temperatures exceeding 35C decreases workers' sleep time, increases the probability of experiencing sleeplessness, and renders workers more likely to feel not well-rested relative to more temperate days. We provide suggestive evidence that these sleep and well-being channels do not meaningfully influence workers' labor supply. Instead, research on the significant impact of sleep and health on workers' productivity (Bubonya, Cobb-Clark, and Wooden 2017; Gibson and Shrader 2018) are consistent with these mechanisms contributing to decreased on-the-job performance.

This study contributes in several ways to existing literature on the consequences of heat stress for productivity and worker well-being (see, for example, Heal and Park (2016) and Lai et al. (2023) for a review). Earlier studies on these topics tend to focus on the effect of temperatures on task productivity in workplaces with more scope for climate control, such as office environments. A meta-review of studies that investigate the relationship between office temperature and work performance, in either the laboratory environment or the field environment, suggests nonlinear decreases in workers' performance when the office temperature is above 25 degrees Celsius (Seppanen, Fisk, and Lei 2006).[1] Similar nonlinear effects on weekly productivity are present with heat ex-

[1]Effects above the 25 degree Celsius threshold are documented in studies such as Niemela et al. (2002), which provided evidence from two call centers in Finland that each one-degree Celsius increase in indoor office temperature is associated with a 5-7% decrease in labor productivity, as measured by the average number of telephone calls per active working hour, when the air temperature exceeded 25 Celsius degrees.

posure in the context of U.S.-based automobile assembly plants (Cachon, Gallino, and Olivares 2012).[2] In comparison, this paper shows sizable effects of heat exposure in an industry with more climate-exposed workers.

More recent causal evidence consistently demonstrate negative productivity consequences of increasing temperatures among labor-intensive manufacturing firms in India and China. Somanathan et al. (2021) use worker-level productivity and firm-level output data to show that productivity declines in Indian manufacturing plants specializing in cloth weaving, garment sewing, and steel production in response to rising temperatures. Adhvaryu, Kala, and Nyshadham (2020) document similar negative effects using microdata from a large Indian garment firm.[3] Among Chinese manufacturing firms, heat exposure adversely impacts both total factor productivity and output (Cai, Lu, and Wang 2018; Zhang et al. 2018; Chen and Yang 2019). A recent study using rich household survey data across 46 developing countries to examine the behavior of interviewers shows that productivity decreases on hot and humid days (LoPalo 2023). While these results generalize to workplaces in developing countries, we aim to complement this literature by providing productivity estimates in the context of an advanced economy. This paper documents meaningful effects in a U.S. sector that should be relatively well-equipped for adaption.

In studying the U.S. airline industry, we are also shifting away from previous studies in manufacturing, call centers, or other contexts that involve piece-rate contracts to a service-oriented industry that compensates workers hourly or annually. Varying incentive structures can yield different optimal worker responses. This distinguishes our findings from most previous literature on the mechanisms underlying the productivity impacts of heat exposure, which yield mixed conclusions. For example, Adhvaryu, Kala, and Nyshadham (2020) find the adverse effect is primarily driven by reductions in productivity per unit labor supplied rather than in the quantity of labor units supplied (worker absenteeism and hours worked). This contrasts somewhat with Somanathan et al. (2021), which find evidence for both channels with magnitudes varying by industry and the presence of

[2] There is a weekly productivity reduction of 8% on average when there are six or more days exceeding 32 degrees Celsius (relative to zero days), but there are no significant effects for fewer days of exposure. The extent of productivity impacts is notable given the availability of cooling systems within these manufacturing facilities.

[3] For mean daily temperatures above 19 degrees Celsius, there is a large, negative impact on efficiency of approximately 2 points for each one-degree Celsius increase in temperature. In comparison, Somanathan et al. (2021) finds that the effect of a uniform one-degree Celsius increase in daily temperature is a 2% decrease in plant output.

climate control.[4] Our findings based on U.S. time-use data suggests that both margins of labor supply and on-the-job productivity contribute to the adverse impact of heat exposure. We furthermore document that higher temperatures disturb sleep and rest, which may affect labor productivity via reduced on-the-job performance, although they do not seem to meaningfully affect the labor supply margin. The focus on sleep and restfulness contributes to a relatively scarce literature investigating the causal effects of these channels.[5]

2 Data

The data used in this paper has two components. In the main analysis, we construct a panel dataset linking flight on-time performance data with hourly climate data to investigate the impact of high temperatures on productivity. In addition, we exploit time-use survey data on individual labor supply, absenteeism, and well-being to explore the potential mechanisms behind the estimated effects. In this section, we describe the sources and construction procedures for these two data sets sequentially.

2.1 Data for the Main Analysis

We measure productivity in the airline industry using flight on-time performance. Data on flight delays and cancellations is retrieved from the Bureau of Transportation Statistics (BTS)'s Airline On-Time Performance (AOTP) Data. It provides detailed information on flights, including origin and destination airports, date of departure, scheduled and actual departure and arrival times, cancellation status, and in particular, the causes of flight cancellations or delays.

We assess the on-time performance of flights across three dimensions: cancellation rate, departure delay rate, and departure delay time. Specifically, these performance measures are based on

[4]Not all studies find negative or null impacts on labor supply. LoPalo (2023) documents *increases* in the hours worked per day in response to hotter days. Workers likely start their days earlier and log more hours due to strong incentives to maintain similar levels of total daily output.

[5]An exception is the role of sleep in mediating heat's negative impact on mental health (Mullins and White 2019).

carrier-caused cancellations and delays.[6] We are particularly interested in flight cancellations and delays caused by carrier-related issues, which include crew problems, baggage loading, fueling, aircraft cleaning, and maintenance, because they correspond most closely to our focus on airline productivity and flight operations. In doing so, we may be underestimating the impact of heat on airline productivity if higher temperatures result in disruptions in air traffic control, security, and other aspects of airport operations that are not accounted for using our outcome measures. For flight delays, our focus is on departure rather than arrival delays. Departure delays are less likely to be correlated with other confounding factors, such as weather en route and congestion at the destination airport, compared to arrival delays. Since we lack sufficient data on these confounding factors, using departure delays helps us minimize omitted variable bias in our estimation.[7]

The AOTP data spans from 1987 to 2021, while information on the causes of delays is only available after 2004. Moreover, we intend to consider only the pre-Covid period to avoid capturing effects driven by the shock of the pandemic. Therefore, we restrict our sample period from January 1, 2004, to December 31, 2019. The AOTP data covers 361 commercial service airports in the contiguous United States and 27 airlines.[8]

Next, we bring in meteorological data on temperature and other weather conditions. Hourly climate data comes from the Automated Surface Observing System (ASOS), made up of airport-based meteorological stations taking minute-by-minute observations to generate weather reports and inputs for the National Weather Service (NWS), the Federal Aviation Administration (FAA), and the Department of Defense (DOD).[9] We retrieve hourly ASOS climate data on air temperature (at 2 meters above the surface), feels-like temperature (also known as apparent temperature), precipitation, snow depth, wind speed and direction, humidity, and visibility from January 1, 2004

[6]BTS classifies the causes of flight cancellations into four categories: (a) Carrier Caused; (b) Weather; (c) National Aviation System (NAS); and (d) Security. For flight delays, in addition to the four causes previously described for cancellations, the BTS classifies a fifth cause—(e) Late Arriving Aircraft. Source: https://www.bts.gov/topics/airlines-and-airports/understanding-reporting-causes-flight-delays-and-cancellations.

[7]Furthermore, many flights that experience departure delays tend to make up for lost time during the flight, resulting in smaller arrival delays compared to departure delays. Consequently, using arrival delays as the performance measure may attenuate the estimated effect of heat on labor productivity.

[8]Commercial service airports are publicly owned airports with scheduled air carrier service and at least 2,500 annual enplanements. For more information on airport categories, see Federal Aviation Administration's website https://www.faa.gov/airports/planning_capacity/categories.

[9]ASOS data are downloaded from Iowa Environmental Mesonet (IEM) https://mesonet.agron.iastate.edu/ASOS/.

to December 31, 2019 for all airports in our sample. Commercial aircraft activities are found to be a major contributor to air quality deterioration at ground-level (Masiol and Harrison 2014; Riley et al. 2021), making it a relevant confounding factor in the context of this paper. To gauge its impact on our results, we collect daily air pollution data from the Air Quality System (AQS) of the Environmental Protection Agency (EPA), focusing on four pollutants: CO, NO_2, PM2.5, and ozone.[10]

Lastly, to assess the heterogeneous impact of heat across airports and flight characteristics, we gather information on airport enplanement (passenger boarding) and calculate the flight length (distance) for each route. We follow the Federal Aviation Administration (FAA) in categorizing airports into four types according to the size of their annual enplanements: large-hub, medium-hub, small-hub, and nonhub.[11] The annual enplanement data between 2004 and 2019 is retrieved from FAA's Air Carrier Activity database.[12] Additionally, we define short-haul flights as those with a distance less than 1000 km, and medium/long-haul flights as exceeding this threshold (Wragg 1973; Crocker 2005).

We create three outcome variables to measure flight on-time performance: the cancellation rate, departure delay rate, and total departure delay time (in minutes). Both the cancellation and delay rates use the number of scheduled flights as the denominator, such that the rate of on-time departure is one minus the sum of these two rates.[13] It is worth noting that the cancellation rate, departure delay rate, and departure delay time are essentially measured at the flight-level. In other words, they are specific to the particular route (a origin-destination pair), carrier, and day-and-time block pair.[14] Next, we merge flight performance data with hourly climate measures by the date of

[10]CO and NO_x are the major air pollutants emitted by airplanes during takeoff, taxiing, and idling (Schlenker and Walker 2016). In addition, like many other mobile sources, aircraft jet engines emit particulates and volatile organic compounds (VOCs) (Federal Aviation Administration 2005). Both VOC, unburned or partially combusted hydrocarbons, and NO_x contribute to ozone formation.

[11]Information about FAA's classification of airport categories can be found on FAA's website https://www.faa.gov/airports/planning_capacity/categories.

[12]Data source: Passenger Boarding (Enplanement) and All-Cargo Data https://www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/passenger.

[13]An alternative method to calculate these rates is by using the number of flights that actually departed as the denominator. However, this alternative method may overestimate the rate of cancellation or delay, as it computes the rate conditional on departure.

[14]We classify 18 time-block groups, with 0-5 a.m. as a single group and each hour during 6-23 as a single group.

flight operation, time block, and the 3-digit identifier of the origin airport.[15] The final sample is nationally representative and consists of 350 airports in the contiguous United States.[16] Figure 1 presents the 350 airports in the sample, with the size of each bubble indicating its average annual enplanements from 2004 to 2019.

We plot the average time of departure delays as a function of temperatures (in Celsius) in Figure 2a. Panel (a) shows a positive linear correlation between departure delays (both in terms of rate and time) and temperatures. Panel (b), on the other hand, suggests a likely non-linear correlation between temperatures and the cancellation rate. This finding motivates our decision to flexibly specify a model with temperatures measured at 5-degree Celsius bins in the main analysis, as described below.

We measure temperature exposure in two ways. First, we classify the current temperature into five categories: less than or equal to 20C (68F), between 20C and 25C (77F), between 25C and 30C (86F), between 30C and 35C (95F), and above 35C. Second, we calculate the number of hours when the temperature exceeds 35C during the day (defined as 5am to 6pm) to measure the cumulative heat exposure for the same day. Our temperature measures are based on the feels-like temperature, also known as the apparent temperature, instead of the real air temperature.[17] The apparent temperature measures how warm or cool the human body perceives the surrounding air. Because the human body can regulate high and low temperatures through, for example, sweating and insulating, real air temperature does not accurately reflect workers' heat exposure. The apparent temperature takes into account weather factors in the function of body temperature regulation, such as humidity and

[15] It is not empirically feasible for us to run the estimation for the entire sample at once due to the large size of our panel data, which consists of about 1 billion observations. Regressions incorporating a rich set of fixed effects for a dataset of this magnitude would require significant computational power. Therefore, we focus on the sub-sample of months from April to September in the main analysis because this period typically experiences high temperatures, making it most relevant to the aim of this study.

