Heat and Productivity: Evidence From Flight On-Time Performance

Zhanhan Yu * Ying Shi †

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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 departure delay rates and lengthening delay times. Complementary analyses using a sample of transportation workers from the American Time-Use Survey (ATUS) suggest that higher temperatures reduce labor supply (fewer hours worked and greater worker absenteeism) and adversely impact well-being measures such as sleep quality, which may affect on-the-job-productivity.

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*Economics Department, Adam Smith Business School, University of Glasgow, Glasgow, UK; Email: yuzhanhan@gmail.com.

†Department of Public Administration and International Affairs, Syracuse University, 426 Eggers Hall, Syracuse, NY 13244-1020, yshi78@syr.edu.

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 (Dell et al., 2012; Deryugina and Hsiang, 2014), as well as industrial and agricultural production (Schlenker et al., 2006; Hsiang, 2010; 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 et al., 2014). Doing so requires building a larger evidence base on the impact of heat on productivity across a range of 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. We focus on cancellations and departure delays due to air carrier-related causes, such as baggage loading and aircraft, ramp, and passenger services. 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 35 degrees Celsius (°C) are 30% more likely to be cancelled, 13% more likely to involve a late departure, and experience 21% longer delay time conditional on late departure. The adverse impact of heat extends beyond immediate exposure and persists throughout later periods of the same day when the temperature is cooler. When controlling for contemporaneous temperatures, an additional hour of heat exposure (at temperatures above 35°C) during the day (5am to 6pm) is estimated to increase the departure delay rate and delay time later in the same day by 4% and 3%, respectively. 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 heat's adverse impacts are decreasing in airport size, with nonhub airports more negatively affected than large and medium hub airports.

We provide suggestive evidence on the mechanisms behind these estimates, with a focus on workers' labor supply and sleep. We use data from the American Time Use Survey (ATUS) linked to daily weather measures to show that heat reduces hours worked and increases absenteeism. Transportation workers spend 1.2-1.4 fewer hours at work and are significantly more likely to be absent on days with maximum temperatures exceeding 35°C. Moreover, heat exposure decreases workers' sleep time and increases the probability of experiencing sleeplessness. We provide suggestive evidence that the mechanism of sleep quality does not meaningfully influence workers' labor supply. Instead, research on the significant impact of sleep and health on workers' productivity (Bubonya et al., 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 labor output, labor supply, and worker well-being.[1] 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.[2] More recent causal evidence consistently demonstrate that increasing temperatures negatively impact labor output in middle-income countries such as India and China (Cai et al., 2018; Zhang et al., 2018; Chen and Yang, 2019; Adhvaryu et al., 2020; Somanathan et al., 2021; Zhang et al., 2023), or across a larger set of developing economies (LoPalo, 2023). This burgeoning literature utilizes a variety of worker- and firm-level output data to illustrate the adverse consequences of heat in predominantly manufacturing and construction

[1]See, for example, Heal and Park (2016) and Lai et al. (2023) for a review. We furthermore provide a systematic overview of studies involving micro evidence on the effects of heat on 1) labor output, 2) labor supply, 3) cognitive performance and decision-making, and 4) worker sleep, mental health, and workplace safety in Appendix Tables B.1-4.

[2]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°C (Seppanen et al., 2006). Effects above the 25°C 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°C.

industries.[3] While these results generalize to workplaces in developing countries, we provide estimates in the context of an advanced economy for which there is a sparser literature (Cachon et al., 2012; Stevens, 2017). Cachon et al. (2012) show a decrease in weekly automobile production when exposed to 6-7 days of 90°F+ (32°C) relative to no days at this temperature, while Stevens (2017) documents decreased agricultural productivity among blueberry pickers in California under heat exposure of 100°F+ (38°C). Our context is closer to the automobile manufacturing case, given the availability of workplace climate control. In contrast to Cachon et al. (2012) who find significant drops in automobile output only for sustained exposure to days-long heat waves, we show that high temperatures in a single day can adversely affect airline productivity.

In examining the U.S. airline industry, we are also shifting away from previous studies focused on industrial and agricultural output to a service-oriented sector. Existing research enriches our understanding of heat stress' effects on individual output in the food and beverage industry (Cai et al., 2018), cloth-weaving (Somanathan et al., 2021), and fruit-picking (Stevens, 2017), as well as production line-, plant- or firm-level industrial output, namely in automobile, garment, and steel production (Cachon et al., 2012; Adhvaryu et al., 2020; Somanathan et al., 2021). Yet there are few studies focused on service-oriented industries, except for data collection and production (LoPalo, 2023) and professional sports (Qiu and Zhao, 2021; Burke et al., 2023). Burke et al. (2023) aims to fill a gap on temperature's effects for workers in the service economy in wealthier nations using a global dataset of professional tennis matches. Even so, we advance that more research is needed to understand how heat affects productivity in other service-oriented sectors, particularly those involving collaborative work environments without a clear mapping of individual effort onto output.

Finally, we provide additional U.S.-based evidence on how changes in labor supply and well-

[3]Somanathan et al. (2021) use worker- and firm-level output data to show that rising temperatures cause productivity declines in Indian manufacturing plants specializing in cloth weaving, garment sewing, and steel production. Adhvaryu et al. (2020) document similar negative effects using microdata from a large Indian garment firm. For mean daily temperatures above 19°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 output for weaving and up to 4-8% decrease for garment production. Among Chinese manufacturing firms, heat exposure adversely impacts both total factor productivity and output (Cai et al., 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).

being may contribute to the observed productivity effects. The existing literature on labor supply mostly focuses on China and India, apart from Graff Zivin and Neidell (2014). Adhvaryu et al. (2020) find the adverse effect on Indian garment production 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 in India with magnitudes varying by industry and the presence of climate control. Our findings based on extensive 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 well-being contributes to a smaller but growing literature investigating the causal effects of these channels (Obradovich et al., 2017; Mullins and White, 2019; Minor et al., 2022).

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 airline 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. Information on flight delays and cancellations derives 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. The Bureau of Transportation Statistics recognizes five categories of flight delays. We only use the air carrier category, which covers delays caused by circumstances within the airline's control and thus corresponds most closely to our focus on airline productivity. Examples of these circumstances include but are not limited to crew issues, baggage and cargo loading, fueling, aircraft cleaning and servicing, maintenance, passenger services, and ramp service. According to the BTS, the air carrier category has comprised an increasing share of flight delays since 2004 and accounts for 41% of total delay minutes in 2020. In excluding the other four categories (extreme weather, National Airspace System, security, and late-arriving aircraft), we forgo examining delays and cancellations due to meteorological conditions such as below minimum conditions, deicing aircrafts, earthquakes, hail damage, holding at gate for enroute weather, hurricanes, lightning, snow storms, thunderstorms, and tornadoes. National Airspace System-related delays cover a broad set of reasons involving non-extreme weather conditions, airport operations, and air traffic control. We furthermore exclude delays due to the evacuation of a terminal or concourse, re-boarding of aircraft because of security breaches, and late-arriving inbound aircrafts given that the likely causes are unrelated to recent heat exposure.[4] In sum, we exclude delays and cancellations induced by extreme temperatures that cannot be mitigated through airlines' corrective actions or can only be addressed with corrective action from airports or the Federal Aviation Administration. As such, we may be underestimating the overall impact of heat on flight operations to focus on causes most related to airline workers.

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

[4]We focus on departure rather than arrival delays because the latter is more likely to be correlated with other confounding factors, such as weather en route and congestion at the destination airport. Since we lack sufficient data on these confounding factors, using departure delays helps us minimize omitted variable bias in our estimation. 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.

contiguous United States and 27 airlines.

Next, we bring in meteorological data on temperature and other weather conditions. Hourly climate data comes from the Automated Surface Observing System (ASOS), made available via the Iowa Environmental Mesonet (IEM). These derive from 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). 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 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.[5]

We create three outcome variables to measure flight on-time performance: the cancellation rate, departure delay rate, and total departure delay time (in minutes).[6] 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. It is worth noting that the cancellation rate, departure delay rate, and departure delay time are essentially measured at the flight-level. They are specific to the particular route (an origin-destination pair), carrier, and day-and-time block pair, with 18 time blocks defined per day (0-5 a.m. is a single group). Next, we merge flight performance data with hourly climate measures by the date of flight operation, time block, and the 3-digit identifier of the origin and destination airports. In our main analysis, we focus on the sub-sample of months from April to September, because this period typically exhibits higher temperatures, making it most relevant to the aim of this study. The final sample is nationally representative and consists of 350

[5]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.

[6]While we focus on flight on-time performance, we acknowledge that there are alternative ways of measuring airline productivity, including passenger enplanement.

airports in the contiguous United States. Figure 1 presents the 350 airports in the sample, with the size of each bubble indicating its average annual enplanements (passenger boarding) from 2004 to 2019.

To demonstrate the descriptive correlation, we plot flight on-time performance measures as a function of temperature (in degree Celsius) in Figure 2. 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 20°C (68°F), between 20°C and 25°C (77°F), between 25°C and 30°C (86°F), between 30°C and 35°C (95°F), and above 35°C. Second, we calculate the number of hours when the temperature exceeds 35°C 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.[7] 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 wind speed.[8]

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 16% and an average departure delay time of approximately 6 minutes. Around 60% of flights operate at temperatures between 20°C

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

[8]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.

and 35°C, while 6% of flights operate at temperatures above 35°C.

2.2 Data for the Exploration of Potential Mechanisms

We rely on data from the American Time Use Survey (ATUS) to explore potential mechanisms. This necessarily limits the scope of what we can determine compared to the ideal case of individual-level worker data obtained from airlines or airport authorities, which are not readily available. We assemble a long panel of time-use data from 2005-2019 that collects detailed information about how individuals spend their time during a diary day.[9] 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. In addition to the regular module, we include the Well-being (WB) Module in the ATUS, which is available for the years 2010, 2012, and 2013. 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.[10] We merge 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. In addition to the full sample, we restrict to workers in the transportation industry, in keeping with the focus on the airline sector. The analyses also examine a sample of workers in transportation and material moving occupations, which comprise 60% of employees in the air

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

[10]The WB module also includes information about the respondent's 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. However, due to the small sample size, the estimates are not precisely estimated. These results are available upon request.

transportation industry (Bureau of Labor Statistics, 2022).

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 weather measures such as minimum and maximum temperatures, precipitation, 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.[11]

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. "$\mathbb{1}$(Absence Last Week)" denotes a binary indicator which equals one if the 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.[12] Moreover, we create two dummy variables signaling the respondent's general health. One indicates whether the respondent felt worse than on 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 20°C, between 20°C and 25°C, between 25°C and 30°C, between 30°C and 35°C, and above 35°C. 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 276 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

[11]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.

