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Too hot to haul? the impact of temperature on labor supply and performance of truck drivers

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ABSTRACT

This paper studies the effects of extreme temperatures on labor supply and performance in the heavy-duty trucking industry, a pivotal sector with broad productivity spillovers and significant road safety externalities. Using rich and high-frequency data on individual truck drivers in China, we find that exposure to extreme heat significantly reduces labor supply and increases the incidence of risky driving. Evidence further suggests that extreme temperatures disrupt off-duty rest and increase on-duty fatigue among drivers. We also document behavioral adaptation: drivers respond to heat by adjusting work schedules and reallocating labor to adjacent days. Furthermore, the estimated temperature effects on labor supply and risky driving are smaller among drivers employed by firms that offer heat subsidies.

1. Introduction

Extreme heat poses increasing risks to workers throughout the global economy. A growing body of research shows that extreme temperatures adversely affect both physical and cognitive performance, reduce labor supply, and increase workplace injury rates across a broad range of sectors, including agriculture, construction, manufacturing, and services (Zivin et al., 2014; Somanathan et al., 2021; Park et al., 2021; Rode et al., 2022; Escobar Carias et al., 2024). These disruptions in labor performance can translate into sizable reductions in aggregate output and substantial economic losses, particularly in sectors with high labor intensity or outdoor work (Zhang et al., 2018; Rode et al., 2022).

This paper studies how extreme temperatures affect driver's labor supply and on-duty safety performance in the heavy-duty trucking industry. Unlike many other labor market settings, truck drivers work extended hours in enclosed, often poorly ventilated cabins, exposed to heat stress both during work and rest. Their job demands long periods of continuous driving, sustained alertness, and rapid responses to external conditions—making it particularly vulnerable to heat-related impairments. Shocks to the transportation industry often result in significant externalities. First, productivity shocks in freight transport spill over to upstream and downstream sectors through supply-chain linkages. Moreover, risky driving behavior and declines in driver performance can endanger other road

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users.[1] Despite these high stakes, empirical evidence on the labor and safety consequences of adverse environmental conditions in freight transportation remains limited.

This paper provides new evidence on truck drivers using a novel dataset that combines high-frequency GPS and sensor records from nearly 10,000 heavy-duty trucks operating in Guangdong, China. Each vehicle is equipped with monitoring systems that track GPS location, speed, engine status, and a real-time accident risk detection system. These technologies generate rich behavioral measures, from which we construct accurate measurements for labor supply, idling, work duration, trip completion, and on-duty safety performance. By spatially matching each driver's location trajectory to hourly high-resolution weather and environmental data derived from satellite imagery, we build individualized profiles of temperature exposure and track the same driver for approximately two years.

We estimate panel models that relate drivers' labor supply and safety outcomes to the distribution of temperature exposure, controlling for a rich set of fixed effects and environmental covariates. Identification leverages within-driver variation across days, isolating the impact of heat exposure net of individual-specific confounders and common daily shocks. Our design combines day-to-day changes in the intraday distribution of temperatures experienced by the same driver. In contrast to approaches based on daily average temperature, our approach exploits both the intensity and duration of extreme heat.[2] This allows us to more precisely characterize the nonlinear relationship between heat stress and labor and safety outcomes. We also show that our estimates are robust to alternative exposure measures commonly used in the literature.

We document three main sets of findings. First, extreme heat reduces labor supply along both extensive and intensive margins. High temperatures decrease the likelihood that a driver works on a given day and significantly shorten the longest continuous driving spell. It also reduces daily productivity, measured by the number of completed trips. These effects are concentrated on hotter days but exhibit partial interday substitution: drivers who reduce labor on extreme heat days are more likely to work more on subsequent days. We also find evidence of intra-day adaptation. Drivers are more likely to delay their start time in response to high temperatures, particularly when assigned short-distance trips that allow greater scheduling flexibility.

Second, extreme heat increases accident-risk warnings per 100 kilometers of driving, reflecting an elevated incidence of unsafe driving episodes such as speeding, tailgating, and unsafe lane changes. The effects accumulate over consecutive days of exposure, consistent with both acute and lagged physiological or cognitive stress. Two pieces of evidence speak to the mechanisms. For one, high temperatures reduce the duration of off-duty rest, and the following day we observe increased yawning events while driving. For another, the intensity of unsafe driving behaviors rises more steeply with temperature exposure during active driving than during rest periods, suggesting a direct impact of on-duty heat stress on cognitive performance and reaction time.