[16] Airports with missing climate data, typically small and public-use airports, are excluded from our sample. The 11 excluded airports are Northeast Florida Regional Airport (UST), Phoenix–Mesa Gateway Airport (AZA), Branson Airport (BKG), Tunica Municipal Airport (UTM), McClellan–Palomar Airport (CLD), Glacier Park International Airport (FCA), Hilton Head Airport (HHH), Sawyer International Airport (MQT), University Park Airport (SCE), Pinehurst Regional Airport (SOP), and Concord-Padgett Regional Airport (USA).

[17] Throughout this manuscript, unless otherwise noted, all temperature references correspond to feels-like or apparent temperature.

wind speed.[18]

We present summary statistics for the main analysis in Table 1. The mean cancellation rate is approximately 1%, with an average departure delay rate of 15% and an average departure delay time of 5.56 minutes. A significant portion of flights operates at temperatures between 20C and 35C, accounting for approximately 62%. Around 7% of flights operate at temperatures above 35C and 30% of flights operate at temperatures below 20C. The statistics for the real air temperature exhibit a similar pattern.

2.2 Data for the Exploration of Potential Mechanisms

We combine time use data with daily weather data to investigate potential mechanisms behind the estimated productivity effects. Specifically, we analyze both the Regular Module and the Well-being (WB) Module of the American Time Use Survey (ATUS). The regular module covers the period from 2005 to 2019 and collects information about how individuals spend their time during a diary day.[19] This includes their intertemporal labor supply as measured by hours worked and work absence status, their sleeping activity, such as sleep time and sleeplessness, and various demographic, educational, and employment characteristics. Importantly, it also contains information on the date of the diary day and the respondent's geographic location, allowing us to link it with weather data. The WB module is available for the years 2010, 2012, and 2013, and all respondents interviewed for the regular module in these years were selected for the WB module. The WB module includes questions about respondents' general health, such as how they felt in general compared to a typical day (matching the day of the week of the diary day) and how well-rested they felt.[20] We merge

[18]Some recent studies have used an alternative temperature measure—the WetBulb Globe Temperature (WBGT) (e.g., Somanathan et al. 2021; LoPalo 2023). WBGT measures the heat stress in direct sunlight, which takes into account temperature, humidity, wind speed, sun angle, and cloud cover (solar radiation). The apparent temperature differs from WBGT as it is calculated for shady areas (National Weather Services). We use apparent temperature instead of WBGT in this study, not only because it is the best available data for us, but also because it is better suited to our empirical setting. Most airport workers, including ground crew members, work in shady areas and are not exposed to direct sunlight for the majority of their work time.

[19]The sample is randomly selected from a subset of households that have completed their eighth month of interviews for the Current Population Survey (CPS).

[20]The WB module also asks respondents about their well-being during specific activities, such as work and work-related activities. The well-being measures include how much pain they felt and how tired/sad/stressed/happy they felt. We also utilize these measures to examine whether high temperatures affect these aspects at work and work-related activities. These results are reported in the Appendix.

the regular module data with the WB module data, thereby creating a cross-sectional dataset that contains comprehensive information on individuals' intertemporal labor supply, sleep patterns, and subjective health and well-being.

The ATUS dataset also contains information on the industry and occupation of each respondent's main job, enabling us to examine the effect of heat exposure on workers in different industries and occupations.[21] Since we are especially interested in understanding the effects of heat stress in climate-exposed industries that are similar to the airline sector, we define four industries as "outdoor" sectors for which work is largely conducted outside: a) Agriculture, Forestry, Fishing, and Hunting, b) Mining, c) Construction, and d) Transportation and Utilities.[22] We run separate analyses for workers who are employed in "outdoor" industries and those who are in transportation and material moving occupations.[23]

Next, we collect daily weather data from the Daymet project (Thornton et al. 2020) and link it with the ATUS data set. The Daymet project provides daily minimum and maximum temperatures, precipitation, vapor pressure, radiation, snow water equivalent, and day length on a 1 km $\times$ 1 km gridded surface. We map these gridded daily weather parameters to counties using the longitude and latitude coordinates of the centroid of each county.[24]

We restrict our sample to full-time employed individuals. To measure workers' intertemporal labor supply, we create two variables: "Working Time" measures minutes spent on work and work-related activities.[25] $\mathbb{1}(\text{Absence Last Week})$ denotes a binary indicator which equals one if the

[21]There are 13 industry categories in the ATUS data: 1) Agriculture, Forestry, Fishing, and Hunting, 2) Mining, 3) Construction, 4) Manufacturing, 5) Wholesale and Retail Trade, 6) Transportation and Utilities, 7) Information, 8) Financial Activities, 9) Professional and Business Services, 10) Educational and Health Services, 11) Leisure and Hospitality, 12) Other Services, and 13) Public Administration.

[22]This is similar to the definitions of heat-exposed industries by the National Institute for Occupational Safety and Health (NIOSH 1986).

[23]ATUS classifies occupations into 10 categories: 1) Management, Business, and Financial Occupations, 2) Professional and Related Occupations, 3) Service Occupations, 4) Sales and Related Occupations, 5) Office and Administrative Support Occupations, 6) Farming, Fishing, and Forestry Occupations, 7) Construction and Extraction Occupations, 8) Installation, Maintenance, and Repair Occupations, 9) Production Occupations, 10) Transportation and Material Moving Occupations.

[24]We merge the 2005-2019 ATUS data with the Daymet weather data using the county FIPS or the CBSA/MSA code. We are able to identify the geographic location for 80% of the entire sample, where about 56% of them are identified by the county FIPS code, 40% of them are identified by the CBSA/MSA code, and 4% of them are identified by the NECTA code.

[25]For work and work-related activities, we include time spent on activities in categories 0501 and 0502. See the American Time Use Survey Activity Lexicon 2003-2019 for more details.

respondent was absent from work in the past week. Two additional variables capture respondents' sleep patterns. The first measures the respondents' sleep time during the diary day in minutes, while the second indicates whether the respondent experienced any sleeplessness.[26] Moreover, we create two dummy variables signaling the respondent's general health. One indicates whether the respondent felt worse than a typical day, while the other indicates whether the respondent felt not well-rested on the diary day.

Similar to the temperature variables defined in the main analysis, we categorize daily maximum temperatures into five bins: less than or equal to 20C, between 20C and 25C, between 25C and 30C, between 30C and 35C, and above 35C. We also calculate the number of days within the past week in which the daily maximum temperature falls into each of the five temperature categories.

We present the summary statistics of the variables used to explore potential mechanisms in Table 2. The average working time is 278 minutes, equivalent to about 4.6 hours, while the average absenteeism rate in the past week is 4%. The average sleep time is about 8.5 hours, and approximately 4% of respondents report experiencing sleeplessness. 21% of respondents from the WB module report not feeling well-rested on the diary day.[27] Lastly, 7% of respondents in the sample report feeling that their general health was worse than on a typical day.

3 Heat and Airline Productivity

3.1 Empirical Strategy

We analyze the causal effect of heat exposure on airline productivity using high-frequency flight performance and weather data that leverages temperature variation within the same micro-context such as flight route. First, we consider the contemporaneous impact of heat exposure by estimating

[26]The ATUS data also collect self-reported sleeplessness time. However, we are concerned that this self-reported variable may suffer from non-negligible measurement error, as it relies on respondents' subjective recall rather than reliable equipment monitoring of their sleep periods. Conversely, while individuals may not have an accurate understanding of the exact time of sleeplessness, they should remember whether they experienced sleeplessness. Therefore, we use a dummy indicator to measure the probability of sleeplessness.

[27]Since the sample size of the regular module is about six times larger than that of the WB module, the proportion of respondents reporting sleeplessness is consistent with the proportion of those reporting not feeling well-rested.

the following model:

$$\text{OnTimePerformance}_{idh} = \sum_{j} \beta_j \text{Temp}_{idh}(B_j) + \zeta \mathbf{X}_{idh} + \gamma + \eta \text{Flights}_{idh} + \varepsilon_{idh} \tag{1}$$

where i denotes the departure airport, d is the day of flight operation, and h indexes the time block of flight departure. The outcome variable is represented by the cancellation rate, departure delay rate, or departure delay time variables as described in Section 2.1. Temp_{idh} denotes the treatment variable categorized in five bins (B_j): $\leq 20C(baseline), (20C, 25C], (25C, 30C], (30C, 35C]$, and $> 35C$. We are interested in the coefficient β_j, which gives the effect of temperatures falling in the bin B_j, relative to the reference bin of temperatures less than or equal to 20C.

To isolate the effect of heat from the impact of other weather-related factors such as rainfall or wind, we control for time-varying weather conditions ($\mathbf{X}_{idh}$), including hourly precipitation and its quadratic polynomial, relative humidity, obscuration (visibility), and wind speed. Flights_{idh} denotes the number of flights departure from airport i in day d at time block h. It indicates the level of traffic congestion in the origin airport. Since traffic congestion plays an important role in affecting flight cancellations and delays, controlling for this confounding factor helps reduce omitted variable bias in the estimation. Moreover, we incorporate a rich vector of fixed effects, denoted by γ. This includes month by year, day of week, and time block fixed effects to account for seasonal, day-of-week, and hourly patterns governing airlines' on-time performance. Crucially, γ embeds origin-destination pair fixed effects, which control for time-invariant factors that are specific to the route between the origin and destination. Given the potential variation in airline productivity across different carriers, our preferred model also includes carrier fixed effects to account for carrier-specific confounding factors. We furthermore experiment with replacing the origin-destination pair fixed effects with origin fixed effects, while still including carrier fixed effects. This allows us to examine whether the estimates are sensitive to changes in model specifications.

In addition to contemporaneous exposure to high temperatures, workers may also suffer from prolonged exposure to heat stress. Its impact may take time to emerge, leading to a lagged effect on labor productivity. For example, workers whose shifts extend to cooler temperature at night could still experience the cumulative impact of heat stress from earlier exposure during the day. To investigate whether this cumulative daytime heat exposure (defined as 5am - 6pm) affects flight on-time performance later in the same day (especially after sunset when the temperature is cooler), we create a discrete variable on same-day cumulative exposure ($\text{CumulativeTemp35C}_{id}$) which counts the number of hours when temperature exceeds $35C$ during 5am-6pm. We regress each on-time performance outcome for flights operating after 8pm on this same-day-cumulative heat exposure measure using the following model:

$$\begin{aligned} \text{OnTimePerformance}_{idh} = \beta_j \sum_j \text{Temp}_{idh}(B_j) + \chi \text{CumulativeTemp35C}_{id} \\ + \zeta \mathbf{X}_{idh} + \gamma + \eta \text{Flights}_{idh} + \varepsilon_{idh}, \text{ where } h \in \{20, 21, 22, 23\} \end{aligned} \tag{2}$$

Conditioning on the concurrent temperature and weather conditions, χ captures the delayed effect of heat stress exposure on the same day.

3.2 The Effect of Contemporaneous Exposure

We first show estimation results corresponding to Equation (1), which regresses flight on-time performance measures on contemporaneous temperature bins. Columns (1) to (3) of Table 3 present the estimated coefficient and the corresponding percentage effect, relative to the sample mean of each outcome, of each temperature group for the cancellation rate, departure delay rate, and delay time, respectively.