[12]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.

approximately 4% of respondents report experiencing sleeplessness. 21% of respondents from the WB module report not feeling well-rested on the diary day. 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 the following model:

$$\begin{aligned} \text{OnTimePerformance}_{ijcdh} = \sum_k \beta_k \text{Temp}_{idh}(B_k) + \alpha \mathbf{X}_{idh} + \delta \mathbf{W}_{jdh} + \theta \mathbf{Q}_{id} \\ + \sigma_{ym} + \rho_s + \tau_h + \kappa_{ij} + \phi_c + \zeta_{im} + \varepsilon_{ijcdh} \end{aligned} \tag{1}$$

where i and j denote the origin airport and destination airport, respectively. d is the day of flight operation, s denotes the day of the week and h indexes the time block of flight departure. The outcome variable is the cancellation rate, departure delay rate, or departure delay time based on air carrier-related causes such as baggage loading, fueling, aircraft cleaning and maintenance, and passenger and ramp services. Since our outcome variables exclude delays due to late-arriving aircraft, general airport conditions such as closed runways and air traffic control issues, and extreme weather events, we may be underestimating the full impact of heat on flight operations. Temp_{idh} denotes the treatment variable categorized in five bins (B_k): ≤ 20°C (baseline), (20°C, 25°C], (25°C, 30°C], (30°C, 35°C], and $>$ 35°C. We are interested in the coefficient β_k, which gives the effect of temperatures falling in the corresponding bin, relative to the reference temperature of less than or equal to 20°C.

To isolate the effect of heat from the impact of related weather phenomena such as wind gusts and thunderstorms at flight departure, we control for time-varying weather conditions measured at the hour level of origin ($\mathbf{X}_{idh}$) and destination ($\mathbf{W}_{jdh}$) airports, including precipitation, relative humidity, obscuration (visibility), and wind speed. Moreover, we incorporate a rich vector of fixed effects, including month by year (σ_{ym}), day of week (ρ_s), and time block (τ_h) fixed effects to account for seasonal, day-of-week, and hourly patterns governing airlines' on-time performance. Crucially, we control for origin-destination pair (κ_{ij}) fixed effects to consider time-invariant factors that are specific to the route between the origin and destination, and origin-month (ζ_{im}) fixed effects, which absorb time variant unobservables.[13] Given the potential variation in airline productivity across different carriers, our model also includes carrier fixed effects (ϕ_c) to account for carrier-specific confounding factors. Standard errors are clustered at the route, or origin-destination pair, level.

Given the possibility that the adverse impact of heat may be mediated through deteriorating air pollution, we furthermore control for daily local air pollution as measured by CO, NO_2, PM2.5, and ozone ($\mathbf{Q}_{id}$). 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. To address the potential endogeneity of air pollution variables, we follow the environmental economics literature and adopt an instrumental variable (IV) strategy.[14] We use atmospheric temperature inversion and its interaction with wind direction as instruments for air pollution. In general, temperature tends to decrease with altitude. However, it increases with altitude during inversion episodes because warmer air at higher altitudes confines cooler air near the surface. As a consequence, this prevents pollutants from rising and dispersing, trapping them close to the ground.[15] This type of instrument produces arguably exogenous variations in air pollution.

In addition to contemporaneous exposure to high temperatures, workers may also suffer from

[13]We experiment with adding origin-by-month fixed effects or destination-by-month fixed effects. The results show minimal variation. Therefore, we only report the results with origin-by-month fixed effects in the main text.

[14]Wind direction and temperature inversion are two canonical instruments for air pollution in environmental economics studies. For example, Sager (2019); Jans et al. (2018); Arceo et al. (2016), among others, use temperature inversion as an instrument for air pollutants such as PM10, PM2.5, and CO. Deryugina and Hsiang (2014); Schlenker and Walker (2016); Chen et al. (2023), among others, instrument for air pollutants such as PM2.5, NO, NO_2, and CO with wind directions and wind patterns. 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.

[15]Following Sager (2019), we collect air temperatures at 925hPa pressure level and the surface level at 3am local time for the contiguous U.S. from NASA's MERRA-2 climate reanalysis product (Global Modeling and Assimilation Office, 2015). Our temperature inversion variable is defined similarly to Sager (2019) as a continuous variable equal to the temperature difference between 925hPa pressure level and the surface level.

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 temperatures 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 (CumulativeTemp35°C$_{id}$) which counts the number of hours when temperature exceeds 35°C 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:

$$\begin{aligned}\text{OnTimePerformance}_{ijcdh} = &\sum_k \beta_k \text{Temp}_{idh}(B_k) + \chi \text{CumulativeTemp35°C}_{id} \\ &+ \alpha \mathbf{X}_{idh} + \delta \mathbf{W}_{jdh} + \theta \mathbf{Q}_{id} + \sigma_{ym} + \rho_s \\ &+ \tau_h + \kappa_{ij} + \phi_c + \zeta_{im} + \varepsilon_{ijcdh}, \text{ where } h \in \{20, 21, 22, 23\}\end{aligned} \tag{2}$$

Conditioning on the concurrent temperature and weather conditions, χ captures the delayed and cumulative 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 0.18 p.p. at temperatures above 35°C, with the corresponding percentage effects estimated at 30% relative to the sample mean cancellation rate. The estimated effects decrease non-linearly for milder temperatures, with the percentage effects estimated at 18%, 10%, and 6% for temperature bins 30°C-35°C, 25°C-30°C, and 20°C-25°C.

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 20°C, the rate of departure delays is between 0.8-2.1 p.p. higher for flights departing during hotter periods. The corresponding percentage effects are estimated at 5%, 7%, 10%, and 13% 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 25°C and 30°C, compared to flights departing at temperatures below 20°C. It is equivalent to an 8% increase relative to the sample average delay time. The magnitude of the effect increases to 14% (0.8 minutes) when operating at temperatures between 30°C and 35°C, and 20% (1 minute) when operating at temperatures above 35°C.

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 in India reduces worker output from 2% to 8%, depending on industry, climate adaptation, and workplace context. Cachon et al. (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°C 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 exploring the impact of higher temperatures on worker productivity in contexts where individual effort maps more cleanly onto output.

3.3 The Effect of Same Day Cumulative Exposure

Next we explore the effects of same-day cumulative heat 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 35°C. We regress the flight on-time performance outcomes measured later in the same day (after 8pm), while controlling for the current temperature. Table 4 shows that the estimated coefficients for the contemporaneous temperature groups are of the same sign and similar magnitudes compared to the previous table. In comparison, the effects of the same-day *cumulative* exposure are generally much smaller. Even so, 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 35°C) during the day is estimated to increase the departure delay rate starting in the early evening by 0.8 p.p. (equivalent to a 4% increase) and the delay time by 0.2 minutes (equivalent to a 3% increase). This suggests that high temperatures can exert a negative productivity effect that endures several hours after the initial exposure.

3.4 Heterogeneous Impacts

We begin our exploration of the heterogeneous impact of heat 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 35°C, relative to the reference bin of temperatures below or equal to 20°C.

We find that the magnitude of the heat effects decreases with airport size, with nonhub airports being more adversely affected compared to their large hub and medium hub counterparts. For example, operating at temperatures above 35°C increases departure delay rates by 39% for nonhub airports, compared to 7% for large hub airports and 14% for medium hub airports. The effect is significantly more pronounced for nonhub airports on the duration of departure delay time, conditional on experiencing departure delays. The productivity impact of operating at temperatures above 35°C on the delay time, relative to flights departing at temperatures below 20°C, is statistically significantly higher for nonhub airports (66%), compared to large hub airports (16%) and medium hub airports (23%). We observe a similar pattern for the cancellation rate. However, the estimated effects do not statistically differ among the different types of 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 other model specifications and to rule out alternative explanations. First, we explore whether the estimates are robust to a different way of accounting for endogenous air pollution. We instrument for PM2.5 using only temperature inversion, rather than both temperature inversion and wind direction. Table B.5 shows that temperature coefficients remain highly stable to the choice of instrument. The switch to this pared-down instrument also offers an opportunity to compare our air pollution coefficients with existing literature on the impact of air pollution on flight delays, namely Chen et al. (2023). In the first stage, we find that each additional 1°C increase in the temperature difference between the 925hPa pressure level and the surface level is associated with slightly larger increases in PM2.5 concentrations in our context. The relationship between PM2.5 and on-flight performance is highly nonlinear, so we compute the marginal effects of air pollution at 45 $\mu g/m^3$ (sample mean for Chen et al. (2023)), which yields an increase delay time of 0.4 minutes for each 1 $\mu g/m^3$ increase in daily PM2.5, compared to less than 0.2 minutes in Chen et al. (2023).

Next, we present a model that excludes all air pollution variables, such that the effects of temperature can be viewed as inclusive of the influence of air pollution induced by changes in temperatures. Columns (1)-(3) in Table B.6 furthermore control for wind direction, in addition to wind speed. Doing so yields minimal changes to our temperature coefficients. Columns (4)-(6) replace our use of apparent or feels-like temperature with the real air temperature. The former considers 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, we find that coefficients are qualitatively unchanged when using actual air temperatures. Finally, Columns (7)-(9) show that all of our estimates remain statistically significant at the 1% level when clustering instead at the origin-month level.

The richness of our data enables the inclusion of a rich set of controls, such as origin-by-year fixed effects in addition to origin-by-month fixed effects. We do so in Table B.7 and find that the coefficients on temperature bins are highly stable to these changes.

A potential concern is that aircraft and other physical equipment may be impacted by extreme heat, with the effects exacerbated for aging or inadequately serviced planes and hardware. We undertook additional analyses by incorporating aircraft age into our models. Specifically, we collected data on the manufacturing year of registered aircraft from the FAA and merged it with our sample using the flight's tail number. Column (1) of Table B.8 re-runs our preferred model while replacing the dependent variable of on-time flight performance with aircraft age. The coefficients on temperature are all insignificant, suggesting that heat does not affect aircraft age. Columns (2), (5), and (8) then report results of the preferred model for a sample with non-missing aircraft age data, while Columns (3), (6), and (9) include a continuous aircraft age variable. The estimated effects of temperature show little change after accounting for aircraft age, which is expected given the lack of association between temperature and aircraft age in the first column. Columns (4), (7), and (10) further include controls for carrier fixed effects interacted with aircraft age to account for the possibility that different airlines may have different aircraft maintenance schedules and procedures that vary by hardware age. The results do not change with their inclusion.

We then conduct a placebo test by separately shuffling the temperature and outcome variables and reproducing our main results. Columns (1) to (3) of Table B.9 present estimation results using the 5-degree bins derived from the shuffled temperatures as the treatment variable. The estimates show no effect of heat. Next, we separately shuffle the three on-time performance variables and re-estimate Equation (1) using 2SLS. As shown in Columns (4) to (6), the shuffled outcome variables also produce no significant effects. In sum, we find no impact of heat in this exercise, suggesting that the effects we obtained are not coincidental.