Third, we examine heterogeneity by firms' provision of high-temperature subsidies. Drawing on a firm survey that documents which transportation companies provide financial compensation for heat exposure, we estimate heterogeneous temperature effects by subsidy status. Drivers employed by companies offering heat subsidies exhibit smaller reductions in labor supply and smaller increases in unsafe driving behaviors under high temperatures. For example, the estimated rise in accident-risk warning intensity among subsidized drivers is roughly half that among unsubsidized drivers. These patterns suggest that firm-provided heat compensation, or other correlated firm practices, may be associated with greater resilience to heat exposure in this setting. Because we cannot isolate the causal effect of subsidy provision from other firm characteristics, we interpret these results as suggestive and as motivation for future work.

Related literature. Our study contributes to three strands of literature. First, we build on the growing body of research examining how climate change and extreme temperatures affect labor supply (Zivin et al., 2014; Garg et al., 2020), productivity (Zivin et al., 2012; Somanathan et al., 2021; Wang et al., 2022; Rode et al., 2022), and worker reallocation (Colmer, 2021; Liu et al., 2023). Recent evidence also documents heat-induced impairments in worker performance (Picchio and van Ours, 2024), poor decision-making under heat stress (Escobar Carias et al., 2024), and increases in workplace accidents (Filomena and Picchio, 2024; Drescher and Janzen, 2025).

This paper constructs high-frequency, behavior-based measures of both labor supply and on-duty performance, including daily work participation, continuous driving hours, completed transport tasks, off-duty rest, on-duty idling, and active driving.[3] In addition, we provide new evidence on a pivotal yet understudied sector: freight transportation. Heavy-duty trucking requires drivers to endure prolonged periods of outdoor exposure while placing substantial demands on both physical stamina and cognitive capacity. Road transportation by heavy-duty trucks is also central to domestic and regional supply chains, as productivity shocks propagate through upstream and downstream linkages. Our findings contribute novel individual-level evidence and highlight a previously underexplored channel through which climate change can disrupt supply chains (Pankratz and Schiller, 2024; Castro-Vincenzi et al., 2024).[4]

[1] This is particularly concerning for heavy-duty vehicles such as dump trucks or buses, given their significantly greater weight compared to other vehicles, which amplifies the severity of collisions (Anderson and Auffhammer, 2014). For example, in the U.S., nearly five non-truck occupants lost their lives for every truck occupant fatality in large truck crashes in 2021. According to Large Truck and Bus Crash Facts 2021 compiled by the U.S. Department of Transportation (DOT), 1008 truck occupants were killed in crashes involving large trucks, while 4780 fatalities occurred among other road users.

[2] This distinction matters: two days with identical average temperatures may have quite different temperature distributions depending on the timing and persistence of heat exposure.

[3] Previous studies based on attendance records or time-use surveys observe only a subset of these dimensions.

[4] Road transport carries 70–90% of domestic freight (by tonnage). For example, according to the U.S. Department of Transportation, trucks accounted for 67% of total domestic freight tonnage and 69% by value in 2018. Source: Freight Mobility Trends Report 2019.

Second, we speak to the literature on how adverse environmental conditions affect workplace safety (Filomena and Picchio, 2024; Drescher and Janzen, 2025) and workers' physical condition, especially in the context of road traffic (Ferris and Newburn, 2017; Xu and Xu, 2020; Leard and Roth, 2019). Previous studies typically relied on aggregated injury and accident records. We advance this line of research by moving beyond aggregate accident statistics to directly measure risky driving behaviors at the individual level. Exploiting an AI-enhanced driver monitoring system, we provide evidence of heat-induced rest deprivation and heightened on-duty fatigue, thereby shedding light on the mechanisms underlying the observed rise in traffic accidents. Furthermore, our findings underscore the importance of accounting for the negative externalities of workplace and traffic safety. The heavy-duty trucking industry is unique because it is associated with significant safety externalities, as risky driving behavior and performance declines endanger other road users.