Column (1) shows that flights are more likely to be cancelled at higher temperatures relative to those operating below 20 degrees Celsius. The effect magnitudes are 0.15 p.p. at temperatures above 35C, with the corresponding percentage effects estimated at 24% relative to the sample mean cancellation rate. The estimated effects decrease non-linearly for milder temperatures, with the percentage effects estimated at 13%, 9%, and 5% for temperature bins 30C-35C, 25C-30C, and 20C-25C.

Conditional on flights not being cancelled, results in Columns (2) and (3) suggest that flights operating at high temperatures would experience not only a higher rate of departure delay, but also longer departure delay time. Column (2) shows that compared to flights departing at temperatures below 20C, the rate of departure delays is between 0.4-1.1 p.p. higher for flights departing during hotter periods. The corresponding percentage effects are estimated at 3%, 4%, 6%, and 7%

for the 5-degree temperature bins, respectively. Note that the relative effect magnitudes are not as apparently non-linear for the delay rate measure as compared to the cancellation rate, which accelerates markedly with higher temperatures.

In addition to affecting the probability of departure delays, high temperatures could also affect the length of delay time. The evidence in Column (3) is consistent with this conjecture. Specifically, we find that on average, flights experience a 0.4 minute longer departure delay at temperatures between 25C and 30C, compared to flights departing at temperatures below 20C. It is equivalent to a 8% increase relative to the sample average delay time. The magnitude of the effect increases to 13% (0.7 minutes) when operating at temperatures between 30C and 35C, and 18% (1 minute) when operating at temperatures above 35C.

Compared to existing studies that quantify the impact of high temperatures on worker productivity in manufacturing and service industries, the magnitudes of our estimated heat effects are at least as large, if not greater. For example, Somanathan et al. (2021) find that exposure to an additional hot day reduces worker output from 2% to 8%, depending on industry, climate adaptation, and workplace context.[28] Cachon, Gallino, and Olivares (2012) use data on weekly automobile production at 64 facilities in the United States and find that a week with six or more days of heat exceeding 32 degrees Celsius is associated with a reduction in weekly production by 8% on average.

We conjecture that several factors contribute to this difference. First, the effect of high temperatures on flight delays can be partly attributed to the performance of airline and airport crews working in outdoor or semi-outdoor environments. For example, workers involved in baggage loading, fueling, or aircraft maintenance may be affected. Compared to existing studies considering indoor workers, effects could be larger in our context as workers are directly exposed to outdoor environments where climate control is unlikely, making them more vulnerable to heat stress and fatigue. Additionally, since we are not considering individual worker output such as the number of phone calls handled per labor unit per work time, our results may not be directly comparable to existing studies that explore the impact of higher temperatures on worker productivity at the plant level.

[28]For example, non-climate controlled garment plants saw a reduction in average daily efficiency by up to 8%, compared to 2% in the weaving industry.

3.3 The Effect of Same Day Cumulative Exposure

In addition to examining the contemporaneous effect of heat exposure, we explore the effect of same-day cumulative exposure. To do so, we estimate Equation (2) where the treatment variable is defined as the number of hours during the period from 5am to 6pm when the temperature exceeds 35C. We regress the flight on-time performance outcomes measured later in the same day (after 8pm), while controlling for the current temperature. Table 4 presents the estimation results corresponding to the cancellation rate, departure delay rate, and departure delay time. The estimated effects of the same-day cumulative exposure are generally much smaller than the effect of same-day contemporaneous exposure. Column (1) shows that same-day cumulative exposure to heat has little impact on flight cancellations later in the day. However, there is evidence that the effect of heat exposure persists and impacts departure delays later in the same day. An additional hour of heat exposure (temperature above 35C) during the day is estimated to increase the departure delay rate starting in the early evening by 0.5 p.p. (2%) and the delay time by 0.1 minutes (1%).[29] This suggests that high temperatures can exert a negative productivity effect that endures several hours after the initial exposure.

3.4 Heterogeneous Impacts

For the rest of this section, we explore heterogeneity in the effect of high temperatures on flight on-time performance. We begin by examining whether the effect varies across origin airports of different sizes, as measured by annual passenger boarding. The impact of heat exposure could be amplified at large hub airports given the complexity of flight operations in a high traffic airport, or it may attenuate if larger airports have more resources for climate adaptation and flexibility around staffing or is more efficient in other aspects of airline operations. To investigate this question empirically, we re-run the model of Equation (1) separately for large-hub, medium-hub, small-hub, and nonhub airports. We summarize the estimation results in Figure 3, which plots point estimates and their 95% confidence intervals of the effect of temperatures greater than 35C, relative to the

[29]Note that estimated coefficients for the contemporaneous temperature groups are of the same sign and similar magnitudes compared to the previous table.

reference bin of temperatures below or equal to 20C.

We find that the effect of operating at temperatures exceeding 35C is significantly more pronounced for small hub and nonhub airports. Operating at temperatures above 35C increases cancellation rates by 47% for nonhub airports and 35% for small hub airports, compared to 22% for large hub airports and 10% for medium hub airports. Similar patterns are found for the departure delay rate. The productivity impact of operating at temperatures above 35C on the departure delay rate, compared to flights departing at temperatures below 20C, is statistically significantly higher for small hub airports (11%) and nonhub airports (12%) compared to large hub airports (5%) and medium hub airports (6%). Additionally, conditional on experiencing departure delays, high temperatures have a substantial impact on the duration of departure delay time for large hub, small hub, and nonhub airports, but a comparatively smaller effect for medium hub airports.

In further exploring these heterogeneous treatment effects across airport types, we stratify by flight characteristics. Specifically, we examine whether the impact of heat exposure varies between short-haul and medium/long-haul flights. Figure 4 shows that the negative effects on cancellations and delays are primarily driven by short-haul flights. The concentration of shorter flights out of smaller regional hubs likely contributes to the findings by airport size above.

3.5 Robustness

We undertake a number of additional analyses to ensure that our findings are insensitive to the choice of temperature measure and model specifications, and are robust to the inclusion of air pollution controls. First, we replace our use of apparent or feels-like temperature with the real air temperature. The former takes into consideration wind and humidity and is designed to better represent the human body's perception of heat. As such, these two scales can sometimes significantly diverge. Reassuringly, Table B.1 finds that coefficients are qualitatively unchanged when using actual air temperatures.

Next we explore whether estimates are sensitive to the inclusion of air carrier and route (destination-origin) fixed effects. Table B.2 shows that our results across all three airline on-time performance measures are nearly unchanged when excluding carrier fixed effects or replacing route with origin airport fixed effects.

Finally, we consider the possibility that the adverse impact of heat may be mediated through deteriorating air pollution.[30] In Table B.3, we control for time-varying pollution measures including CO, NO2, ozone, and PM2.5 to better distinguish the impact of higher temperatures from poor air quality.[31] Panel A replicates our main findings on the contemporaneous effect of heat exposure using a smaller sample with non-missing air quality data. The results from Panel B, based on a model that includes controls for various types of air pollution, show coefficients that are statistically indistinguishable from estimates using the original model.

4 Exploration of Mechanisms

4.1 Conceptual Framework and Extant Literature

Heat can affect the productivity of the airline industry through several channels. The first is through reductions in labor supply. Higher temperatures can change the marginal cost of providing labor or the marginal productivity of labor, thereby influencing individual decisions to allocate time to work. Labor shortages can arise when workers choose not to work or reduce the hours worked on hotter days. While empirical evidence on this topic is limited, existing research show moderate decreases in labor supply in response to high temperatures, with larger effects concentrated in more climate-exposed industries such as mining, construction, and transportation and utilities (Graff Zivin and Neidell 2014).[32] Worker absenteeism and reduced hours can also have spillover effects by imposing extra burdens on colleagues and changing their labor supply via channels such as increased absenteeism (Godøy and Dale-Olsen 2018).

Another channel through which heat can influence productivity is through on-the-job performance. Higher temperatures can adversely affect the task performance of workers in the airline

[30]Chen et al. (2023) use flight-level data and granular air pollution measures to show that rising levels of PM2.5 significantly increase flight departure delays.

[31]Following Schlenker and Walker (2016), daily airport-level air pollution is measured by taking the average of monitor readings from all monitors within 100 km of the airport, weighting by the inverse distance between the monitor and the airport.

[32]In addition to heat, individuals' time allocation also adjust to changes in other environmental factors such as rainfall (Connolly 2008).

sector, particularly those with greater exposure to heat, such as ground crews.[33] A substantial literature documents the negative impacts of heat on dimensions of health, including reduced physical work capacity, occupational health issues, and increased mortality (Deschênes and Greenstone 2011; Heal and Park 2016; Barreca et al. 2016; Ebi et al. 2021; Carleton et al. 2022). In a meta-analysis of 447 million workers across 40 countries, the consequences of occupational exposure to heat stress included productivity losses, hyperthermia, and kidney disease or acute kidney injury (Flouris et al. 2018). In addition to the physiological effects described above, heat exposure has also been shown to diminish cognitive performance, with the effect varying by type of task (Hancock and Vasmatzidis 2003). The economics literature, for example, has documented negative effects of extreme temperatures on cognition, as measured by student performance in countries such as the United States, Canada, and India (Park et al. 2020; Park 2020; Cook and Heyes 2020; Garg, Jagnani, and Taraz 2020; Park, Behrer, and Goodman 2021).

Lastly, heat may have productivity effects on airline operations via non-labor channels. Flights operating in high temperatures may have more mechanical issues and are subject to different operating thresholds. Specifically, warmer air is less dense and generates less lift at a given speed, such that there are temperature thresholds above which airplanes must be weight restricted (Coffel and Horton 2015). These can generate flight cancellations and delays, although instances are limited to more extreme temperatures.

4.2 Empirical Strategy

The effects we estimate in this paper are inclusive of all three channels discussed above. We undertake several analyses to illuminate the underlying mechanisms. First, we utilize time-use data to investigate whether workers, particularly those in the transportation and logistics sector, adjust their labor supply in response to high temperatures. Next, employing the same time-use data, we analyze the impact of high temperatures on workers' sleep patterns (sleep time and quality) and well-being. Specifically, we estimate whether individuals exposed to heat experience a reduction in sleep duration, an increased likelihood of sleeplessness, and reduced well-being as measured by

[33] Airport workers can be at particularly high risk of heat stress due to the heat-amplifying effects of asphalt and the need for wearing protective gear (Gelles and Andreoni 2023).

feeling not well-rested and worse than in a typical day.[34]

We adopt the following models to investigate the effect of high temperatures on worker labor supply, sleep, and well-being. We use j to denote a respondent, t to denote a diary day, and c to denote the geographic unit the respondent resides. Following Connolly (2008) and Graff Zivin and Neidell (2014), we set up our baseline model as:

$$Y_{jct} = \delta_j \sum_j \text{Max Temp}_{ct}(B_j) + \omega \mathbf{V}_j + \theta \mathbf{Z}_{ct} + f(month, year, dow, c) + \varepsilon_{jct} \tag{3}$$

where Y_{jct} denotes outcome variables measuring worker labor supply, sleep, and well-being, including working and sleep time (both in minutes) and the sleeplessness indicator for individual j on a diary day t. Following the specification in the main analysis, we categorize the daily maximum temperature (Max Temp$_{ct}$) into five bins (denoted as B_j): $\leq 20C, (20C, 25C], (25C, 30C], (30C, 35C]$, and $> 35C$, and set $\leq 20C$ as the reference bin. We control for other time-varying weather attributes ($\mathbf{Z}_{ct}$) that are potentially correlated with the outcome, such as day length and daily precipitation. $\mathbf{V}_j$ is a vector of individual-level covariates as listed in Table 2. $f(month, year, dow, c)$ denotes a set of dummy variables, including day of week dummies to account for differences in schedules throughout the week, and year and month dummy variables to control for seasonal and annual time trends in the outcome. It also includes location dummies that capture all time-invariant observable and unobservable attributes that affect the outcome. The parameter of interest is δ_j, which captures the effect of high temperatures on individuals' hours worked, sleep patterns, and well-being. Moreover, because the absenteeism indicator is measured in the last week, we adopt a slightly different model where the treatment variable of maximum temperatures and weather attributes are also measured at the weekly level. Instead of using a day of week dummy (dow), we substitute it with a week dummy.[35]

[34]We employ Equation (3) and regress working time, measures of sleep patterns, and well-being outcomes on heat indicators and weather covariates. For the work absenteeism outcome, we estimate Equation (4). All regressions are weighted by the corresponding final weights provided by ATUS.