Finally, we expand our analysis to a full-year sample spanning from January to December, covering the years 2004 to 2019. Since estimating the preferred model using the entire full-year sample at once requires substantial computational capacity and time, we address this limitation by randomly sampling 50% of the observations from the entire full-year sample and reproducing our main analysis using this random sample.[16] We report the estimation results of the full-year randomized sample in Table B.10 Columns (4) to (6) for the three on-time performance outcomes. For comparison, we estimate the same model using the April-to-September sample and present the results in Columns (1) to (3). We do not find discernible differences between the estimates from these two samples.

[16]In addition, considering the lower temperatures during the winter season, we categorize temperatures into 8 bins instead of 5: $\leq$5°C, (5°C, 10°C], (10°C, 15°C] (baseline), (15°C, 20°C], (20°C, 25°C],(25°C, 30°C], (30°C, 35°C], and $>$35°C.

4 Exploration of Mechanisms

4.1 Conceptual Framework and Extant Literature

There are multiple mechanisms that may underlie our estimated effects of heat on productivity. Most pertinent to our context are reductions in labor supply and on-the-job task performance.[17] Higher temperatures can influence individual decisions to allocate time to work, with labor shortages arising if workers choose not to work or reduce the hours worked on hotter days. Existing research shows moderate decreases in labor supply in response to high temperatures, with larger effects concentrated in more climate-exposed industries (Graff Zivin and Neidell, 2014). 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). We contribute to previous research by investigating whether workers in transportation adjust their labor supply in response to heat.

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 sector, particularly those with greater climate exposure. Airport workers such as ground crews 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). A substantial literature documents the negative impacts of heat on dimensions of health, including reduced physical work capacity, occupational health issues, and increased morbidity and mortality (Deschênes and Greenstone, 2011; Heal and Park, 2016; Barreca et al., 2016; White, 2017; Ebi et al., 2021; Carleton et al., 2022). Occupational exposure to heat stress can have physiological effects such as hyperthermia, and kidney disease or acute kidney injury (Flouris et al., 2018). Heat exposure has also been shown to diminish cognitive performance (Hancock and Vasmatzidis, 2003), with a number of papers in economics documenting the negative effects of extreme temperatures on cognition, test scores,

[17] We acknowledge that heat can affect productivity via non-labor channels, particularly in extreme cases in which runway integrity may be compromised or flights are subject to different operating thresholds and must be weight restricted (Coffel and Horton, 2015). Closed runways and other events affecting airport operations fall under the category of National Airspace System (NAS)-related delays, which are excluded from our outcome measures of flight delays and cancellations resulting from air carrier-related causes only.

and decision-making (Graff Zivin et al., 2018; Heyes and Saberian, 2019; Graff Zivin et al., 2020; Garg et al., 2020; Park et al., 2020; Park, 2022). While data constraints and the complexity of airline operations render it difficult to parse out individual contributions to productivity, we provide suggestive evidence by analyzing the impact of high temperatures on workers' rest and well-being. Specifically, we estimate whether heat-exposed individuals experience changes in sleep duration, likelihood of sleeplessness, feeling not well-rested and worse than on a typical day, using an ATUS time-use panel from 2005-2019.[18] Workers' on-the-job performance may be adversely affected if heat exposure undermines sleep quality and rest.

4.2 Empirical Strategy

We adopt models in the manner of Connolly (2008); Graff Zivin and Neidell (2014) to investigate the effect of high temperatures on worker labor supply, sleep, and well-being:

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

where Y_{kct} denotes outcome variables such as working and sleep time (both in minutes) and a sleeplessness indicator for individual k on diary day t and geographic unit of residence c. Following the specification in the main analysis, we categorize the daily maximum temperature (MaxTemp_{ct}) into five bins (denoted as B_j): $\leq 20°\text{C}$, $(20°\text{C}, 25°\text{C}]$, $(25°\text{C}, 30°\text{C}]$, $(30°\text{C}, 35°\text{C}]$, and $> 35°\text{C}$, and set $\leq 20°\text{C}$ 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. $\mathbf{V}_k$ 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,

[18] We conduct our own analyses using ATUS, instead of relying on Graff Zivin and Neidell (2014), to maintain greater temporal overlap with our main sample, examine additional outcomes such as sleep quality, and to focus on transportation workers in particular.

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.[19] Standard errors in both models are clustered at the state-year level.

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

Panel A of Table 5 summarizes the estimated effects of heat exposure on working time. The negative effects appear to increase alongside the highest daily temperature among the full sample of employees, although the estimates are statistically insignificant. This is more apparent when restricting to transportation workers as defined by the major industry and occupation codes (Columns 2 and 3). Individuals working in daily maximum temperatures between 20°C and 30°C do not reduce their hours, but those facing maximum temperatures above 35°C decrease work time by approximately 1.2-1.4 hours. The size of these magnitudes relative to the 14-minute decrease for the full sample may reflect the transportation sector's designation as a heat-exposed industry by bodies such as the National Institute for Occupational Safety and Health (NIOSH, 1986).

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. Column (1) shows that, on average, having one additional day with a daily maximum temperature above 35°C 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 transportation workers, the effect becomes even larger at around 0.8-1.1 p.p.

Our estimates of the impact of high temperatures on work absenteeism is consistent with the

[19] Specifically, we consider the following model:

$$\mathbb{1}(Absence_{kcw}) = \sum_j \alpha_j \sum \mathbb{1}(\text{MaxTemp}_{c,w} \in B_j) + \sigma \mathbf{V}_k + \eta \mathbf{W}_{cw} + f(month, year, w, c) + \varepsilon_{kcw} \quad (4)$$

where w denotes the week before the week of the diary day t. $\sum \mathbb{1}(\text{MaxTemp}_{c,w} \in B_j)$ 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.

magnitude of findings from Indian manufacturing industries (Adhvaryu et al., 2020; Somanathan et al., 2021). For example, in Somanathan et al. (2021), an additional day above 35°C in the six preceding days causes a 0.5 p.p. increase in the probability of missing work for weavers in India working in a non-climate controlled setting. Our estimates across a range of samples is inclusive of this point estimate.

Table 6 presents the estimated heat effects on workers' 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 35°C, compared to days when the temperature does not exceed 20°C. Sleep among workers in the transportation industry decreases by 20 minutes when the temperature is between 25-30°C, while the effects of even hotter days are in the expected negative direction but not precisely estimated. 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 35°C, by about 2 p.p. Among transportation workers, the negative consequences of heat exposure for this aspect of sleep quality is already apparent for daily maximum temperatures between 25-30°C, and continues to increase the incidences of sleeplessness for days above 30°C.[20]

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 35°C, although the effect is only marginally significant. 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.

The analyses using ATUS data focus on the transportation sector. Small samples prevent us

[20]One caveat is that our choice of maximum temperatures may not accurately capture individuals' precise indoor temperature exposure during the night. We furthermore do not observe climate control at home. These omissions likely lead to underestimates of the negative effect of heat on worker sleep, to the extent that climate control and other adaptive strategies can moderate the adverse consequences of heat on sleep.

from disaggregating further to examine the effects of heat exposure on air transportation workers only. To do so, we turn to a supplementary dataset - Severe Injury Reports from the Occupational Safety and Health Administration - to examine how high temperatures affect workplace injuries across detailed industry classifications.[21] Heat can adversely impact workers' occupational health by impairing cognition and concentration, thereby increasing the likelihood of workplace injuries (Park et al., 2021). Table B.11 shows that higher temperatures exert nonlinear effects on the likelihood of at least one severe injury, with magnitudes rising quickly for the top temperature bin of 35°C in the full sample (Column 1) and across transportation industry subsectors (Columns 2-4). The evidence indicates that heat's effects on air transportation is at least comparable to the aggregated transportation industry in this dimension of labor response to heat.

Taken together, the evidence shows that heat can lead to a decrease in labor supply, resulting in fewer hours worked and an increase in absenteeism among transportation workers. Furthermore, our results suggest that heat negatively affects workers' sleep (both duration and quality) and well-being. Previous studies have established a strong correlation between sleep, well-being, and workers' labor productivity (Bubonya et al., 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.[22]

[21] Injury reports are mandated for all severe work-related injuries involving in-patient hospitalization, amputation, or loss of an eye. These reports contain detailed industry codes along with information on the time and place of each incident. We merge all incidents with corresponding weather data at the county-day level from Daymet from 2015-2019, then estimate models that examine the likelihood of any incident occurring as a function of heat and a rich set of covariates that incorporate time-varying weather patterns and county and time fixed effects.

[22] 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.12. Comparing Panel A of Table 5 and Table B.12, 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.

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).[23] Zones 1 and 2 comprise the hottest zones with an average temperature of approximately 30°C. 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 24°C covering significant portions of southern and southwestern states. The coldest zones, Zones 6 and 7, range from eastern Washington to the Rockies, Minnesota, and Wisconsin all the way to the northeastern states of New York, Vermont, New Hampshire, and Maine.[24]

Figure A.2 shows the estimated results across climate zones for temperatures greater than 35°C, relative to the reference bin of temperatures less than or equal to 20°C.[25] The estimated heat effect on cancellation rates is similar across climate zones, while differences for departure delays are discernible across zones. Both the delay probability and duration in Zones 3 and 4 show greater vulnerability to heat exposure, whereas the hottest climate regions in our sample (Zones 1 and 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. Flight cancellations in cooler areas (Zones 6 and 7) are not differentially affected by heat, but these regions experience lower delay rates than Zones 3 and 4.

[23] Panel (a) of Figure A.1 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.

[24] 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 A.1b 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.

[25] We estimate a version of Equation (1) that includes the temperature variables interacted with climate zone dummies, as well as temperature bins interacted with airport type, flight length, and weather covariates.

To explore potential variation in adaptation across regions, we examine effects on the labor supply and sleep quality of workers from different climate zones. The upper panels of Figure A.3 illustrate that worker hours and absenteeism rates in hotter regions (Zone 1 and Zone 2) are insensitive to high temperatures exceeding 35°C, 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. 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, and alternative air pollution instruments and temperature measures.

In addition, we find that nonhub airports are particularly vulnerable to rising temperatures relative to their medium and large hub counterparts, and this may be driven by the concentration of shorter flights out of smaller airports. Our finding of heterogeneous effects across different enplanement and flight characteristics underscores how climate change disproportionately affects certain locations.

Supplemental analyses employing time use data illuminate potential mechanisms behind the effects of heat stress. We find that higher temperatures reduce workers' intertemporal labor supply, with pronounced effects among transportation workers, 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 can contribute to erosion in labor productivity, namely through deteriorating on-the-job-performance.