Third, we present a new measure of individual heat exposure. The standard approach in this literature assigns individuals to a fixed location—based on footprints (Fesselmeyer et al., 2024), recorded activities (Shr et al., 2023), or place of residence (Harris, 2025)—and aggregates temperature conditions at that level. In contrast, we leverage high-frequency GPS data to construct heat exposure using each individual's realized, time-varying footprint. As a robustness check, we also implement the conventional aggregated approach, and find that our preferred specification yields more conservative estimates.

Fourth, we contribute to the growing literature on policy interventions that facilitate adaptation to extreme temperatures. A number of recent studies have examined how public or institutional responses can help individuals and communities reduce the adverse effects of heat.[5] While these interventions have been shown to improve health and resilience, most are broad in scope and not directly tied to occupational heat exposure.[6] This paper adds suggestive evidence on employer-provided high-temperature subsidies. We find that drivers at firms offering heat subsidies exhibit smaller temperature effects on both labor supply and safety performance. These results suggest that financial compensation tied directly to heat exposure may be associated with greater workplace resilience.

Outline. The rest of the paper proceeds as follows. Section 2 describes the data and variable construction. Section 3 summarizes key patterns of heat exposure. Section 4 outlines our empirical strategy. Section 5 presents the main results, including mechanisms and heterogeneity in employer heat subsidies. Section 6 concludes.

2. Data and variable construction

This paper combines high-frequency GPS and vehicle sensor data with high-resolution weather data. Our sample spans from March 2023 to June 2025 and covers approximately 10,000 trucks and 130 freight companies operating in Guangdong province. We measure two sets of outcomes of interest, labor supply and on-duty safety performance, using detailed GPS and sensor data from trucks. Descriptive patterns on labor outcomes are presented in Section 3. Below we describe each data source and the construction of key variables.[7]

Labor outcome variables. Each heavy-duty vehicle in our sample is equipped with real-time GPS that records location, speed, and engine status. GPS signals are logged automatically every 20 s while the vehicle is in motion and every two minutes when stationary. Because the GPS unit is battery-powered, data continue to be recorded even when the engine is off. Combining instantaneous velocity with consecutive location records, we classify each time point into one of three mutually exclusive states: *off-duty rest*, *on-duty idle*, or *actively driving*. Off-duty rest is identified when a vehicle has zero velocity and does not move for over six consecutive hours. If a vehicle is not in off-duty rest, we classify it as *labor supply* or *on-duty*. For any on-duty vehicle, if it has zero velocity and does not move for over ten consecutive minutes, we label this interval as on-duty idle. This includes time spent under duty status but idle, such as inspections, refueling, waiting for loading/unloading, or taking short breaks. For on-duty vehicles that are not idling, we classify the status as actively driving—that is, we assume the driver is hands-on-wheel.

Based on the three labor statuses, we aggregate data to the driver-date level to construct labor supply outcomes. A driver is classified as working on a given day if any time interval is recorded as on-duty. Maximum consecutive driving (or working) hours are calculated by identifying uninterrupted on-duty periods and recording the longest duration among them.[8] We define a completed trip as a continuous sequence of GPS records in which the vehicle moves a positive distance with the engine on, separated from the next trip by a sufficiently long stop (e.g., more than one hour with the zero speed or the vehicle stationary). The indicator for starting work late is a binary variable equal to one if the driver's first movement record on a given day occurs later than their personal median start time over the sample period. On non-driving days, these outcomes are defined in a manner consistent with their economic meaning: the number of completed trips and maximum consecutive driving hours are set to zero, and the indicator for starting work late is set to one.

[5] Such as expanded healthcare access (Mullins and White, 2020; Cohen and Dechezleprêtre, 2022), unconditional or conditional cash transfers (Sarmiento et al., 2024; Garg et al., 2025), and improved weather forecasting systems (Shrader et al., 2023)

[6] Among the few exceptions, Behrer et al. (2024) document the effectiveness of a mandated workplace heat safety standard in California in reducing injuries on high-heat days.

[7] For additional details on context, data, and variable construction, we refer readers to Ding et al. (2025).

[8] Note that the maximum consecutive driving time may exceed the total driving hours recorded for a single day, since a continuous trip can span across multiple days.