[35]Specifically, we consider the following model:

$$\mathbb{1}(Absence_{jcw}) = \alpha_j \sum_j \sum \mathbb{1}(\text{Max Temp}_{c,w} \in B_j) + \sigma \mathbf{V}_j + \eta \mathbf{W}_{cw} + f(month, year, w, c) + \varepsilon_{jcw} \tag{4}$$

4.3 The Effect on Worker Labor Supply, Sleep, and Well-being

Panel A of Table 5 summarizes the estimated effects on working time. Results from Column (1) using the full-time employed individual sample suggest a negative effect of high temperatures on hours worked. Restricting to respondents who work in outdoor industries in Column (2) yields a substantially larger effect. For example, workers are found to work about 39 minutes fewer on days with daily maximum temperature above 35C and about 30 minutes fewer on days with daily maximum temperature between 30C and 35C.[36] Column (3) further limits the sample to workers in transportation and material moving occupations. The reduction in hours worked in response to high temperatures for this type of worker is larger than the effects found for outdoor workers. Specifically, workers in transportation and material moving occupations reduce their average hours worked by about an hour on high temperature days with daily maximum temperature between 30C and 35C and by 82 minutes on extreme heat days when daily maximum temperature exceeds 35C.

Turning to the effect on work absenteeism, Panel B of Table 5 suggests that the changes in workers' intertemporal labor supply in response to high temperatures are not limited to their hours worked but also manifest in their likelihood of going to work on the same day. For instance, Column (1) shows that, on average, having one additional day with a daily maximum temperature above 35C in the past week yields a statistically significant increase in the probability of work absence of approximately 0.3 p.p. for full-time employed respondents. In the case of workers in the outdoor sector, the effect becomes even larger, at around 0.7 p.p. The estimates for the transportation and material moving occupations sample are of a similar magnitude (0.8 p.p.).

Our estimates of the impact of high temperatures on work absenteeism is consistent with the magnitude of findings from India manufacturing industries (Adhvaryu, Kala, and Nyshadham 2020; Somanathan et al. 2021). For example, in Somanathan et al. (2021), an additional day above 35 degrees Celsius in the six preceding days causes a 0.5 p.p. increase in the probability of missing

where w denotes the week before the week of the diary day t. $\sum \mathbb{1}(\text{Max Temp}_{c,w} \in B_j)$ denotes the count of days with maximum temperature that falls within a certain temperature bin (B_j) in the past week. $\mathbf{W}_{cw}$ denotes weekly weather attributes, including weekly mean daylight and weekly accumulated precipitation. The parameter α_j captures the change in the work absenteeism rate with respect to high temperatures.

[36]Recall that we classify four industries as the "outdoor sector": 1) Agriculture, Forestry, Fishing, and Hunting, 2) Mining, 3) Construction, and 4) Transportation and Utilities. We classify respondents' working industry using the major industry code for the main job provided by the ATUS.

work for weavers in India working in a non-climate controlled setting. Our estimates of 0.3 to 0.8 p.p. across a range of samples is inclusive of this point estimate.

Table 6 presents the estimated heat effects on worker's sleep duration and quality. We find suggestive evidence that high temperatures negatively affect workers' sleep by reducing their average sleep time and increasing their likelihood of sleeplessness. For example, Column (1) of Panel A shows that on average, individuals sleep 9 minutes less on hotter days when daily maximum temperature exceeds 35C, compared to days when the temperature does not exceed 20C. However, results for the sub-samples of outdoor workers (Column 2) and workers in transportation and material moving occupations (Column 3) are not sufficiently precise, likely due to their small sample size. In Panel B, Column (1) shows that on average, workers are more likely to experience sleeplessness on hotter days when daily maximum temperature is above 35C, by about 2 p.p.. Although we do not find statistically significant effects for outdoor workers (in Column 2), Column (3) shows that the effect is of greater size and statistically different from zero for workers in transportation and material moving occupations, at about 6 p.p..

In Table 7, we report the estimation results of two well-being outcomes, one indicating whether the respondent felt not well-rested (Column 1), with the other indicating whether the respondent felt worse than a typical day (Column 2). Column (1) shows that individuals are 6 p.p. more likely to report that they felt not well-rested on days with daily maximum temperature above 35C, relative to a mild day with daily maximum temperature below 20C. This finding echoes the result in Panel B of Table 6 that individuals are more likely to experience sleeplessness on hotter days. There is no statistically significant evidence that individuals become more likely to feel worse in terms of general health than typical, although supplemental analyses using a much smaller sample suggests significant adverse impacts on well-being.[37]

The evidence presented in this section indicates that labor channels, including reductions in labor supply and declines in on-the-job performance, likely contribute to the adverse impact of heat on airline productivity found in the main analysis. Specifically, we find evidence suggesting

[37]Appendix Table B.4 shows that full-time employed workers are more likely to report feeling not happy (by about 14%), in pain (by about 8%), and sad (by about 6%) at work and work-related activities on hotter days when daily maximum temperature exceeds 35C.

that heat can lead to a decrease in labor supply, resulting in fewer hours worked and an increase in work absenteeism. Furthermore, our results suggest that heat negatively affects workers' sleep (both duration and quality) and well-being, leading them to feel unhappy, tired, and not well-rested. Previous studies have established a strong correlation between sleep, well-being, and workers' labor productivity (Bubonya, Cobb-Clark, and Wooden 2017; Gibson and Shrader 2018). Thus, we provide indirect evidence suggesting that heat is likely to be negatively correlated with workers' on-the-job performance through channels that result in poorer sleep and declines in well-being.[38]

5 Exploration of Adaptive Strategies

In this section we consider the possibility that workers and airlines have differing abilities to acclimatize to high temperatures depending on the region's usual climate conditions. To gauge whether heat effects vary across average temperatures, we borrow the classification of climate zones from the International Energy Conservation Code (IECC 2015), which defines various climate regions based on average temperatures, precipitation, and related temperature-based metrics (International Code Council 2015). Panel (a) of Figure 5 illustrates the distribution of climate zone for the contiguous U.S. according to the definition of IECC 2015, while Panel (b) plots the number of airports for each climate zone along with their average daily temperatures from April to September. Zones 1 and 2 comprise the hottest zones with an average temperature of approximately 30C. This group includes airports in some of the warmest areas of the Southeast and Southwest including Phoenix, Houston, Miami, and Orlando. This is followed by Zone 3 with an average temperature of 24C covering significant portions of southern and southwestern states. The coldest zones 6 and 7 range from eastern Washington to the Rockies, Minnesota, and Wisconsin all the way to the

[38]Another possibility is that poorer sleep can also affect workers' intertemporal labor supply, reducing hours worked and increasing the likelihood of work absenteeism. To investigate this conjecture, we conduct a complementary analysis by regressing hours worked on temperature variables, adopting the model in Equation (3), while including additional controls for the duration of sleep time and a dummy variable indicating the occurrence of sleeplessness. Due to data limitations, we are unable to conduct a similar analysis for the work absenteeism rate. We report the estimation results in Appendix Table B.5. Comparing Panel A of Table 5 and Table B.5, we find that the corresponding estimates are similar and not significantly different from each other. We interpret these results as supporting evidence that poorer sleep likely has a limited impact on hours worked and labor supply.

northeastern states of New York, Vermont, New Hampshire, and Maine.[39]

Figure 6 shows the estimated results across climate zones for temperatures greater than 35C, relative to the reference bin of temperatures less than or equal to 20C.[40] The estimated heat effect exhibits an inverse-U-shaped relationship across airports located in warmer and cooler regions. Zones 3-5 experiencing milder climates show greater vulnerability to heat exposure, whereas consistently hot areas (Zone 1 and Zone 2) are relatively less affected. We conjecture that factors such as the infrequent occurrence of higher temperatures in milder zones and the adoption of adaptive strategies by workers and airlines in the hottest regions may contribute to the smaller effect. Notably, cooler areas (Zone 6 and Zone 7) also demonstrate lower levels of impact.

To explore potential variation in adaptation across regions, we examine effects on the labor supply and sleep quality of workers from different climate zones.[41] The upper panels of Figure 7 illustrate that worker hours and absenteeism rates in hotter regions (Zone 1 and Zone 2) are insensitive to high temperatures exceeding 35C, while workers in Zone 4 had fewer hours worked and those in Zone 3 showed elevated absenteeism rates. We find similar patterns when shifting to sleep patterns, with workers in Zone 3 exhibiting a significant reduction in sleep time, and those in Zones 3 and 4 experiencing an uptick in incidences of sleeplessness. The lack of any notable shifts along these margins for those residing in the hottest climate zones suggests that adaptive measures may extend outside of the workplace context into other aspects of the built environment, such as residential homes.

6 Conclusion

Rising global temperatures underscore the urgency of establishing the impact of heat on productivity across workplace contexts. In this paper, we investigate the effects of heat on productivity in a U.S.

[39] We consolidate airports in Zone 1 and Zone 2 into one group and airports in Zone 6 and Zone 7 into one group, because i) a relatively small share of airports are located in Zone 1 and Zone 7 (1% in Zone 1 and 5% in Zone 7), as shown in Figure 5b and ii) the average temperatures during our sample period are similar between Zone 1 and Zone 2, as well as between Zone 6 and Zone 7.

[40] We estimate a slightly modified model of Equation (1). The adjusted model additionally includes the temperature variables interacted with climate zone dummies, as well as climate zone and airport type fixed effects.

[41] Due to the small sample size of the well-being data, we are unable to explore the heterogeneous impacts on this aspect.

sector that is climate-exposed: the airline industry. By utilizing granular data on flight on-time performance linked with hourly meteorological variables, and employing a model augmented with a rich set of fixed effects, we find statistically significant evidence that high temperatures increase the cancellation rate, departure delay rate, and departure delay time of flights. The negative effect on flight on-time performance is not limited to immediate exposure but also persists through later periods during the same day. Our estimates remain robust across different model specifications, accounting for the impact of air pollution, and various measures of heat.

We find that small-hub and nonhub airports are particularly vulnerable to the shock of rising temperatures, with flight routes connecting these airports experiencing larger productivity losses. In addition, airports located in regions with milder climates are found to be more adversely affected by heat, compared to those in the hottest climate zones. Our finding of heterogeneous effects across areas with different climate conditions, market sizes, and enplanement underscores how climate change disproportionately affects certain regions and undermines equitable development.

Supplemental analyses employing time use data illuminates potential mechanisms behind the effects of heat stress. We find that higher temperatures reduce workers' intertemporal labor supply, with more pronounced effects among workers in outdoor sectors or engaged in transportation and material moving, suggesting that declines in airlines' on-time performance can be partially attributed to reduced hours and higher absenteeism. We also find negative impacts on sleep duration and quality as well as measures of well-being. These relatively under-studied channels of heat stress contribute further to erosion in labor productivity, namely through deteriorating on-the-job-performance.

Our analysis reveals heterogeneous heat effects across regions, where airlines and workers may have different acclimatization abilities. This underscores the importance of assessing effective adaptive strategies and designing appropriate policies. Moreover, this paper's focus on a service-based industry in the United States expands existing evidence on the consequences of heat exposure to non-manufacturing sectors that are vulnerable to the changing climate. Adaptation via climate control is expensive or infeasible in many similar contexts, and alternative long-term adaptive strategies may be necessary. These topics are fertile grounds for future research.