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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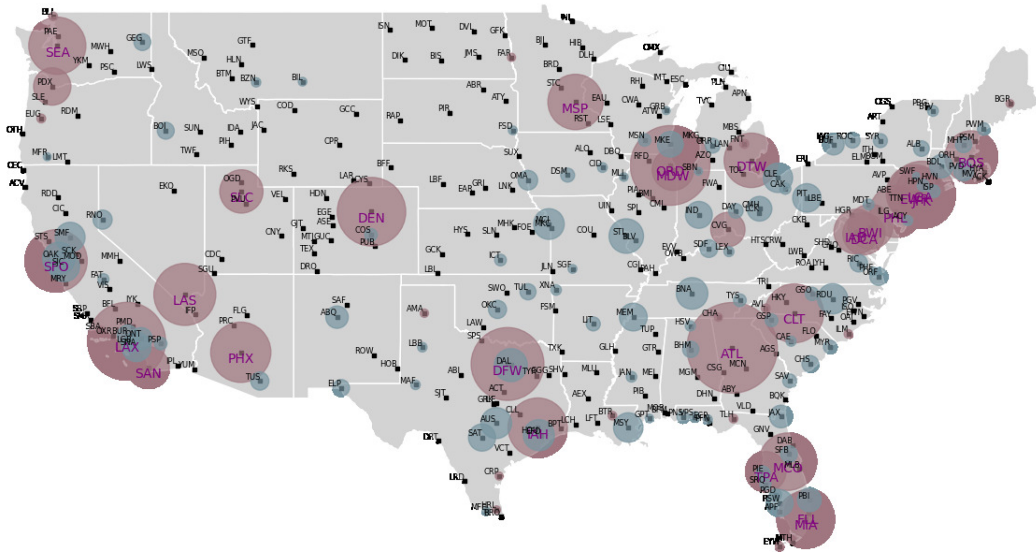
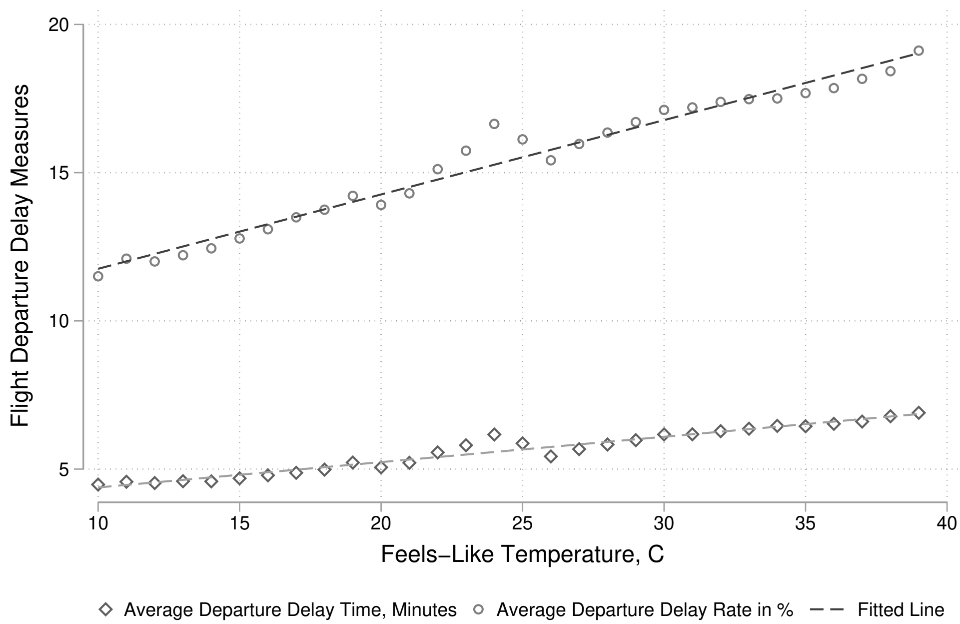
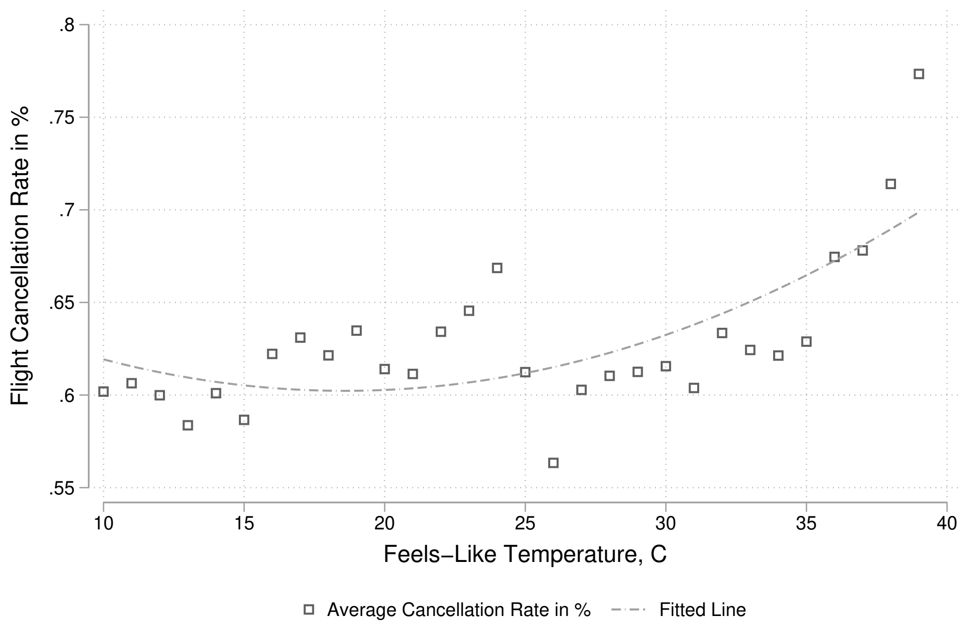


Figure 1: Airports in Sample and Their Average Annual Enplanements, 2004-2019

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.



(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.

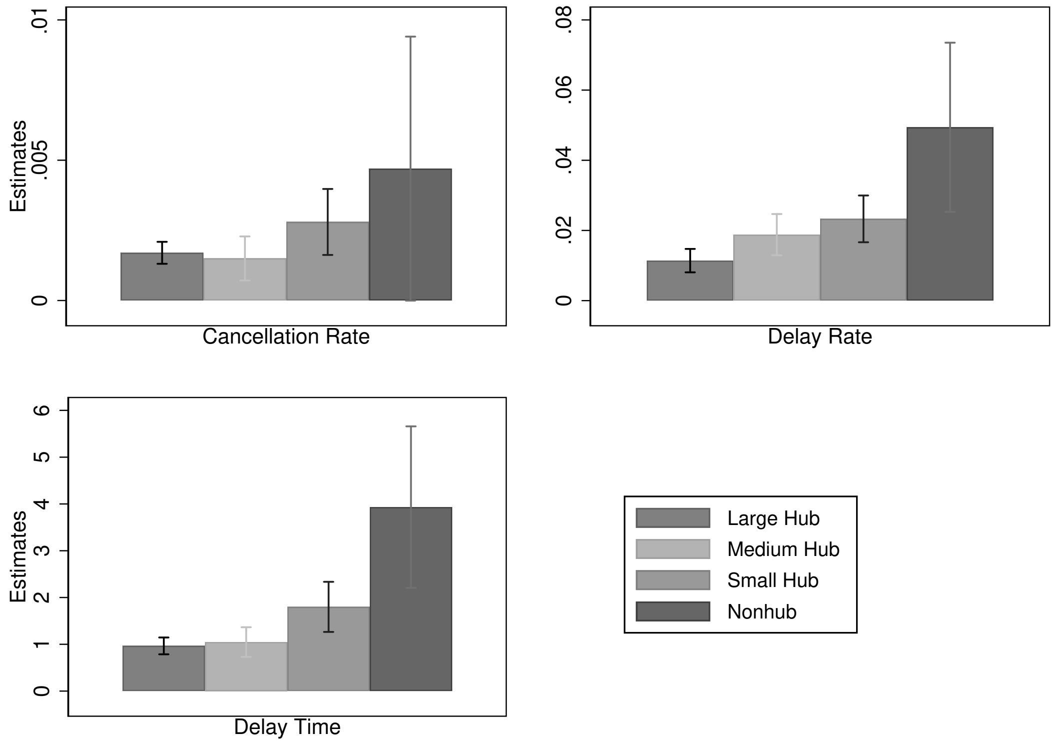


Figure 3: Heterogeneous Effects by Origin Airport Type

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

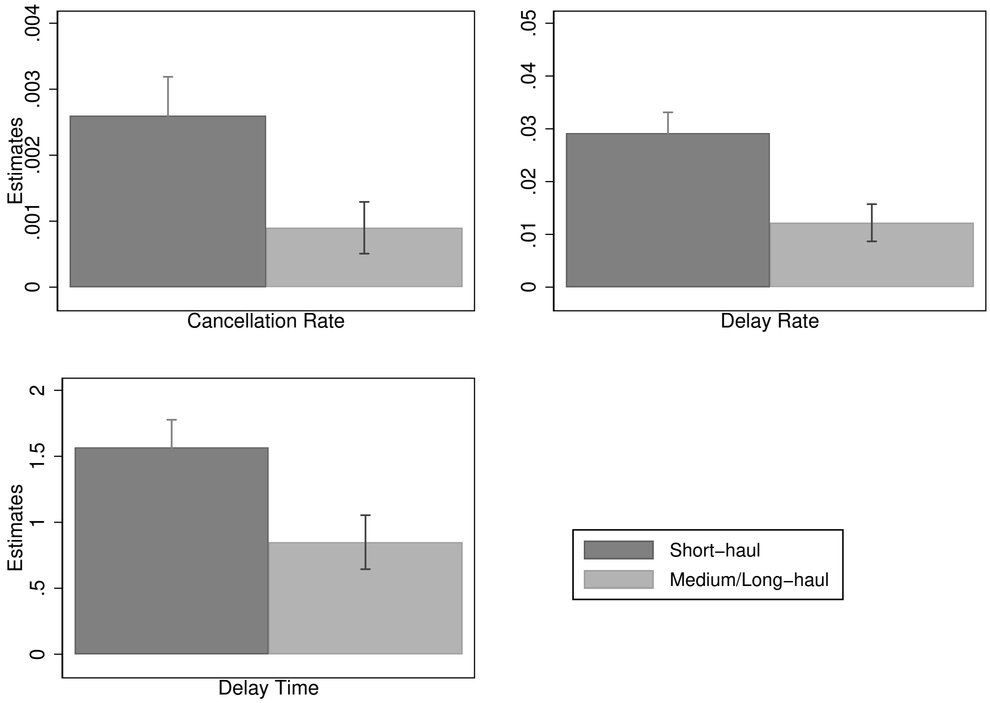


Figure 4: Heterogeneous Effects by Flight Length

Notes: This figure summarizes the point estimates and their 95% confidence intervals of temperatures falling in the treatment bin of greater than 35°C, relative to the reference bin of temperatures below 20°C, 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.