On-duty performance. To measure on-duty safety performance, we use sensor-based accident-risk warnings. The truck fleet in our study is equipped with AI-enhanced driver-monitoring systems that generate alerts through onboard safety technologies when risky driving behaviors are detected, such as unsafe lane departures, collision warnings, tailgating (following too closely), and speeding. Our primary safety performance measure is the total number of accident-risk warnings per 100 kilometers driven at the daily level, which captures the intensity of unsafe driving episodes detected by the monitoring system. On non-driving days, we set both the number and the intensity of accident-risk warnings to zero. Since these warnings may not correspond directly to realized accidents, we interpret them as proxies for unsafe driving episodes rather than direct measures of accident occurrences.

In addition to accident-risk warnings, we employ in-cab cameras that monitor drivers' faces and apply computer vision techniques to detect and record instances of yawning, thereby identifying the mechanism of temperature-induced fatigue.

Weather data. We obtain hourly weather variables from the ERA5-Land reanalysis product developed by the European Centre for Medium-Range Weather Forecasts (ECMWF). The data are provided on a 0.1° by 0.1° grid (approximately 9 km resolution), and include hourly air temperature, precipitation, wind speed, etc. These high-resolution weather grids are spatially matched to each vehicle's trajectory, allowing us to construct flexible measures of the time each driver spends in different temperature ranges on a given day. We elaborate on these temperature bins when they become relevant in the empirical design section.[9]

Air pollution. We collect hourly air quality data from all monitoring stations in Guangdong province, including AQI and major pollutant concentrations. Station-level records are interpolated using inverse distance weighting to generate pollution exposure at the grid-cell level, which is then assigned to drivers based on their locations and driving hours. These variables are used as controls in our regression models.

Geographic and route characteristics. To account for variations in terrain and route conditions, we compile elevation and slope data from the ASTER Global Digital Elevation Model (GDEM) Version 3, at 30-meter resolution. We also overlay road and waterway features from OpenStreetMap. These variables are used to calculate the average slope, elevation, and land cover characteristics along each driving route.

Driver characteristics. Our administrative records do not include demographic information. To explore heterogeneity, we conducted an online survey of 190 randomly selected drivers from our sample, collecting data on age, gender, and prior driving experience. We use these data in subgroup analyses to examine how temperature effects vary with driver characteristics.

High-temperature subsidies. We conducted a phone survey of transportation companies, asking whether they provide financial compensation to drivers working under hot conditions. Based on this information, we classify each firm by whether it offers any type of high-temperature subsidies and link this to individual drivers for heterogeneity analysis.

3. Time allocation and heat exposure of truck drivers

Before proceeding with the estimation, we exploit the rich individual-level information in our data to document patterns regarding truck drivers' labor supply and performance. These new patterns related to the heavy-duty truck industry are valuable on their own and provide important context for the empirical analysis that follows. Table S1 shows the summary statistics.

Labor supply, rest, and on-duty performance. Fig. 1 plots the average time allocation and the incidence of accident-risk warnings across hours of the day. Several patterns emerge. First, drivers spend on average about 6.7 hours in active driving, which is intensive given the physical stamina and cognitive concentration required; the mid-day dip in driving time suggests that drivers take breaks during the hottest hours. Second, overall labor supply is extremely high, averaging 13.6 hours per day, with 23% of drivers on duty for more than 18 hours. Moreover, nighttime activity is substantial, as 76% of drivers remain on duty between 6 p.m. and midnight, indicating that excessive work hours and overtime driving at night are common in this industry. Third, accident-risk warnings peak in the middle of the day, with on-duty performance showing a reverse pattern relative to labor supply.

Overall, we find that in the truck transportation industry both labor supply and active driving hours follow an inverted U-shape over the course of the day, consistent with general labor supply patterns observed in other industries, but the extreme length of workdays and the prevalence of nighttime work are distinctive features of this context. In particular, the working hours observed in our data are substantially longer than those typically permitted in the United States or the European Union. This likely reflects institutional differences in the trucking sector in our study setting, where enforcement of working-time limits is less strict and drivers often face strong incentives to extend their working hours. In addition, our measure of on-duty time captures the span between the first and last recorded driving activity within a day and may therefore include waiting or idle periods between trips.

Exposure to heat waves. Fig. 2 presents the distribution of daily average temperature exposure by labor supply status. Two patterns stand out. First, the distributions of exposure across active driving, on-duty idle, and off-duty rest overlap substantially, consistent with earlier evidence that nighttime driving and excessive work are common features of this industry. Second, within this overlap,

[9] For a detailed discussion of the construction of temperature exposure measures for non-stationary objects, see Ding et al. (2025).