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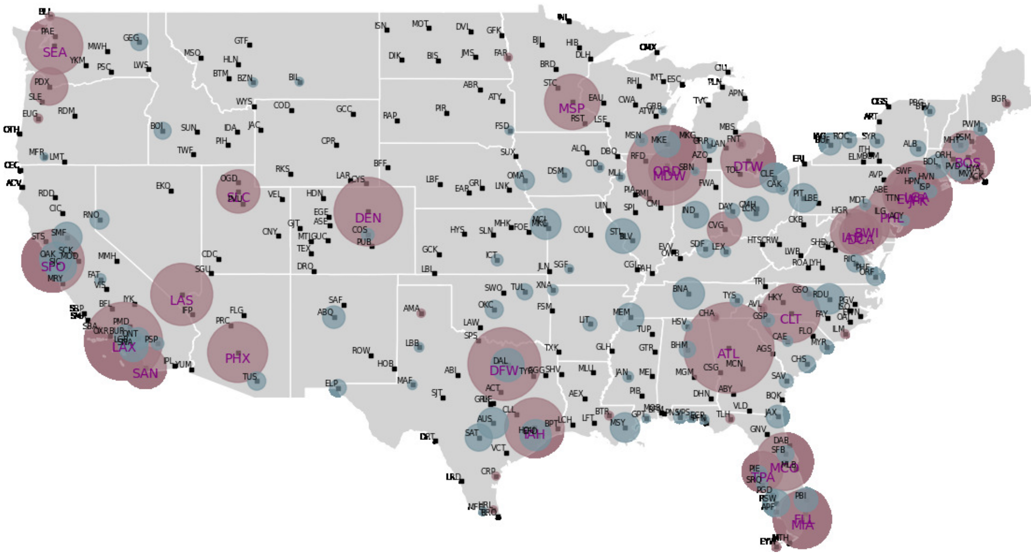
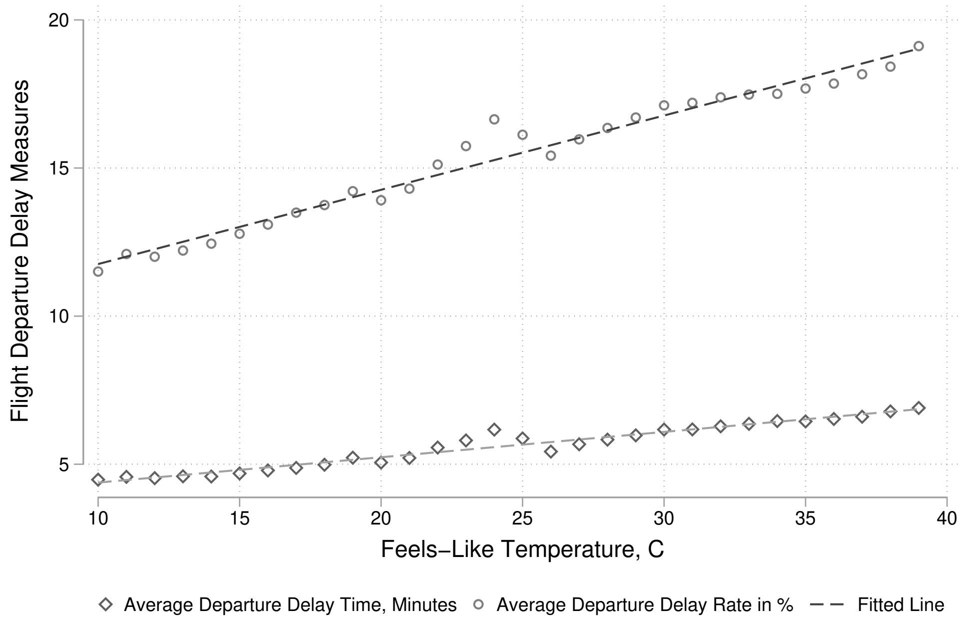
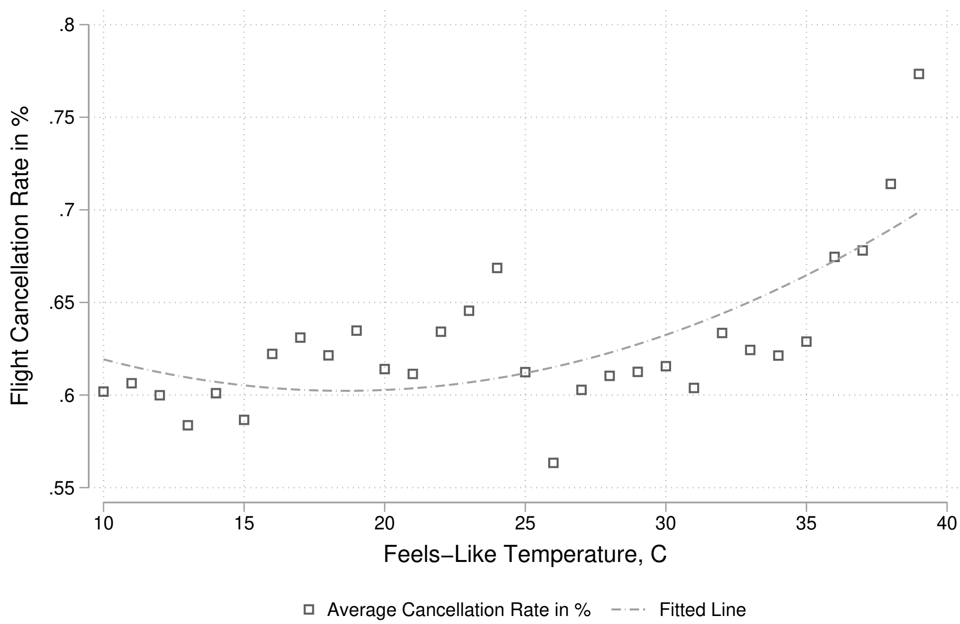


Figure 1: Airports in Sample and Their Average Annual Enplanements, 2004-2019

Notes: This bubble map summarizes airports in the sample and their average annual passenger boarding (enplanements) over 2004-2019. The size of the bubble indicates the share of airport's annual enplanements. We use red to flag large hub airports, defined by FAA as airports receiving 1 percent or more of the annual U.S. commercial enplanements.



(a) Departure Delay Measures



(b) Cancellation

Figure 2: Association Between Temperatures and Flight On-Time Performance

Notes: This figure plots the correlation between feels-like temperatures (in Celsius) and the average flight departure delay time (in minutes), departure delay rate, and cancellation rate, over flights departed at given temperature levels.

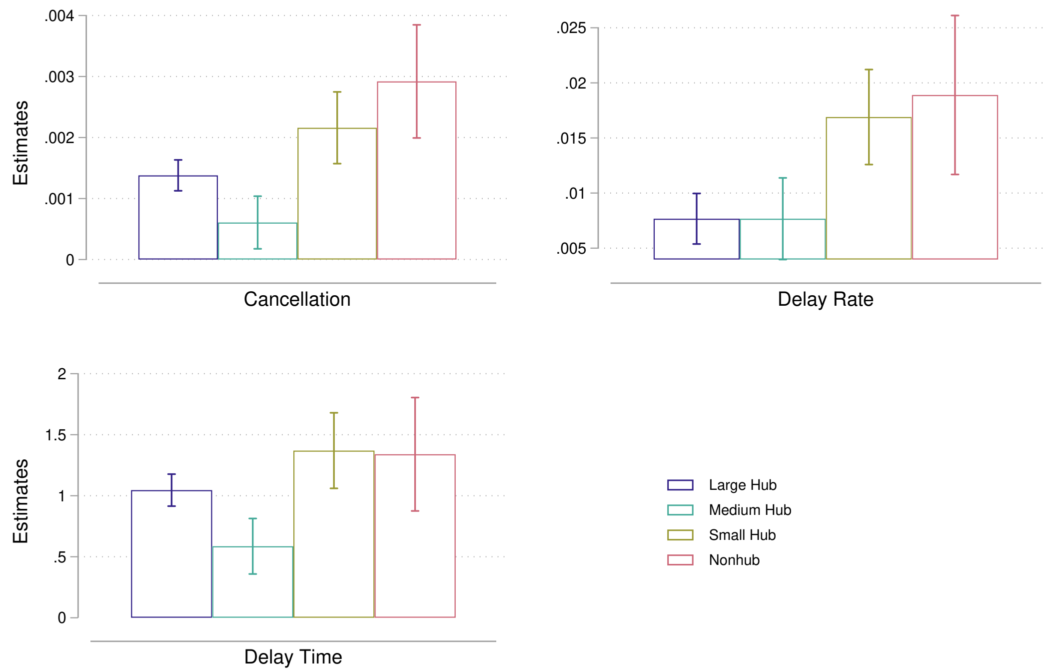


Figure 3: Heterogeneous Effects by Origin Airport Type

Notes: This figure summarizes the point estimates and their 95% confidence intervals of the effect of temperatures falling in the bin $> 35C$, relative to the reference bin of temperatures below or equal to 20C by the origin airport type and for outcomes of the cancellation rate, departure delay rate, and delay time, respectively