Table 1: Summary Statistics: Main Analysis

	N	Mean	Std.	Min	Max
Flight On-Time Performance					
Cancellation Rate	29005757	0.01	0.08	0	1
Departure Delay Rate	29005757	0.16	0.36	0	1
Departure Delay Time (Minutes)	29005757	5.65	26.11	0	2450
Temperature					
Temperature Groups (°C)					
≤ 20	29005757	0.34	0.47	0	1
$\in (20,25]$	29005757	0.26	0.44	0	1
$\in (25,30]$	29005757	0.21	0.41	0	1
$\in (30,35]$	29005757	0.13	0.34	0	1
> 35	29005757	0.06	0.24	0	1
Hours of Temp >35°C, 5am-6pm	29005679	0.37	1.44	0	8
Covariates					
Origin					
Precipitation Indicator	29005757	0.07	0.26	0	1
One hour precipitation (inches)	29005757	0.00	0.03	0	4
Wind Speed (mph)	29005730	8.91	5.00	0	126
Pressure altimeter (inches)	29005757	29.98	0.15	1	40
Relative Humidity (%)	29005757	58.18	21.84	1	100
Temperature Inversion (925hPa − Surface)	29005757	0.06	2.97	-5	18
Air Pollution					
CO	29005757	0.33	0.17	0	3
NO_2	29005757	11.20	6.68	0	77
Ozone	29005757	0.03	0.01	0	0.10
PM2.5	29005757	10.38	5.95	0	287
Destination					
Precipitation Indicator	29005757	0.08	0.26	0	1
One hour precipitation (inches)	29005757	0.00	0.03	0	5
Wind Speed (mph)	29005757	8.83	5.07	0	266
Pressure altimeter (inches)	29005757	29.98	0.15	1	40
Relative Humidity (%)	29005757	58.28	21.89	1	106

Notes: Table 1 presents the summary statistics of variables in the estimation 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)	68750	276.19	270.07	0	1380
1(Absence Last Week)	68750	0.04	0.19	0	1
Sleeping:					
Sleep Time on a Diary Day (Minutes)	68750	507.73	130.21	0	1428
Any Sleeplessness on a Diary Day	68750	0.04	0.20	0	1
Well-being:					
Not Well-Rested	13167	0.21	0.41	0	1
Worse-Than a Typical Day	13167	0.07	0.26	0	1
Weather:					
Daily Max Temperature (°C) $\in (20,25]$	68750	0.16	0.37	0	1
Daily Max Temperature (°C) $\in (25,30]$	68750	0.20	0.40	0	1
Daily Max Temperature (°C) $\in (30,35]$	68750	0.15	0.36	0	1
Daily Max Temperature (°C) > 35	68750	0.04	0.21	0	1
Minimum Temperature (°C)	68750	7.44	10.07	-38	33
Maximum Temperature (°C)	68750	20.23	10.68	-20	47
Accumulated Precipitation (mm/day)	68750	3.06	7.87	0	185
Day Length (s/day)	68750	43064.81	6705.56	28921	57432
# Days Max Temp $\in (20,25]$ Last Week	68750	1.13	1.56	0	7
# Days Max Temp $\in (25,30]$ Last Week	68750	1.38	1.91	0	7
# Days Max Temp $\in (30,35]$ Last Week	68750	1.09	1.97	0	7
# Days Max Temp > 35 Last Week	68750	0.31	1.21	0	7
Weekly Avg Precipitation Last Week	68750	21.13	27.45	0	473
Weekly Avg Day Length Last Week	68750	43040.20	6709.58	29053	57468
Covariates:					
Diary day a holiday	68750	0.02	0.13	0	1
Male	68750	0.54	0.50	0	1
Married	68750	0.56	0.50	0	1
Has Child <18	68750	0.51	0.50	0	1
Age	68750	43.22	11.96	15	85
% Age >65	68750	0.03	0.16	0	1
Paid Hourly	68750	0.44	0.50	0	1
% Reside in Urban Area	68750	0.99	0.11	0	1
% Hispanic	68750	0.15	0.36	0	1
% Black	68750	0.14	0.34	0	1
% Asian	68750	0.05	0.22	0	1
% < High School	68750	0.05	0.23	0	1
% High School Graduate	68750	0.21	0.41	0	1
% Some College	68750	0.55	0.50	0	1

Notes: Table 2 shows the summary statistics of variables in the estimation sample which contains full-time employed workers. 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 ∈ (20°C, 25°C]	0.0004***	0.0084***	0.294***
	(0.00007)	(0.0005)	(0.0266)
Temp ∈ (25°C, 30°C]	0.0006***	0.0117***	0.426***
	(0.00009)	(0.0008)	(0.0404)
Temp ∈ (30°C, 35°C]	0.0011***	0.0159***	0.783***
	(0.00012)	(0.0011)	(0.0587)
Temp >35°C	0.0018***	0.0205***	1.184***
	(0.00016)	(0.0014)	(0.0758)
Percentage Effects (in %)			
Temp ∈ (20°C,25°C]	6.25	5.36	5.20
Temp ∈ (25°C,30°C]	9.55	7.45	7.53
Temp ∈ (30°C,35°C]	17.67	10.13	13.85
Temp >35°C	29.67	13.06	20.94
N	29005757	29005757	29005757
R^2	0.0002	0.012	0.005
KP F-Stats	316.2	316.2	316.2

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. All models controls 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 further controls for destination weather conditions, daily local air pollution measured by CO, NO_2, PM2.5, and ozone, as well as origin by month fixed effects. Percentage Effect (in %) indicates the percentage effect relative to the corresponding baseline sample mean. Standard errors are clustered at the origin-destination pair level. First Stage Kleibergen-Paap Wald F statistics are reported.

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 >35°C, 5am-6pm	0.0001	0.0080***	0.2416***
	(0.0001)	(0.0005)	(0.0290)
Temp $\in$ (20°C, 25°C]	0.0005***	0.0216***	0.6836***
	(0.0002)	(0.0012)	(0.0650)
Temp $\in$ (25°C, 30°C]	0.0009***	0.0162***	0.3199***
	(0.0003)	(0.0019)	(0.1050)
Temp $\in$ (30°C, 35°C]	0.0015***	0.0125***	0.2204
	(0.0004)	(0.0024)	(0.1364)
Temp >35°C	0.0017***	0.0179***	0.4786**
	(0.0005)	(0.0036)	(0.2035)
Percentage Effects (in %)			
Hours of Temp >35°C, 5am-6pm	1.72	3.53	3.33
N	3345949	3345949	3345949
R^2	0.0004	0.006	0.0009
KP F-Stats	157.0	157.0	157.0

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. All models controls 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 further controls for destination weather conditions, daily local air pollution measured by CO, NO_2, PM2.5, and ozone, as well as origin by month fixed effects. Percentage Effect (in %) indicates the percentage effect relative to the corresponding baseline sample mean. Standard errors are clustered at the origin-destination pair level.

Table 5: The Effect of Temperature on Worker Labor Supply

	(1)	(2)	(3)
		Transportation	
	All	Industry	Occupation
Panel A.	Working Time		
Max Temp ∈ (20°C, 25°C]	1.275	-23.44	-7.954
	(3.858)	(18.32)	(20.48)
Max Temp ∈ (25°C, 30°C]	-2.981	1.136	-20.40
	(4.173)	(23.72)	(25.37)
Max Temp ∈ (30°C, 35°C]	-6.658	-34.50	-60.89**
	(5.635)	(27.60)	(30.95)
Max Temp >35°C	-13.60	-69.45*	-82.35*
	(8.512)	(40.91)	(44.49)
Sample Mean	277.7	294.9	297.7
R^2	0.370	0.411	0.420
Panel B.	1(Absence Last Week)		
Days Max Temp ∈ (20°C, 25°C] Last Week	0.0002	0.0037	0.0016
	(0.0008)	(0.0031)	(0.0032)
Days Max Temp ∈ (25°C, 30°C] Last Week	0.0007	0.0069**	0.0047
	(0.0007)	(0.0027)	(0.0032)
Days Max Temp ∈ (30°C, 35°C] Last Week	0.00061	0.0081**	0.0037
	(0.0010)	(0.0041)	(0.0041)
Days Max Temp > 35°C Last Week	0.0028*	0.0113**	0.0078
	(0.0015)	(0.0056)	(0.0060)
Sample Mean	0.038	0.042	0.039
R^2	0.034	0.214	0.198
N	68750	3508	3175

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (1) includes the entire sample of full-time employed individuals. Column (2) includes full-time employed individuals who work in the transportation industry, based on the major industry code for the respondent's main job. Column (3) includes full-time employed individuals who work in transportation and material moving occupations, as classified by the major occupation code for the main job. Standard errors are clustered at the state-year level.

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

	(1)	(2)	(3)
		Transportation	
	All	Industry	Occupation
Panel A.	Sleep Time on a Diary Day (in Minutes)		
Max Temp ∈ (20°C, 25°C]	-1.535	2.935	-5.775
	(2.190)	(10.69)	(11.66)
Max Temp ∈ (25°C, 30°C]	-6.411**	-19.88*	-16.780
	(2.544)	(11.85)	(13.78)
Max Temp ∈ (30°C, 35°C]	-6.865**	-6.476	-14.230
	(3.251)	(15.01)	(17.17)
Max Temp >35°C	-9.197**	-14.39	7.226
	(4.367)	(22.11)	(26.54)
Sample Mean	507.2	505.4	515.9
R^2	0.124	0.234	0.282
Panel B.	Any Sleeplessness on a Diary Day		
Max Temp ∈ (20°C, 25°C]	-0.0006	0.0035	0.0096
	(0.0037)	(0.0159)	(0.0152)
Max Temp ∈ (25°C, 30°C]	0.0069	0.0476**	0.0403**
	(0.0048)	(0.0205)	(0.0167)
Max Temp ∈ (30°C, 35°C]	0.0051	0.0328	0.0534**
	(0.0058)	(0.0262)	(0.0226)
Max Temp >35°C	0.0180**	0.0409	0.0572*
	(0.0083)	(0.0392)	(0.0295)
Sample Mean	0.04	0.04	0.04
R^2	0.027	0.204	0.252
N	68750	3508	3175

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. Column (1) includes the entire sample of full-time employed individuals. Column (2) includes full-time employed individuals who work in the transportation industry, based on the major industry code for the respondent's main job. Column (3) includes full-time employed individuals who work in transportation and material moving occupations, as classified by the major occupation code for the main job. Standard errors are clustered at the state-year level.