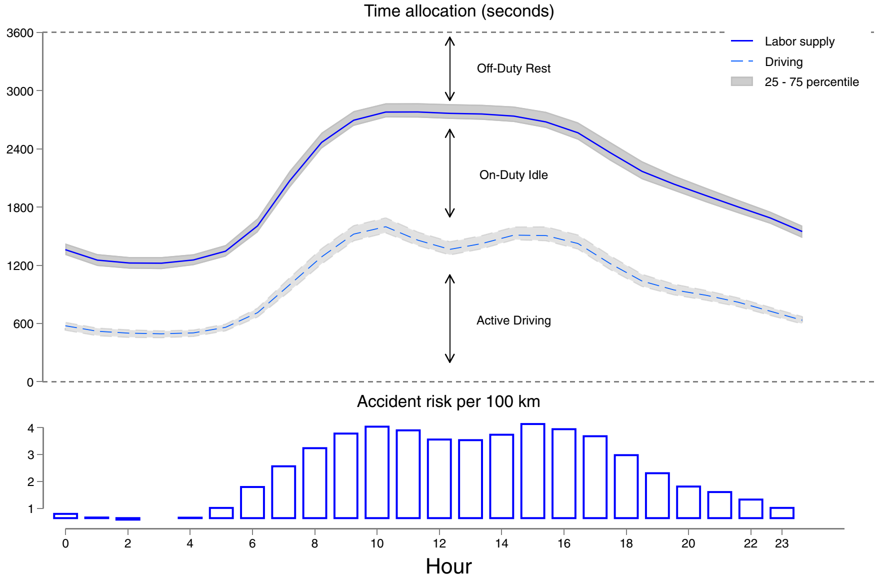


Fig. 1. Time allocation of Truckers and incidence of Accident-Risk warnings across hours of the Day. *Notes*: This figure plots the average time allocation and the incidence of accident-risk warnings across hours of the day. The upper panel shows time allocation by hour across three labor supply states: *off-duty rest*, *on-duty idle*, and *active driving*. The sum of active driving and on-duty idle is classified as labor supply (on-duty), with the average shown by the solid blue line. The blue dashed line shows the average of active driving, defined as periods when the vehicle is moving and the driver is hands-on-wheel for at least ten consecutive minutes. The shaded gray area represents the 25th to 75th percentiles of on-duty and driving status in our sample. The bottom panel shows the average distribution of on-duty performance over the day, measured by the number of accident-risk warnings per 100 kilometers driven. We exclude observations for driver-dates without any on-duty time. (For interpretation of the references to colour in this figure legend, the reader is referred to the web Version of this article.)

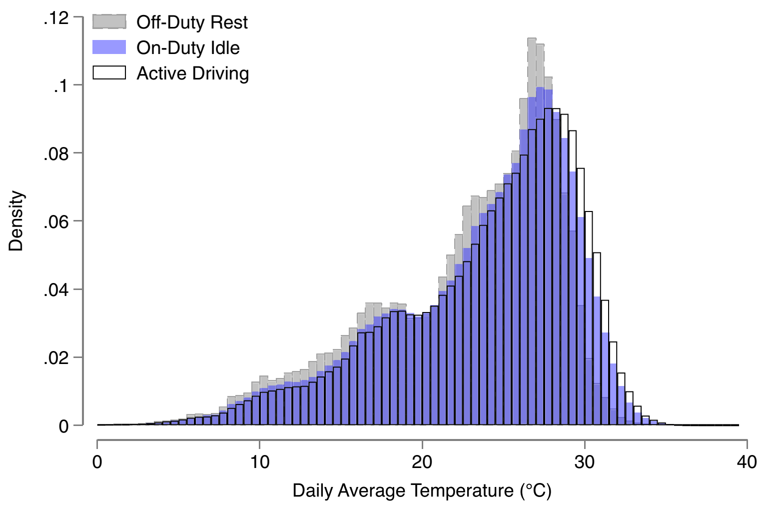


Fig. 2. Distribution of daily average exposure to heat by labor status. *Notes*: This figure plots the distribution of daily average temperature by three labor supply statuses: *off-duty rest*, *on-duty idle*, and *active driving*. The average daily temperature exposure is computed as a weighted average of the duration of exposure to hourly temperature, using data from the ERA5-Land reanalysis product.

active driving periods are concentrated at the highest temperatures, followed by on-duty idle, while off-duty rest tends to occur at relatively lower temperatures.