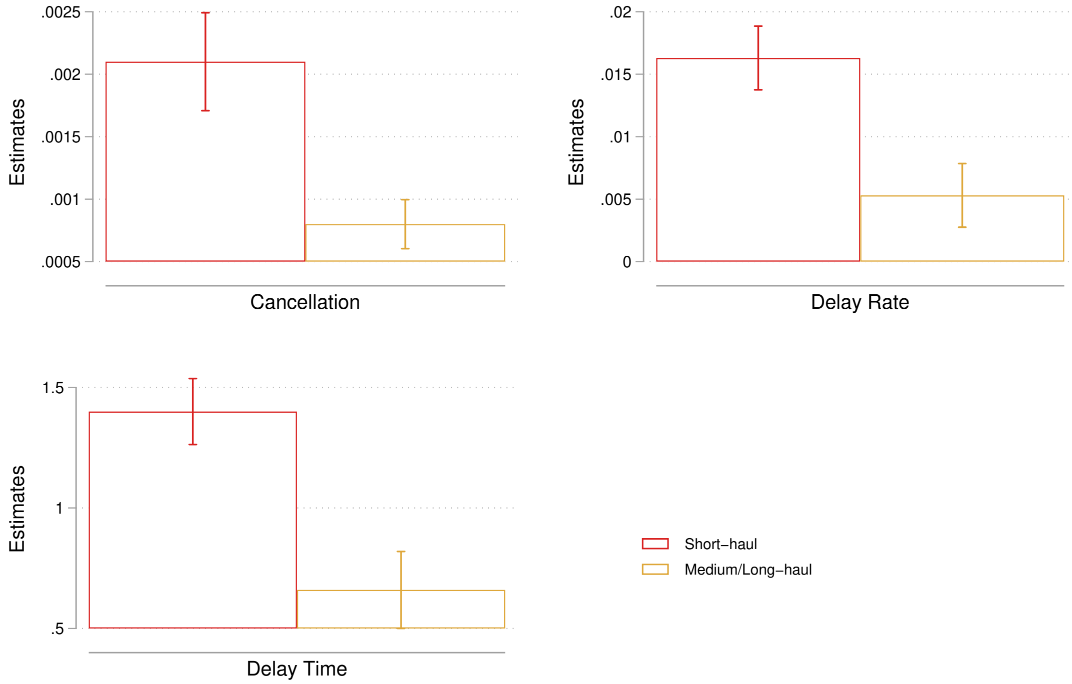
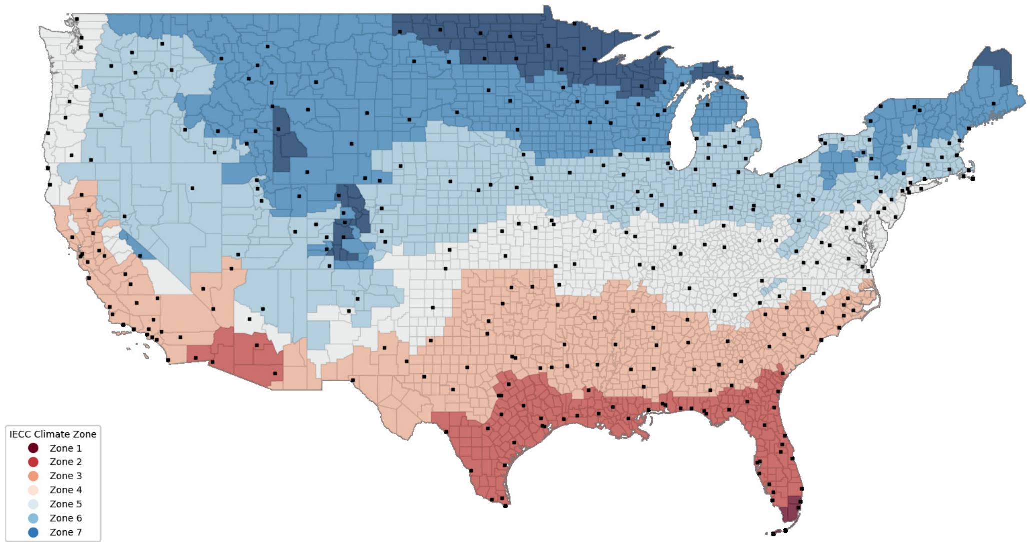
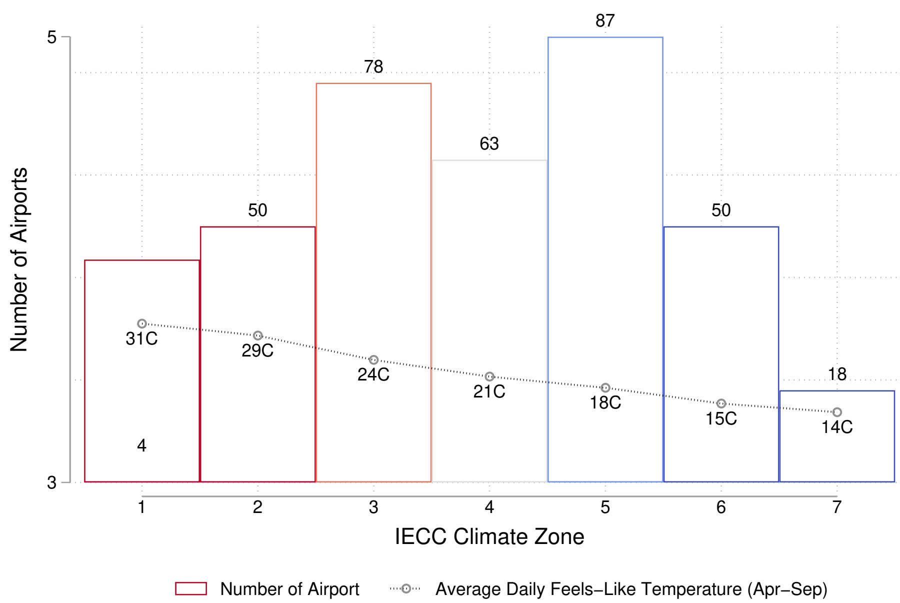


Figure 4: Heterogeneous Effects by Flight Length

Notes: This figure summarizes the point estimates and their 95% confidence intervals of temperatures falling in the treatment bin of greater than 35C, relative to the reference bin of less than or equal to 20C, for outcomes cancellation rate, departure delay rate, and delay time, separately for short-haul and medium/long-haul flights. Following Wragg (1973) and Crocker (2005), we define medium/long-haul flights as those with a distance greater than 1000 km and short-haul flights as those with a distance less than 1000 km.



(a) U.S. Climate Zone



(b) Airport Distribution and Average Temperature

Figure 5: U.S. Climate Zone and Airports

Notes: This figure presents airports in our sample by climate zone and their distribution across climate zones. Panel (a) illustrates the climate zone of the contiguous U.S. according to the IECC 2015 definition, while Panel (b) shows a histogram of airports by climate zone and the average temperature for each climate zone over months April to September in Celsius.

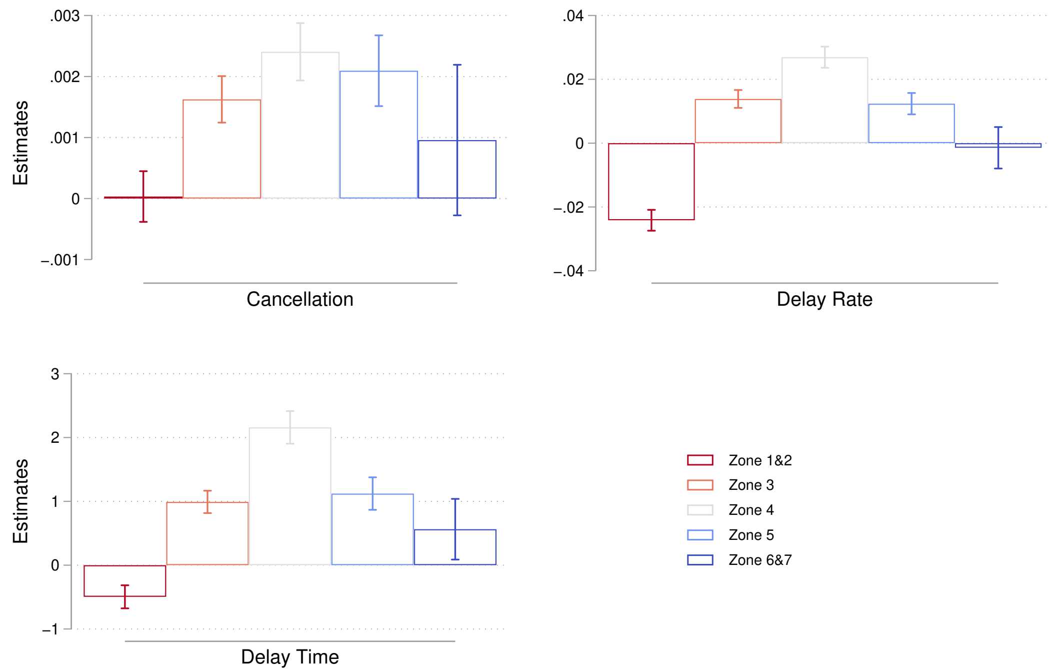


Figure 6: Heterogeneous Effects on Flight On-Time Performance by Climate Zone

Notes: This figure summarizes the point estimates and their 95% confidence intervals of the effect of temperatures falling in the bin $> 35C$, relative to the reference bin of temperatures less than or equal to 20C, by climate zone and for outcomes of the cancellation rate, departure delay rate, and delay time, respectively. The negative effects on departure delays found for Zone 1 and Zone 2 are likely driven by the fact that temperatures below or equal to 20C are comparatively colder compared to their usual climate of 30C. Appendix Figure A.1 shows that the corresponding effects turn positive for Zone 1 and Zone 2 when the reference temperature group is changed from below or equal to 20C to between 30C and 35C (which aligns with the average temperature range for these two Zones).

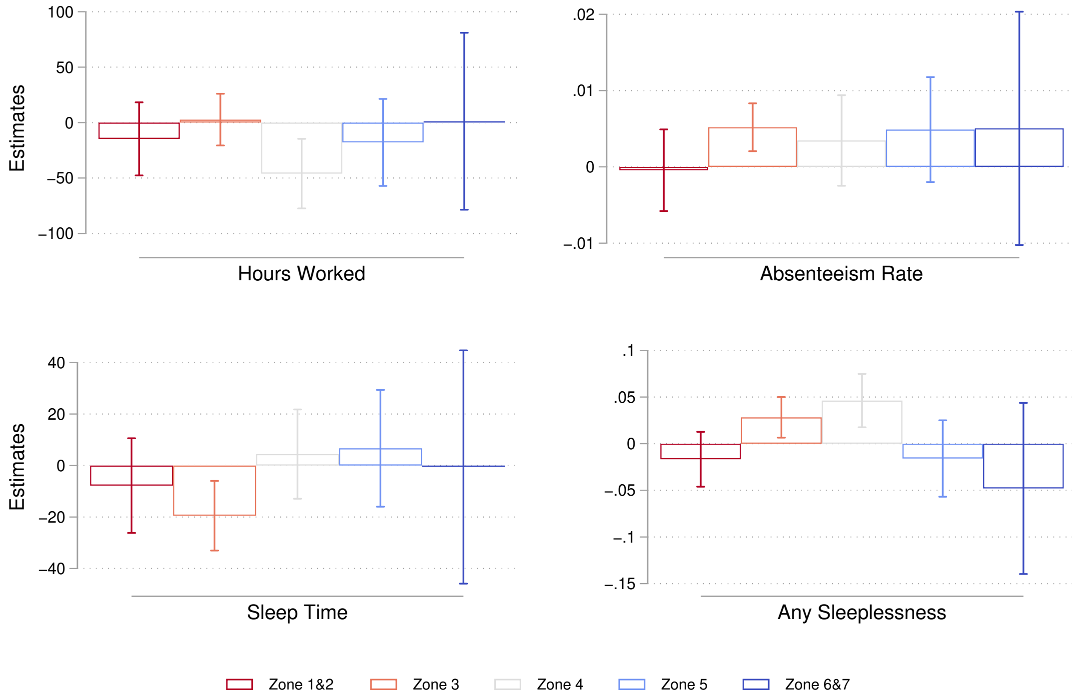


Figure 7: Heterogeneous Effects on Labor Supply, Sleep, and Well-being by Climate Zone

Notes: This figure plots the estimated effect of temperatures above 35C, relative to the reference bin of temperatures below or equal to 20C, by climate zone for outcomes hours worked, absenteeism rate, sleep time, and sleeplessness indicator, respectively.

Table 1: Summary Statistics: Main Analysis

	N	Mean	Std.	Min	Max
Flight On-Time Performance					
Cancellation Rate	51111092	0.01	0.08	0	1
Departure Delay Rate	51111092	0.15	0.36	0	1
Departure Delay Time (Minutes)	51111092	5.56	26.30	0	2450
Temperature					
Temperature Groups (C)					
≤ 20	51111092	0.30	0.46	0	1
$\in (20,25]$	51111092	0.25	0.43	0	1
$\in (25,30]$	51111092	0.23	0.42	0	1
$\in (30,35]$	51111092	0.14	0.35	0	1
> 35	51111092	0.07	0.26	0	1
Real Air Temperature Groups (C)					
≤ 20	51111092	0.30	0.46	0	1
$\in (20,25]$	51111092	0.25	0.43	0	1
$\in (25,30]$	51111092	0.26	0.44	0	1
$\in (30,35]$	51111092	0.14	0.35	0	1
> 35	51111092	0.04	0.19	0	1
Hours of Temp $> 35C$, 5am-6pm	51110591	0.44	1.52	0	14
Covariates					
Numbers of Scheduled Flights	51111092	25.38	22.03	1	123
Precipitation Indicator	51111092	0.08	0.26	0	1
One hour precipitation (inches)	51107125	29.98	0.16	1	55
Precipitation Quadratic Term	51111092	0.00	0.03	0	29
Wind Speed (mph)	51111018	8.85	5.07	0	266
Pressure altimeter (inches)	51107125	29.98	0.16	1	55
Relative Humidity (%)	51111092	57.99	21.78	1	167
Obscuration					
Clear	51111092	0.93	0.26	0	1
Fog	51111092	0.00	0.05	0	1
Mist	51111092	0.03	0.16	0	1
Haze	51111092	0.04	0.20	0	1

Notes: Table 1 presents summary statistics of variables in the sample for the main analysis. It spans months April to September and contains data on cancellation rate, departure delay rate, and departure delay time aggregated by origin-destination pair, carrier, date, and time block.