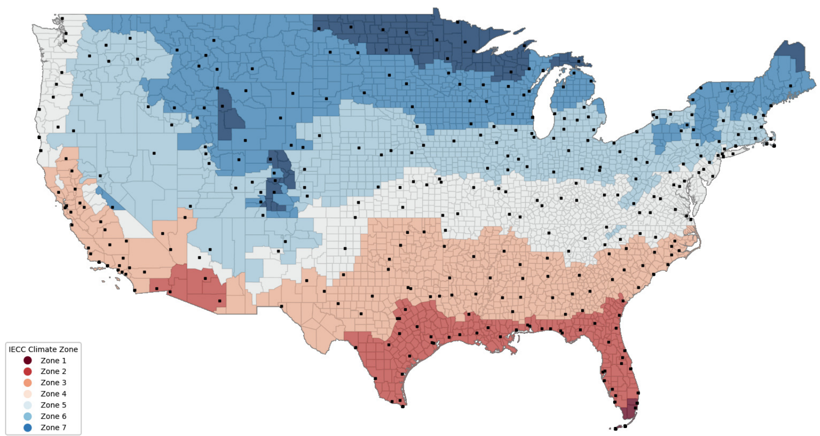
Table 7: The Effect of Temperature on General Well-Being

	(1)	(2)
	Not Well-Rested	Worse-Than Typical
Max Temp $\in$ (20°C,25°C]	-0.0056	-0.0072
	(0.0151)	(0.0112)
Max Temp $\in$ (25°C,30°C]	0.0067	0.0036
	(0.0163)	(0.0141)
Max Temp $\in$ (30°C,35°C]	0.0413	0.0011
	(0.0263)	(0.0169)
Max Temp $>$35°C	0.0632*	0.0097
	(0.0360)	(0.0171)
Sample Mean	0.207	0.068
R^2	0.066	0.101
N	13167	13167

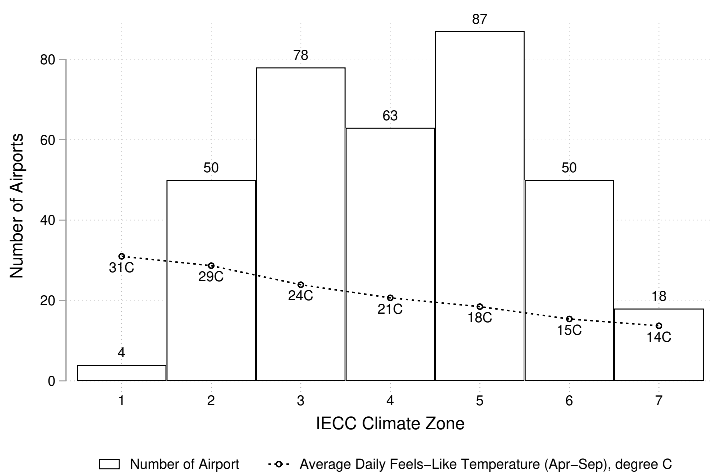
Note: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. The shown results are for all full-time employed respondents. Following the instruction in the data codebook of the ATUS Well-being Module, we use the WB respondent-level final weights in the estimation of Columns (1)-(2).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

Online Appendix

1 Figures



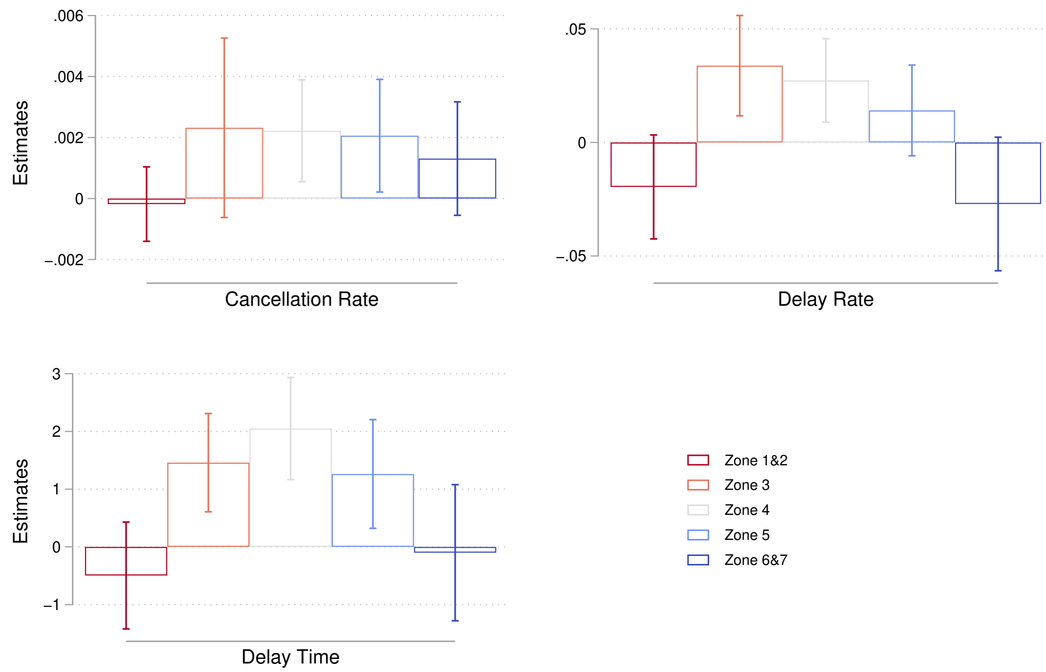
(a) U.S. Climate Zone



(b) Airport Distribution and Average Temperature

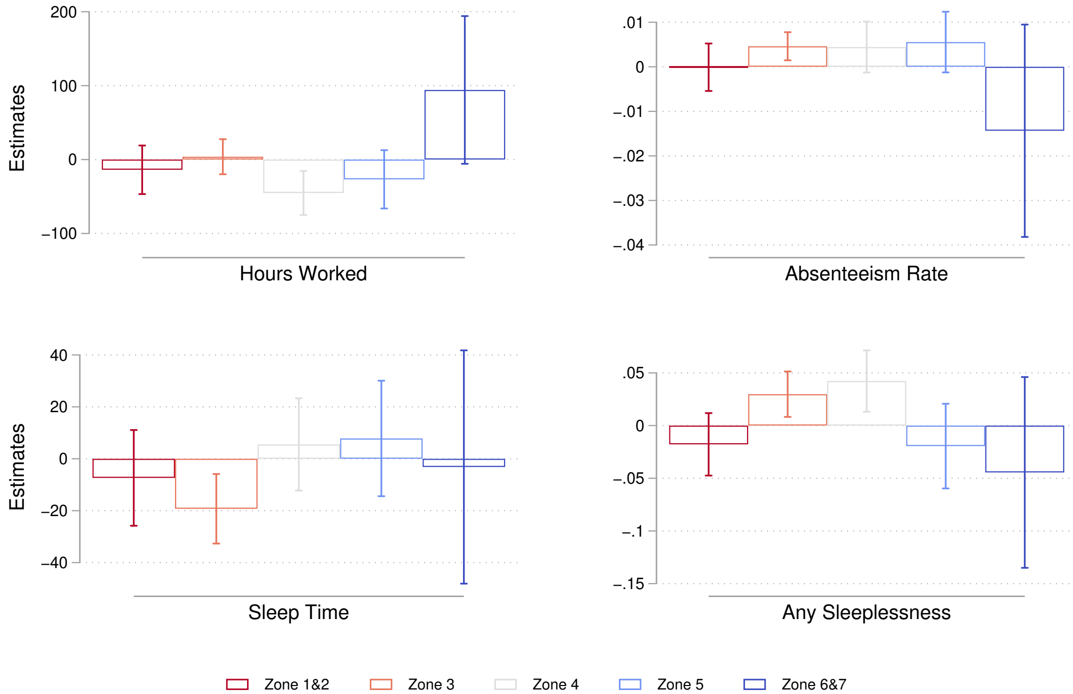
A.1: U.S. Climate Zone and Airports

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.



A.2: Heterogeneous Effects on Flight On-Time Performance by Climate Zone

Notes: This figure summarizes the effect of temperatures falling in the bin >35°C, relative to the reference bin of temperatures less than or equal to 20°C, by climate zone and for outcomes of the cancellation rate, departure delay rate, and delay time, respectively. We estimate a version of Equation (1) that includes the temperature variables interacted with climate zone dummies, as well as temperature bins interacted with airport type, flight length, and weather covariates.



A.3: Heterogeneous Effects on Labor Supply, Sleep, and Well-being by Climate Zone

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

2 Tables

B.1: Literature Overview (1/4) - Micro Evidence on Labor Output

Study	Country	Context	Outcome Measure	Data	Key findings
Cachon et al. (2012)	US	Manufacturing: automobile production	Weekly production for each model	Weekly production data from 64 automobile plants from one automotive manufacturer, from 1994-2005	Six or more days with a temperature of 90°F or more reduces weekly production by 8 percent
Cai et al. (2018)	China	Manufacturing: producer of paper cups	Percentage of daily output over specified product's target	Daily administrative data from manufacturing firm from Oct 2012 - Feb 2014	8.5 percent lower productivity at temperatures above 95°F
Zhang et al. (2018)	China	Manufacturing: large sample of Chinese plants	Firm-level total factor productivity, factor inputs, and outputs	Firm-level data for all large industrial firms in China (94% manufacturing) from 1998-2007	A day with temperatures above 90°F decreases TFP by 0.56 percent, relative to a day with temperatures between 50-60°F.
Chen and Yang (2019)	China	Manufacturing: large sample of Chinese plants	Industrial output (value-added per worker)	Firm-level data for all large industrial firms in China (94% manufacturing) from 1998-2007	A 1 percent temperature increase during the summer decreases labor productivity by 3.4-4.5 percent. An additional day at 30°C reduces annual industrial output by 0.21 percent.
Adhvaryu et al. (2020)	India	Manufacturing: garment factories	Production line efficiency (output over target output)	Daily production data, daily working hours and monthly wage contracts from a large garment firm operating around Bangalore, India	At average temperatures above the mean daily wet bulb globe temperature of 19°C (equivalent to 27-28°C at average humidity levels), there is a 2 efficiency point decrease for every 1°C increase
Somanathan et al. (2021)	India	Manufacturing: cloth weaving, garment sewing, and steel production firms, as well as panel of manufacturing plants	Cloth weaving: daily meters woven; Garment sewing: daily production from sewing lines; Steel production: number of blocks of steel per shift	Micro datasets with information on worker output and attendance, a national panel of manufacturing plants, and a panel of Indian districts with manufacturing GDP	Effects of temperatures above 35°C, relative to 29°C or less, are heterogeneous and range from a 2 percent decrease for weaving up to 4-8 percent decrease for garments
Zhang et al. (2023)	China	Construction: construction firms	Province-level industrial product divided by total construction labor force	Construction enterprises at province level from 2006-2019	Decline in labor productivity past "ideal level" of approximately 25°C
Stevens (2017)	US	Agriculture: blueberry pickers in California	Weight-per-hour harvested	Worker level data from over 2000 blueberry pickers from 2014-2016 paid by piece rates	Workers are 12 percent less productive at temperatures above 100°F, compared to 80-85°F
LoPalo (2023)	46 developing countries	Outdoor workers: interviewers for the Demographic and Health Surveys	Number of completed interviews	Data on the daily work schedules and output for interviewers in the Demographic and Health Surveys	Interviewers work longer days in order to achieve the same daily output of interviews (1.3 percent more hours relative to days with mild temperatures)
Qiu and Zhao (2021)	China	Sports: professional archery competitions	Individual-contest performance	longitudinal data set of 3196 professional archers in 57 competitions during 2010-2016	10 percent decrease in performance when the heat index exceeds 34°C (relative to the most comfortable range of 18–22°C)
Burke et al. (2023)	Global	Sports: tennis matches	Within-match performance outcomes	Player-match-level data for men's and women's professional tennis over 15 years	Heat reduces labor productivity, as measured by more double faults, more frequent retirement, shorter rallies, and less total distance run, and also reduces win probability in the subsequent match.