Figure S1 digs deeper into this pattern by showing the distribution of the daily share of time that drivers are exposed to each temperature bin. It shows that off-duty rest is more common at lower temperature ranges, while active driving becomes more frequent at higher temperatures, with on-duty idle lying in between. This pattern consistently suggests that drivers face their greatest heat exposure during the most physically and cognitively demanding tasks, raising concerns about productivity and safety under extreme heat.

4. Empirical strategy

The core of this paper's measure is to construct heat exposure metrics based on GPS trajectories, which we refer to as dynamic heat exposure. This route-based approach allows us to take advantage of the richer variation, but also imposes potential empirical challenges. This section describes our empirical strategies.

4.1. Constructing dynamic heat exposure

Defining route of a day. We define individual driver i's routes on a day t as,

$$\mathcal{R}_{it} = f\left(\mathrm{Work}_{it}, \mathrm{Origin}_{it}, \mathrm{Destination}_{it}, \mathrm{Path}_{it}^{OD}, \mathrm{Schedule}_{it}^{OD}(h)\right)$$

$\mathcal{R}_{it}$ is characterized by the driver's duty status on day t, Work_{it}; the trip origin and destination; the route between them, Path_{it}^{OD}, which is a geometric object; and the scheduling scheme, $\mathrm{Schedule}_{it}^{OD}(h)$, which captures the timing of departure, breaks taken during the trip (on-duty idle time), and other aspects of trip timing.[10]

Dynamic temperature exposure. In our main specification, the driver's exposure to heat in a day measurement is defined as,

$$H_{it}(k) = \mathcal{H}(\mathcal{R}_{it}, k) = \sum_{h=1}^{24} \sum_{p} \mathbf{1}(T_{p,h} \in k) \cdot D(\mathcal{R}_{it}, \mathcal{P}_p) \tag{1}$$

where $D(\cdot,\cdot)$ is the measurement function that defines the geometric intersection between the route $\mathcal{R}_{it}$ and the polygon of pixel p, $\mathcal{P}_p$ at a given hour h. In the baseline specification, we define $D(\cdot,\cdot)$ as the overlap-duration function—it measures the length of time a given path intersects a given pixel.

For drivers who do not work on a day, the GPS reading remains static, with their route remaining as a single stationary point at the location of the previous trip's destination. Thus, $D(\mathcal{R}_{it}, \mathcal{P}_p)$ is equal to one if p contains the stationary location, and zero otherwise. In this special case, the heat exposure is, $H_{it}^{0}(k) = \sum_{h=1}^{24} \mathbf{1}(T_{p^0,h} \in k)$.[11]

The key advantage of Eq. (1) over a static measure of heat exposure is that it exploits richer within-driver spatial variation by using each driver's realized route footprint, rather than assigning the driver to a fixed location. Therefore, it combines variations from both temperature within a pixel and the driver's route that spans across multiple pixels.

4.2. Alternative heat exposure measurements

While measurement Eq. (1) captures richer variations, we acknowledge that it also brings in additional empirical challenges. One potential concern is that the $\mathcal{R}_{it}$ could potentially be affected by endogenous decisions regarding workload and scheduling,[12] which simultaneously impact both the outcome and heat exposure measures.

Among the factors that determine $\mathcal{R}_{it}$, Origin_{it} and $\mathrm{Destination}_{it}$ are allocated by the freight company in our context and thus are arguably exogenous. The trajectory Path_{it}^{OD} could be changed by the driver. However, China's freight transportation system operates under a relatively regulated road-use regime. As discussed in Appendix A, these institutional features limit drivers' feasible route sets once the origin and destination are determined. Indeed, we show in Appendix B that, for repeated origin-destination pairs of a given driver, trajectory similarity across trips exceeds 90%.[13] This suggests that drivers typically follow a stable route and rarely take detours.