Table 2: Summary Statistics: Labor Supply, Well-being, and Temperature

	N	Mean	Std.	Min	Max
Labor Supply:					
Working Time (Minutes)	85623	277.69	271.53	0	1380
1(Absence Last Week)	85623	0.04	0.19	0	1
Sleeping:					
Sleep Time on a Diary Day (Minutes)	85623	507.19	129.86	0	1428
Any Sleeplessness on a Diary Day	85623	0.04	0.20	0	1
Well-being:					
Not Well-Rested	16320	0.21	0.41	0	1
Worse-Than a Typical Day	16320	0.07	0.25	0	1
Weather:					
Daily Max Temperature (C) $\in (20,25]$	69281	0.16	0.37	0	1
Daily Max Temperature (C) $\in (25,30]$	69281	0.20	0.40	0	1
Daily Max Temperature (C) $\in (30,35]$	69281	0.15	0.36	0	1
Daily Max Temperature (C) > 35	69281	0.04	0.21	0	1
Minimum Temperature (C)	69281	7.45	10.07	-38	33
Maximum Temperature (C)	69281	20.24	10.68	-20	47
Accumulated Precipitation (mm/day)	69281	3.07	7.89	0	185
Day Length (s/day)	69281	43064.51	6702.25	28921	57432
# Days Max Temp $\in (20,25]$ Last Week	69281	1.13	1.56	0	7
# Days Max Temp $\in (25,30]$ Last Week	69281	1.38	1.91	0	7
# Days Max Temp $\in (30,35]$ Last Week	69281	1.09	1.97	0	7
# Days Max Temp >35 Last Week	69281	0.32	1.22	0	7
Weekly Avg Precipitation Last Week	69281	21.12	27.48	0	473
Weekly Avg Day Length Last Week	69281	43039.83	6706.37	29053	57468
Covariates:					
Diary day a holiday	85623	0.02	0.13	0	1
Male	85623	0.54	0.50	0	1
Married	85623	0.57	0.50	0	1
Has Child <18	85623	0.51	0.50	0	1
Age	85623	43.26	12.08	15	85
% Age >65	85623	0.03	0.17	0	1
Paid Hourly	85623	0.46	0.50	0	1
% Reside in Urban Area	85623	0.84	0.37	0	1
% Hispanic	85623	0.14	0.35	0	1
% Black	85623	0.13	0.33	0	1
% Asian	85623	0.04	0.20	0	1
% < High School	84954	0.06	0.23	0	1
% High School Graduate	84954	0.23	0.42	0	1
% Some College	84954	0.55	0.50	0	1

Notes: Table 2 shows the summary statistics of variables of the full-time employed sample. Labor supply data comes from ATUS regular module 2005-2019. Well-being data comes from ATUS Well-being module 2010, 2012, and 2013.

Table 3: The Same-Day Contemporaneous Effect of Temperature on Flight On-Time Performance.

	(1)	(2)	(3)
	Cancellation Rate	*Delay Rate*	*Delay Time*
Temp $\in (20C, 25C]$	0.0003***	0.0040***	0.2610***
	(0.0000)	(0.0004)	(0.0205)
Temp $\in (25C, 30C]$	0.0005***	0.0066***	0.4260***
	(0.0001)	(0.0005)	(0.0303)
Temp $\in (30C, 35C]$	0.0008***	0.0086***	0.7210***
	(0.0001)	(0.0007)	(0.0424)
Temp $> 35C$	0.0015***	0.0106***	1.0210***
	(0.0001)	(0.0009)	(0.0542)
Percentage Effects (in %)			
Temp $\in (20C, 25C]$	4.59	2.65	4.69
Temp $\in (25C, 30C]$	8.61	4.31	7.65
Temp $\in (30C, 35C]$	13.03	5.62	12.96
Temp $> 35C$	23.81	6.98	18.35
N	51105670	51105670	51105670
Origin-Destination Pair FEs	✓	✓	✓
Carrier FEs	✓	✓	✓

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. All models controls for month by year, day of week, and time block fixed effects, and time-varying weather covariates, including a binary indicator and quadratic polynomials of hourly precipitation, a factor variable measuring visual obscuration, and continuous variables for humidity, and wind speed. Our model also controls for airport traffic measured by the total number of flight departure during each time block. Percentage Effect (in %) indicates the percentage effect relative to the corresponding baseline sample mean.

Table 4: The Same-Day Cumulative Effect of Temperature on Flight On-Time Performance

	(1)	(2)	(3)
	Cancellation Rate	*Delay Rate*	*Delay Time*
Hours of Temp $> 35C$, 5am-6pm	-0.0000	0.0050***	0.0922***
	(0.0000)	(0.0003)	(0.0145)
Temp $\in (20C, 25C]$	0.0006***	0.0180***	0.7821***
	(0.0001)	(0.0008)	(0.0428)
Temp $\in (25C, 30C]$	0.0011***	0.0214***	0.8872***
	(0.0002)	(0.0012)	(0.0592)
Temp $\in (30C, 35C]$	0.0010***	0.0148***	0.9213***
	(0.0002)	(0.0015)	(0.0796)
Temp $> 35C$	0.0021***	0.0119***	1.0775***
	(0.0004)	(0.0025)	(0.1350)
Sample Mean	0.0060	0.2240	7.0629
N	5033686	5033686	5033686
Origin-Destination Pair FEs	✓	✓	✓
Carrier FEs	✓	✓	✓

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. All models controls for month by year, day of week, and time block fixed effects, and time-varying weather covariates, including a binary indicator and quadratic polynomials of hourly precipitation, a factor variable measuring visual obscuration, and continuous variables for humidity, and wind speed. Our model also controls for airport traffic measured by the total number of flight departure during each time block.

Table 5: The Effect of Temperature on Worker Labor Supply

	(1)	(2)	(3)
	All	Outdoor	Transportation
Panel A.	Working Time		
Max Temp $\in (20C, 25C]$	1.275	4.908	-7.954
	(2.877)	(8.846)	(16.22)
Max Temp $\in (25C, 30C]$	-2.981	11.29	-20.40
	(3.332)	(10.34)	(18.71)
Max Temp $\in (30C, 35C]$	-6.658	-29.77**	-60.89**
	(4.207)	(13.01)	(24.12)
Max Temp $> 35C$	-13.60**	-38.97**	-82.35**
	(5.996)	(17.98)	(33.24)
Sample Mean	277.7	289.3	297.7
Panel B.	1(Absence Last Week)		
Days Max Temp $\in$ (20C, 25C] Last Week	0.0002	-0.0001	0.0016
	(0.0006)	(0.0018)	(0.0029)
Days Max Temp $\in$ (25C, 30C] Last Week	0.0007	0.0024	0.0047*
	(0.0006)	(0.0017)	(0.0027)
Days Max Temp $\in$ (30C, 35C] Last Week	0.00061	0.0039*	0.0037
	(0.0007)	(0.0021)	(0.0036)
Days Max Temp $>$ 35C Last Week	0.0028***	0.0069**	0.0078*
	(0.0010)	(0.0028)	(0.0045)
Sample Mean	0.038	0.037	0.039
N	68750	8495	3175

Notes: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Column (1) presents the result of the entire sample of full-time employed individuals. Column (2) reports the result of a sub-sample of full-time employed individuals who work in industries that usually requires workers to perform tasks in outdoor or semi-outdoor environments. Specifically, these industries are Agriculture, Forestry, Fishing, and Hunting, Mining, Construction, and Transportation and Utilities. We classify respondents' working industry using the major industry code for the main job provided by the ATUS. Column (3) further presents the result of a sub-sample of full-time employed individuals who work in transportation and material moving occupations, classified by the major occupation code for the main job from ATUS.

Table 6: The Effect of Temperature on Sleep Time and Sleeplessness

	(1)	(2)	(3)
	All	Outdoor	Transportation
Panel A.	Sleep Time on a Diary Day (in Minute)		
Max Temp $\in (20C, 25C]$	-1.535	5.169	-5.775
	(1.631)	(4.922)	(9.494)
Max Temp $\in (25C, 30C]$	-6.411***	-5.002	-16.780
	(1.889)	(5.752)	(10.95)
Max Temp $\in (30C, 35C]$	-6.865***	6.880	-14.230
	(2.384)	(7.239)	(14.120)
Max Temp $> 35C$	-9.197***	0.911	7.226
	(3.398)	(10.010)	(19.460)
Sample Mean	507.2	506.8	515.9
Panel B.	Any Sleeplessness on a Diary Day		
Max Temp $\in (20C, 25C]$	-0.0006	0.00234	0.0096
	(0.0027)	(0.0080)	(0.0132)
Max Temp $\in (25C, 30C]$	0.0069**	0.0116	0.0403***
	(0.0032)	(0.0093)	(0.0153)
Max Temp $\in (30C, 35C]$	0.0051	0.0100	0.0534***
	(0.0040)	(0.0117)	(0.0197)
Max Temp $> 35C$	0.0180***	-0.0055	0.0572**
	(0.0057)	(0.0162)	(0.0271)
Sample Mean	0.04	0.04	0.04
N	68750	8495	3175

Notes: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Column (1) presents the result of the entire sample of full-time employed individuals. Column (2) reports the result of a sub-sample of full-time employed individuals who work in industries that usually requires workers to perform tasks in outdoor or semi-outdoor environments. Specifically, these industries are Agriculture, Forestry, Fishing, and Hunting, Mining, Construction, and Transportation and Utilities. We classify respondents' working industry using the major industry code for the main job provided by the ATUS. Column (3) further presents the result of a sub-sample of full-time employed individuals who work in transportation and material moving occupations, classified by the major occupation code for the main job from ATUS.

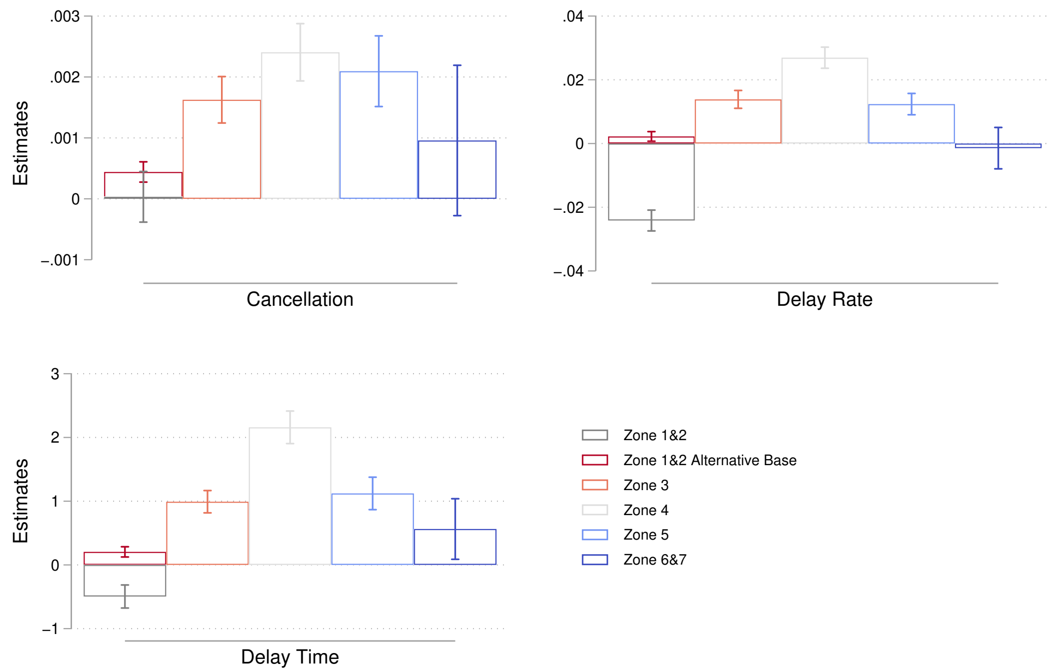
Table 7: The Effect of Temperature on General Well-Being

	(1)	(2)
	Respondent	
	Not Well-Rested	Worse-Than Typical
Max Temp $\in (20C, 25C]$	-0.0056	-0.0072
	(0.0131)	(0.0081)
Max Temp $\in (25C, 30C]$	0.0067	0.0036
	(0.0157)	(0.0097)
Max Temp $\in (30C, 35C]$	0.0413**	0.0011
	(0.0198)	(0.0123)
Max Temp $> 35C$	0.0632**	0.0097
	(0.0271)	(0.0168)
Sample Mean	0.207	0.068
N	13167	13167

Note: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. The shown results are for all full-time employed respondents. Following the instruction in the data codebook of the ATUS Well-being Module, we use the WB respondent-level final weights in the estimation of Columns (1)-(2).