B.2: Literature Overview (2/4) - Micro Evidence on Labor Supply

Study	Country	Context	Outcome Measure	Data	Key findings
Graff Zivin and Neidell (2014)	US	All: workers in American Time Use Survey	Daily time allocated to labor and leisure activities	American Time Use Survey from 2003-2006	Workers in climate-exposed industries reduce daily labor time by as much as one hour for daily max temperatures of 85°F or higher. No significant effects for those in low climate risk industries.
Cai et al. (2018)	China	Manufacturing: producer of paper cups	Daily absenteeism and hours worked	Daily administrative data from manufacturing firm from Oct 2012 - Feb 2014	No effects on absenteeism or working hours
Garg, Gibson, et al. (2020)	China	All: workers in China Health and Nutrition Survey	Weekly time allocation to working, household chores, and childcare	Individual-level panel data from nine Chinese provinces from 1989-2011 (China Health and Nutrition Survey)	An additional day of average temperatures above 80°F reduces weekly work time by 1.2 hours, with larger reductions for farmers.
Adhvaryu et al. (2020)	India	Manufacturing: garment factories	Working hours	Daily production data, daily working hours and monthly wage contracts from a large garment firm operating around Bangalore, India	No meaningful effects on working hours
Somanathan et al. (2021)	India	Manufacturing: cloth weaving, garment sewing, and steel production firms, as well as panel of manufacturing plants	Daily absenteeism at worker or team levels	Micro datasets with information on worker output and attendance, a national panel of manufacturing plants, and a panel of Indian districts with manufacturing GDP	High lagged temperatures increase absenteeism in climate-controlled garment and steel factories, and non-climate-controlled weaving plants

B.3: Literature Overview (3/4) - Micro Evidence on Cognitive Performance and Decision-Making

Study	Country	Context	Outcome Measure	Data	Key findings
Graff Zivin et al. (2018)	US	Children aged five and above in the National Longitudinal Survey of Youth (NLSY79)	Standardized test scores: math, reading recognition, and reading comprehension	NLSY79, with test data available from 1988-2006	Large negative effects on cognitive performance in the short run (significant declines in math performance for temperatures above 26°C), but no measurable effects for long-run human capital accumulation.
Heyes and Saberian (2019)	US	Immigration judges	Asylum grant rate	Universe of cases for 266 immigration judges from 2000-2004	A 10°F degree increase in case-day temperature reduces favorable decisions by 6.6 percent, despite a climate-controlled context.
Graff Zivin et al. (2020)	China	Students taking the National College Entrance Examination, or gaokao	Exam scores	National College Entrance Examination data from 2005-2011	A one-standard-deviation increase in temperature decreases total test scores by 0.68 percent, or 0.06 standard deviations
Garg, Jagnani, et al. (2020)	India	Students in primary and secondary schools answering survey-based math and reading questions	Exam scores	India-wide repeated cross-section dataset (Annual Status of Education Report) from 2006-2014 and individual panel (Young Lives Survey) for single state from 2002-2011	10 extra days with average daily temperatures above 29°C reduces math and reading test scores by 0.03 and 0.02 standard deviations. One mechanism is reduced agricultural yields and income.
Park et al. (2020)	US	Universe of students taking the PSATs	Exam scores	College Board data on PSAT math and reading scores from 2001-2014	Cumulative heat exposure is detrimental to learning: 1°F hotter lagged school year lowers test scores by 0.2 percent of a standard deviation. Extreme heat has larger effects.
Park (2022)	US	High school students in New York City taking the Regents Exam	Exam scores	Regents Exam data from 1999-2011	A one-standard deviation increase in temperature reduces performance by 5.5 percent of a standard deviation. Taking an exam on a 90°F day leads to a 10 percent lower change of passing a subject, and reduces graduation likelihood.

B.4: Literature Overview (4/4) - Micro Evidence on Sleep, Mental Health, and Workplace Safety

Study	Country	Context	Outcome Measure	Data	Key findings
Obradovich et al. (2017)	US	US residents in Centers for Disease Control and Prevention Behavioral Risk Factor Surveillance Survey (BRFSS)	Days respondents felt they did not get enough rest or sleep during last 30 days	BRFSS from 2002–2011	1°C increase in minimum nighttime temperature leads to three additional nights of insufficient sleep per 100 individuals per month
Mullins and White (2019)	US	Respondents in BRFSS and American Time Use Survey (ATUS)	Suicides, emergency department visits, number of poor mental health days, number of nights of poor sleep and minutes slept	BRFSS (1993-2012) and ATUS (2003-2017)	Higher temperatures increase suicides, emergency department visits for mental health, and self-reported poor mental health days. Sleep disruption as potential mechanism - increasing nighttime temperatures increase number of nights of poor sleep (BRFSS) and decrease minutes slept (ATUS).
Minor et al. (2022)	Global	Those wearing sleep-tracking wristbands	Sleep duration and timing	Large-scale sleep dataset from 2015-2017 of residents in 68 countries wearing accelerometry-based sleep-tracking wristbands linked to a smartphone application	Adults fall asleep later, rise earlier, and sleep less during hot nights.
Park et al. (2021)	US	California workers	Injury count	Claims-level injury data from the California Worker's Compensation System from 2001-2018	Maximum daily temperature above 100°F leads to a 10-15 percent increase in same-day injury risk, relative to a day in the 60s Fahrenheit.
Dillender (2021)	US	Texas workers	Occupational health outcomes (injuries)	Administrative worker compensation data from Texas from 2006-2014	A day with a high temperature over 100°F increases same-day claim rates by 7.6–8.2 percent and three-day claim rates by 3.5–3.7 percent.
Ireland et al. (2023)	Australia	Workers in the Australian state of Victoria	Occupational health claims	Australian worker health records from mandatory insurance scheme (1985-2020)	A one-degree Celsius increase in the daily maximum increases claims by 0.24%

B.5: Robustness Check (1/6) - Instrument for PM2.5 Following Chen et al (2023)

	(1)	(2)	(3)
First Stage:	*PM2.5*		
Temperature Inversion	0.592***		
	(0.0227)		
First Stage KP F-Stats	333.86		
Second Stage:	*Cancellation Rate*	*Delay Rate*	*Delay Time*
Temp $\in$ (20°C, 25°C]	0.0003***	0.0082***	0.2904***
	(0.00006)	(0.00047)	(0.02660)
Temp $\in$ (25°C, 30°C]	0.0005***	0.0110***	0.4029***
	(0.00009)	(0.00073)	(0.04188)
Temp $\in$ (30°C, 35°C]	0.0010***	0.0135***	0.6971***
	(0.00015)	(0.00115)	(0.06934)
Temp $>$35°C	0.0017***	0.0169***	1.0634***
	(0.00021)	(0.00156)	(0.09298)
PM2.5	-0.0001	-0.0068***	-0.1530***
	(0.00011)	(0.00090)	(0.04703)
PM2.5^2	0.0000	0.0002***	0.0058***
	(0.00000)	(0.00003)	(0.00189)
Marginal Effect of PM2.5 @ 45 $\mu g/m^3$	0.000	0.014***	0.373***
	(0.0003)	(0.0023)	(0.1236)
N	29005727	29005727	29005727
R^2	0.0002	0.012	0.005

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. All models controls 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 further controls for destination weather conditions and origin by month fixed effects. We control for daily local air pollution measured by PM2.5 and instrument for PM2.5 using only the temperature inversion IV. Standard errors are clustered at the origin-destination pair level. First Stage Kleibergen-Paap Wald F statistics are reported.

B.6: Robustness Check (2/6) - Alternative Model Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Diff. Weather and Air Pollution Controls			*Real Air Temperatures*			*Alternative Clustering Level*		
	Cancellation Rate	Delay Rate	Delay Time	Cancellation Rate	Delay Rate	Delay Time	Cancellation Rate	Delay Rate	Delay Time
Temp ∈ (20°C, 25°C]	0.0003***	0.0049***	0.252***	0.0004***	0.0089***	0.295***	0.0004**	0.0084***	0.294***
	(0.00006)	(0.0004)	(0.0245)	(0.0001)	(0.0005)	(0.0273)	(0.0002)	(0.0021)	(0.0793)
Temp ∈ (25°C, 30°C]	0.0004***	0.0064***	0.378***	0.0006***	0.0106***	0.387***	0.0006***	0.0117***	0.426***
	(0.00007)	(0.0006)	(0.0341)	(0.0001)	(0.0008)	(0.0424)	(0.0002)	(0.0026)	(0.108)
Temp ∈ (30°C, 35°C]	0.0008***	0.0090***	0.738***	0.0010***	0.0151***	0.762***	0.0011***	0.0159***	0.783***
	(0.00009)	(0.0008)	(0.0492)	(0.0001)	(0.0012)	(0.0631)	(0.0003)	(0.0033)	(0.147)
Temp >35°C	0.0015***	0.0126***	1.126***	0.0014***	0.0248***	1.022***	0.0018***	0.0205***	1.184***
	(0.00013)	(0.0012)	(0.0682)	(0.0002)	(0.0020)	(0.105)	(0.0005)	(0.0048)	(0.200)
N	29005730	29005730	29005730	29005757	29005757	29005757	29005757	29005757	29005757
R^2	0.007	0.068	0.024	0.0002	0.012	0.005	0.0002	0.012	0.005

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. This table reports the robustness estimation results of different models. Columns (1)-(3) excludes all air pollution controls from the model and includes a continuous covariate for wind direction, Columns (4) to (6) use the real air temperature as the treatment variable, and Columns (7) to (9) cluster the standard errors at the origin-by-month level. Standard errors are clustered at the origin-destination pair level for Columns (1) to (6).