Therefore, the major concern arises from endogenously responding in Work_{it} and $\mathrm{Schedule}_{it}^{OD}(h)$. To address this, we construct two alternative exposure measures.

Average temperature exposure. To address the potential endogeneity from the intensive margin $\mathrm{Schedule}_{it}^{OD}(h)$, we eliminate from the temperature exposure measure all within-day hourly variation that may be driven by drivers' scheduling or driving patterns. Specifically, we redefine the route as

$$\tilde{\mathcal{R}}_{it} = f\left(\mathrm{Work}_{it}, \mathrm{Origin}_{it}, \mathrm{Destination}_{it}, \mathrm{Path}_{it}^{OD}\right),$$

which captures the fixed route footprint traversed by a driver during the day, abstracting from when and how long the driver stays at different locations.[14] In this way, we mechanically eliminate any possible source of endogeneity from $\mathrm{Schedule}_{it}(h)$. We then define

[10] If the driver is off duty, the trip collapses to a stationary location (a point), in which case Origin_{it} and $\mathrm{Destination}_{it}$ are identical.

[11] Since no individual i's element contributes to the measurement of $H_{it}^{0}(k)$, the bin-wise temperature exposure distribution simplifies to the original temperature distribution measurements.

[12] Such as choosing whether to work on a certain day, determining departure times, deciding when to rest, and selecting routes

[13] Two trajectories are regarded as similar if they traverse essentially the same set of heat-image pixels, even if they do not perfectly overlap point by point.

[14] For example, we treat two routes with the same starting point and endpoint as identical, even if one departures at 10 AM and arrives at 6 PM, while the other departures at 8 AM and arrives at 7 PM.

the average temperature exposure as:

$$H_{it}(k) = \mathcal{H}(\tilde{\mathcal{R}}_{it}, k) = \frac{\sum_{h=1}^{24} \sum_p \mathbf{1}(T_{p,h} \in k) \cdot D(\tilde{\mathcal{R}}_{it}, \mathcal{P}_p)}{\sum_p D(\tilde{\mathcal{R}}_{it}, \mathcal{P}_p)}, \tag{2}$$

where $D(\cdot, \cdot)$ now becomes an indicator function equal to one if the route intersects a given grid cell. Intuitively, we compute the number of hours in a day with temperature falling into each bin for the ERA5 grid cells overlapping with this fixed route footprint and then take the simple average across these cells. With this measurement, the value of each temperature bin no longer represents drivers' actual duration of exposure to that temperature. Instead, it reflects the average bin-wise heat exposure across all pixels that intersect with the routes. For this reason, we call it average temperature exposure.[15]

Predicted heat exposure. For the extensive margin, Work_{it}, the major concern is that drivers may decide whether to work based on forecasted temperatures, in which case we do not observe the counterfactual trips that would have been taken had an off-duty driver chosen to work. We exploit the panel structure of our data, which allows us to observe the same driver repeatedly across trips. We then construct a driver-specific typical route and use it as the predicted route that would have been taken on non-working days. Specifically, for trips that are unobserved because the driver is off duty, we impute the route the driver would have taken using the driver-specific typical route, constructed as the algorithm-detected route that is both most representative and most frequently observed among all routes taken by that driver in our data.[16] The interpolation procedure is illustrated in Figure S2. Then we calculate the average heat exposure along this predicted route following Eq. (2).

4.3. Estimating equation

To examine the non-linear impact of temperature exposure on labor supply and on-duty safety performance, we estimate outcome variables using a flexible model of the heat exposure distribution. Our baseline specification is as follows,

$$Y_{it} = \sum_{k \in \mathcal{B}} \rho_k H_{it}(k) + \gamma' \mathbf{X}_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{3}$$

where the outcome variable Y_{it} denotes a labor or safety-related measure for driver i on day t. For example, driver i exposure to the temperature bin [30 – 33 °C] for 0.5 hour on date t. The key explanatory variables $H_{it}(k)$ represent the number of hours in which the driver is exposed to temperatures in bin k, where $k \in \mathcal{B} = \{[\leq 6\,°\text{C}], [6 - 9\,°\text{C}], \dots, [30 - 33\,°\text{C}], [> 33\,°\text{C}]\}$. The reference category is [18–21 °C]. We use $H_{it}(k)$ calculated in Eq. (1) as the baseline measure, and also report results using average and predicted heat exposure as robustness checks. The coefficients ρ_k thus capture the effect of an additional hour of exposure in temperature bin k relative to the reference range.