Online Appendix

A Figures



A.1: Effects on Flight On-Time Performance by Climate Zone, Alternative Reference Group

Notes: This figure plots the estimated effect of temperatures falling in the bin $> 35C$, relative to the reference bin of temperatures between 30C and 35C, by climate zone for outcomes cancellation rate, departure delay rate, and delay time, respectively.

B Tables

B.1: Robustness Check: Real Air Temperature

	(1)	(2)	(3)
	Real Air Temperature Level Groups		
	Cancellation Rate	Delay Rate	Delay Time
Real Air $\in (20C, 25C]$	0.00026***	0.00478***	0.269***
	(0.00004)	(0.00037)	(0.0209)
Real Air $\in (25C, 30C]$	0.00051***	0.00574***	0.409***
	(0.00006)	(0.00054)	(0.0309)
Real Air $\in (30C, 35C]$	0.00083***	0.00926***	0.780***
	(0.00008)	(0.00075)	(0.0443)
Real Air $> 35C$	0.00130***	0.0147***	1.053***
	(0.00015)	(0.00129)	(0.0712)
Percentage Effects (in %)			
Real Air $\in (20C, 25C]$	4.16	3.13	4.83
Real Air $\in (25C, 30C]$	8.12	3.76	7.36
Real Air $\in (30C, 35C]$	13.25	6.07	14.01
Real Air $> 35C$	20.86	9.65	18.93
N	51105670	51105670	51105670
Origin-Destination Pair FEs	✓	✓	✓
Carrier FEs	✓	✓	✓

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. We use the real air temperature as the treatment variable and adopt our preferred model controlling for origin-destination pair, carrier, month by year, day of week, and time block fixed effects, and time-varying weather covariates, including a binary indicator and quadratic polynomials of hourly precipitation, a factor variable measuring visual obscuration, and continuous variables for humidity, and wind speed. Our model also controls for airport traffic measured by the total number of flight departure during each time block. Percentage Effect (in %) indicates the percentage effect relative to the corresponding baseline sample mean.

B.2: Robustness Check: Various Model Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Cancellation Rate			Departure Delay Rate			Departure Delay Time		
Temp $\in (20C, 25C]$	0.00028***	0.00031*	0.00029***	0.00396***	0.00404*	0.00404***	0.254***	0.255***	0.261***
	(0.00005)	(0.00017)	(0.00004)	(0.00047)	(0.00219)	(0.00037)	(0.0278)	(0.0811)	(0.0205)
Temp $\in (25C, 30C]$	0.00055***	0.00055*	0.00054***	0.00638***	0.00638**	0.00658***	0.411***	0.406***	0.426***
	(0.00006)	(0.00028)	(0.00006)	(0.00069)	(0.00309)	(0.00053)	(0.0424)	(0.132)	(0.0303)
Temp $\in (30C, 35C]$	0.00084***	0.00083**	0.00081***	0.00844***	0.00816*	0.00858***	0.703***	0.679***	0.721***
	(0.00008)	(0.00037)	(0.00007)	(0.00096)	(0.00429)	(0.00072)	(0.0601)	(0.206)	(0.0424)
Temp $> 35C$	0.00152***	0.00150**	0.00149***	0.0106***	0.0104*	0.0106***	1.006***	0.982***	1.021***
	(0.00011)	(0.00060)	(0.00010)	(0.00125)	(0.00518)	(0.00092)	(0.0780)	(0.242)	(0.0542)
Percentage Effects (in %)									
Temp $\in (20C, 25C]$	4.60	4.96	4.59	2.59	2.65	2.65	4.57	4.58	4.69
Temp $\in (25C, 30C]$	8.85	8.83	8.61	4.18	4.18	4.31	7.39	7.30	7.65
Temp $\in (30C, 35C]$	13.42	13.29	13.03	5.54	5.35	5.62	12.64	12.21	12.96
Temp $> 35C$	24.43	24.03	23.81	6.97	6.82	6.98	18.07	17.65	18.35
N	51106389	51107050	51105670	51106389	51107050	51105670	51106389	51107050	51105670
Origin-Destination Pair FEs	✓		✓	✓		✓	✓		✓
Origin FEs		✓			✓			✓	
Carrier FEs		✓	✓		✓	✓		✓	✓

Note: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. All models controls for month by year, day of week, and time block fixed effects, and time-varying weather covariates, including a binary indicator and quadratic polynomials of hourly precipitation, a factor variable measuring visual obscuration, and continuous variables for humidity, and wind speed. Our model also controls for airport traffic measured by the total number of flight departure during each time block. Percentage Effect (in %) indicates the percentage effect relative to the corresponding baseline sample mean. We experiment with excluding carrier fixed effects in Columns (1), (4), and (7) and substituting origin-destination pair fixed effects with origin fixed effects in Columns (2), (5), and (8). Columns (3), (6), and (9) report the estimates adopting the preferred model for the cancellation rate, delay rate, and delay time, respectively. We do not find substantial variations in the magnitude of the estimated coefficients using these alternative models.

B.3: Robustness Check: Include Controls for Air Pollution

	(1)	(2)	(3)
	Cancellation Rate	*Delay Rate*	*Delay Time*
Panel A. Original Model			
Temp $\in (20C, 25C]$	0.0003***	0.0066***	0.344***
	(0.0001)	(0.0004)	(0.0237)
Temp $\in (25C, 30C]$	0.0004***	0.0098***	0.549***
	(0.0001)	(0.0006)	(0.0343)
Temp $\in (30C, 35C]$	0.0008***	0.0131***	0.910***
	(0.0001)	(0.0008)	(0.0492)
Temp $> 35C$	0.0013***	0.0144***	1.165***
	(0.0001)	(0.0011)	(0.0652)
Panel B. Include Air Pollution Controls			
Temp $\in (20C, 25C]$	0.0003***	0.0078***	0.382***
	(0.0001)	(0.0004)	(0.0232)
Temp $\in (25C, 30C]$	0.0004***	0.0120***	0.615***
	(0.0001)	(0.0006)	(0.0346)
Temp $\in (30C, 35C]$	0.0008***	0.0157***	0.990***
	(0.0001)	(0.0009)	(0.0519)
Temp $> 35C$	0.0012***	0.0168***	1.239***
	(0.0001)	(0.0012)	(0.0676)
N	31258066	31258066	31258066
Origin-Destination Pair FEs	✓	✓	✓
Carrier FEs	✓	✓	✓

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. All models controls for month by year, day of week, and time block fixed effects, and time-varying weather covariates, including a binary indicator and quadratic polynomials of hourly precipitation, a factor variable measuring visual obscuration, and continuous variables for humidity, and wind speed. Our model also controls for airport traffic measured by the total number of flight departure during each time block. Panel b includes air pollution controls for CO, NO_2, ozone, and PM2.5. Following Schlenker and Walker (2016), daily airport-level air pollution is measured by taking the average of monitor readings of all monitors within 100 km of the airport, weighting by the inverse distance between the monitor and the airport.

B.4: The Effect of Temperature on Well-being at Work and Work-Related Activities

	(1)	(2)	(3)	(4)	(5)
	Work and Work-Related Activity				
	Not Happy	Pain	Sad	Stressed	Tired
Max Temp $\in (20C, 25C]$	0.0551*	0.0151	0.0311**	0.0364	-0.0311
	(0.0312)	(0.0191)	(0.0156)	(0.0265)	(0.0290)
Max Temp $\in (25C, 30C]$	0.00934	0.0583**	0.00182	-0.0181	-0.0517
	(0.0379)	(0.0232)	(0.0190)	(0.0322)	(0.0352)
Max Temp $\in (30C, 35C]$	0.107**	0.0302	0.0469**	-0.00526	-0.0515
	(0.0473)	(0.0290)	(0.0237)	(0.0403)	(0.0440)
Max Temp $> 35C$	0.137**	0.0832**	0.0582*	-0.0381	0.0631
	(0.0646)	(0.0396)	(0.0324)	(0.0550)	(0.0601)
Sample Mean	0.268	0.077	0.046	0.131	0.212
N	2937	2937	2937	2937	2937

Note: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. We define five dummy variables for the well-being measures, where "Not Happy" equals one if WUHAPPY≤ 3 (WUHAPPY ranges from 0 to 6, where 0 means not happy and 6 means very happy), "Pain" equals one if WUPAIN> 3 (WUPAIN ranges from 0 to 6, where 0 means did not feel any pain at all and 6 means in severe pain), "Sad" equals one if WUSAD> 3 (WUSAD ranges from 0 to 6, where 0 means not sad at all and 6 means very sad), "Stressed" equals one if WUSTRESS > 3 (WUSTRESS ranges from 0 to 6, where 0 means not stressed at all and 6 means very stressed), and "Tired" equals one if WUTIRED > 3 (WUTIRED ranges from 0 to 6, where 0 means not tired at all and 6 means very tired). The shown results are obtained by regressing these five dummy indicators of the well-being measures at work and work-related activities on the daily maximum temperature bins, using the full-time employed individual sample and adopting the model of Equation (3) and weight the regression by ATUS's activity-level weights for pooled estimates.

B.5: More on The Effect of Temperature on Worker Labor Supply

	(1)	(2)	(3)
	All	Outdoor	Transportation
Panel A.	Working Time		
Max Temp $\in (20C, 25C]$	0.242	8.426	-11.03
	(2.670)	(8.215)	(14.90)
Max Temp $\in (25C, 30C]$	-6.954**	8.259	-28.28
	(3.093)	(9.601)	(17.21)
Max Temp $\in (30C, 35C]$	-10.99***	-24.90**	-65.91***
	(3.905)	(12.08)	(22.19)
Max Temp $> 35C$	-19.01***	-38.51**	-72.57**
	(5.565)	(16.70)	(30.55)
Sample Mean	277.7	289.3	297.7
N	68750	8495	3175
Sleeplessness Dummy	✓	✓	✓
Sleep Time Control	✓	✓	✓

Notes: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Column (1) presents the result of the entire sample of full-time employed individuals. Column (2) reports the result of a sub-sample of full-time employed individuals who work in industries that usually requires workers to perform tasks in outdoor or semi-outdoor environments. Specifically, these industries are Agriculture, Forestry, Fishing, and Hunting, Mining, Construction, and Transportation and Utilities. We classify respondents' working industry using the major industry code for the main job provided by the ATUS. Column (3) further presents the result of a sub-sample of full-time employed individuals who work in transportation and material moving occupations, classified by the major occupation code for the main job from ATUS.