B.7: Robustness Check (3/6) - Additional Fixed Effects

	(1)	(2)	(3)
	Cancellation Rate	*Delay Rate*	*Delay Time*
Temp $\in$ (20°C, 25°C]	0.0004***	0.0088***	0.310***
	(0.00006)	(0.0005)	(0.0269)
Temp $\in$ (25°C, 30°C]	0.0005***	0.0122***	0.442***
	(0.00008)	(0.0008)	(0.0404)
Temp $\in$ (30°C, 35°C]	0.0010***	0.0161***	0.780***
	(0.00011)	(0.0011)	(0.0587)
Temp $>$35°C	0.0017***	0.0201***	1.177***
	(0.00015)	(0.0014)	(0.0769)
N	29005757	29005757	29005757
R^2	0.0002	0.012	0.005
Origin$\times$Year FE	✓	✓	✓

Notes: Standard errors in parentheses. * $p < 0.10$, **$p < 0.05$, *** $p < 0.01$. All models controls 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 further controls for destination weather conditions, daily local air pollution measured by CO, NO_2, PM2.5, and ozone, as well as origin by month fixed effects.

B.8: Robustness Check (4/6) - Aircraft Age

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Aircraft Age	Cancellation Rate			Departure Delay Rate			Departure Delay Time		
Temp ∈ (20°C, 25°C]	-0.0087	0.0003***	0.0003***	0.0003***	0.0084***	0.0084***	0.0084***	0.296***	0.296***	0.296***
	(0.0073)	(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.0005)	(0.0005)	(0.0282)	(0.0282)	(0.0282)
Temp ∈ (25°C, 30°C]	-0.0131	0.0004***	0.0004***	0.0004***	0.0114***	0.0114***	0.0114***	0.420***	0.419***	0.419***
	(0.010)	(0.0001)	(0.0001)	(0.0001)	(0.0008)	(0.0008)	(0.0008)	(0.0427)	(0.0427)	(0.0427)
Temp ∈ (30°C, 35°C]	-0.0059	0.0006***	0.0006***	0.0006***	0.0155***	0.0155***	0.0155***	0.786***	0.784***	0.784***
	(0.0129)	(0.0001)	(0.0001)	(0.0001)	(0.0011)	(0.0011)	(0.0011)	(0.0620)	(0.0620)	(0.0621)
Temp >35°C	0.0005	0.0012***	0.0012***	0.0012***	0.0196***	0.0195***	0.0193***	1.183***	1.181***	1.174***
	(0.0189)	(0.0001)	(0.0001)	(0.0001)	(0.0014)	(0.0014)	(0.0014)	(0.0800)	(0.0799)	(0.0801)
Aircraft Age			0.0001***			0.0011***			0.0467***	
			(0.0000)			(0.0000)			(0.0019)	
N	26012253	26012256	26012256	26012256	26012256	26012256	26012256	26012256	26012256	26012256
R^2	0.000	0.0001	0.0002	0.0003	0.013	0.013	0.013	0.005	0.006	0.006
Aircraft Age × Carrier FEs				✓			✓			✓

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the origin-destination pair level. For reference, Column (1) regresses aircraft age on temperature bins, employing the same model specification as in the main analyses. Columns (2), (5), and (8) report the result of Equation (1) without controlling for aircraft age. Columns (3), (6), and (9) include a continuous variable for aircraft age. Columns (4), (7), and (10) add carrier fixed effects interacted with the continuous aircraft age variable.

B.9: Robustness Check (5/6) - Placebo Test

	(1)	(2)	(3)	(4)	(5)	(6)
	Randomized Temperature			*Randomized Outcome*		
	Cancellation Rate	Delay Rate	Delay Time	Cancellation Rate	Delay Rate	Delay Time
Temp ∈ (20°C, 25°C]	-0.00002	0.00037	0.00862	-0.00001	-0.0003	0.00355
	(0.00004)	(0.00018)	(0.0130)	(0.00005)	(0.00024)	(0.0174)
Temp ∈ (25°C, 30°C]	-0.00001	-0.00002	-0.00350	0.00009	-0.00043	0.0182
	(0.00004)	(0.00018)	(0.0135)	(0.00007)	(0.00035)	(0.0247)
Temp ∈ (30°C, 35°C]	-0.00002	-0.00003	0.00235	0.000176	-0.000440	0.0264
	(0.00004)	(0.00021)	(0.0150)	(0.00010)	(0.00046)	(0.0326)
Temp >35°C	-0.00005	0.00023	-0.00175	0.00014	-0.00007	0.0430
	(0.00006)	(0.00027)	(0.0197)	(0.00012)	(0.00057)	(0.0416)
N	29005757	29005757	29005757	29005757	29005757	29005757
R^2	0.0002	0.012	0.005	0.00000	0.00000	0.00000

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the estimation results for shuffled treatment (Columns 1 to 3 and outcome variables (Columns 4 to 6), adopting the preferred model Equation (1) and 2SLS. Standard errors are clustered at the origin-destination pair level.

B.10: Robustness Check (6/6) - Results of Randomized Full-Year Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	April - September Sample			*Full-Year Sample*		
	Cancellation Rate	Delay Rate	Delay Time	Cancellation Rate	Delay Rate	Delay Time
Temp < 5°C	0.0009***	0.0208***	0.7014***	0.0018***	0.0248***	0.8661***
	(0.0002)	(0.0009)	(0.0543)	(0.0001)	(0.0006)	(0.0325)
Temp ∈ (5°C, 10°C]	0.0006***	0.0068***	0.1581***	0.0004***	0.0057***	0.2178***
	(0.0001)	(0.0006)	(0.0397)	(0.0001)	(0.0005)	(0.0302)
Temp ∈ (15°C, 20°C]	0.0002**	0.0037***	0.1113***	0.0001**	-0.0004	0.0303
	(0.0001)	(0.0006)	(0.0304)	(0.0001)	(0.0005)	(0.0267)
Temp ∈ (20°C, 25°C]	0.0005***	0.0112***	0.3746***	0.0003***	0.0025***	0.1712***
	(0.0001)	(0.0008)	(0.0415)	(0.0001)	(0.0007)	(0.0404)
Temp ∈ (25°C, 30°C]	0.0007***	0.0139***	0.4853***	0.0005***	0.0046***	0.2883***
	(0.0001)	(0.0011)	(0.0551)	(0.0001)	(0.0011)	(0.0591)
Temp ∈ (30°C, 35°C]	0.0012***	0.0176***	0.8275***	0.0008***	0.0079***	0.5952***
	(0.0002)	(0.0014)	(0.0718)	(0.0002)	(0.0014)	(0.0803)
Temp >35°C	0.0019***	0.0218***	1.2174***	0.0013***	0.0120***	0.9533***
	(0.0002)	(0.0016)	(0.0876)	(0.0002)	(0.0017)	(0.0948)
N	29005757	29005757	29005757	25707944	25707944	25707944
R^2	0.0002	0.012	0.005	0.0002	0.011	0.005

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results are estimated using a sample that randomly draws 50% of the observations from a full-year sample spanning January to December for the years 2004 to 2019. All models controls 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 further controls for destination weather conditions, daily local air pollution measured by CO, NO_2, PM2.5, and ozone, as well as origin by month fixed effects.

B.11: The Contemporaneous Effect of Temperature on Workplace Injuries

	(1)	(2)	(3)	(4)
	Any Injury			
	All	Transportation	Air Transport	Truck Transport
Temp $\in$ (20°C, 25°C]	0.000385***	0.0000211	0.00000945	0.00000885
	(0.000129)	(0.0000272)	(0.0000106)	(0.0000198)
Temp $\in$ (25°C, 30°C]	0.000674***	0.0000273	0.00000819	0.0000243
	(0.000148)	(0.0000315)	(0.0000120)	(0.0000225)
Temp $\in$ (30°C, 35°C]	0.00198***	0.000157***	0.0000230*	0.000105***
	(0.000177)	(0.0000369)	(0.0000136)	(0.0000273)
Temp $>$ 35°C	0.00295***	0.000128*	0.0000377	0.000150***
	(0.000324)	(0.0000697)	(0.0000297)	(0.0000504)
Percentage Effects (in %)				
Temp $\in$ (20°C, 25°C]	4.41	5.14	13.65	4.17
Temp $\in$ (25°C, 30°C]	7.72	6.66	11.82	11.44
Temp $\in$ (30°C, 35°C]	22.72	38.28	33.25	49.60
Temp $>$ 35°C	33.84	31.22	54.42	70.87
N	5673925	5673925	5673925	5673925

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample combines county-day Daymet weather information with data on severe injuries from the Occupational Safety and Health Administration from 2015-2019. Outcome variables are indicators for any injury across all industries (Column 1), and separately by industry type (Columns 2-4). All models control for other weather conditions such as day length, daily precipitation, and daily minimum temperatures, and separate county, year, and day of week fixed effects. Percentage Effects (in %) indicate the percentage effect relative to the corresponding baseline sample mean. Standard errors are clustered at the county-year level.

B.12: More on The Effect of Temperature on Worker Labor Supply

	(1)	(2)	(3)
		Transportation	
	All	Industry	Occupation
Panel A.		Working Time	
Max Temp ∈ (20°C, 25°C]	0.242	-21.25	-11.03
	(3.538)	(17.27)	(18.65)
Max Temp ∈ (25°C, 30°C]	-6.954*	-11.69	-28.28
	(3.665)	(21.82)	(22.44)
Max Temp ∈ (30°C, 35°C]	-10.99**	-38.18	-65.91**
	(5.090)	(26.62)	(28.47)
Max Temp >35°C	-19.01**	-78.55**	-72.57*
	(7.785)	(37.88)	(38.95)
Sample Mean	277.7	294.9	297.7
N	68750	3508	3175
Sleeplessness Dummy	✓	✓	✓
Sleep Time Control	✓	✓	✓

Notes: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Column (1) includes the entire sample of full-time employed individuals. Column (2) includes full-time employed individuals who work in the transportation industry, based on the major industry code for the respondent's main job. Column (3) includes full-time employed individuals who work in transportation and material moving occupations, as classified by the major occupation code for the main job. Standard errors are clustered at the state-year level.