The vector $\mathbf{X}_{it}$ includes a rich set of controls to account for environmental and geographic conditions that may correlate with both temperature and the outcomes of interest. Specifically, we control for average precipitation, wind speed (and their quadratic terms), relative humidity, air quality (measured by AQI), elevation, and slope. These controls are constructed using the same geographic and temporal resolution as the temperature exposure variables. We include driver fixed effects α_i to absorb all time-invariant individual characteristics, such as baseline productivity, driving style, and long-term health conditions. Date fixed effects δ_t control for shocks common to all drivers on the same day, such as national holidays, fuel price changes, or demand fluctuations. Standard errors are two-way clustered by driver and date to account for within-driver serial correlation and common shocks affecting drivers on the same day.

By exploiting the panel structure and granularity of our data, our identification strategy relies on within-driver variation in hourly temperature exposure across days, which allows us to control for both individual and temporal unobservables. Unlike approaches that rely solely on average or maximum daily temperature, our model captures the intensity and duration of heat exposure by explicitly incorporating the number of hours spent in each temperature bin. This approach enables us to distinguish between exposure profiles that share the same daily average temperature but differ in their intraday distribution, thereby providing a more accurate assessment of non-linear temperature effects.[17]

In our main analysis, we estimate the effect of temperature using the full sample of driver–day observations, including days without driving. This specification therefore captures the net effect of temperature on driver performance, incorporating both intensive-margin changes in driving behavior and extensive-margin labor supply adjustments (i.e., the decision to drive on a given day). In this framework, participation responses are part of the equilibrium effect of heat. We believe this estimand is policy-relevant because it reflects the overall performance outcomes that arise when drivers can adjust their participation decisions. As a robustness check, we also estimate the specifications using only the subsample of driving days or consider alternative coding approaches for non-driving days. The results remain similar across these specifications. Detailed discussions and results are provided in Section 5.4.

[15] An alternative approach is to replace $\text{Schedule}_{it}^{OD}(h)$ with an average schedule scheme for the same route on days other than t, $\widehat{\text{Schedule}}_i^{OD}(h)$, so that the endogeneity link is muted by removing the subscript t. The limitation of this approach in our context is that for drivers who are not working on recurring tasks with the same OD, we do not have enough statistical power to accurately estimate $\widehat{\text{Schedule}}_i^{OD}(h)$

[16] We elaborate on the algorithm used to select the typical route in Appendix B.

[17] For example, a day with eight hours at 33 °C and sixteen hours at 18 °C may have very different implications than a day with shorter or milder exposure, even if average temperatures are similar.

While our baseline specification assumes contemporaneous effects of temperature on outcomes, we also explore dynamic responses by estimating distributed lag models that incorporate lagged exposure to extreme heat. These models allow us to assess both the cumulative effects of sustained high temperatures and the possibility of interday labor reallocation, i.e., whether drivers postpone or advance work in response to weather fluctuations. We discuss these analyses in detail in Sections 5.1.3 and 5.2.3.

5. Results

This section presents empirical findings on how extreme heat affects labor supply and on-duty safety performance of truck drivers. Section 5.1 quantifies the impact of high temperatures on drivers' labor participation, work intensity, and productivity. Section 5.2 addresses the effects on unsafe driving behaviors. Finally, Section 5.3 examines the heterogeneity in temperature effects based on firms' provision of heat subsidies.

5.1. Effects on labor supply and performance

5.1.1. Baseline results

Fig. 3 presents the estimated effects of temperature exposure on truck drivers' labor supply, based on our main specification in Eq. (3). Blue dots represent coefficient estimates, and gray segments show the corresponding 95% confidence intervals. Across all three labor outcomes, we find consistent evidence that extreme heat reduces drivers' labor supply.

On the extensive margin, Panel (a) shows that the probability of driving on a given day declines significantly at high temperatures. An additional hour of exposure to temperatures above 33 °C reduces the likelihood of driving by 0.2 percentage points relative to the reference bin of 18–21 °C. Given an average work participation rate of 95 percentage points, this corresponds to a 0.21% relative decline. We also examine intensive margin responses. In Panel (b), we examine the effect on drivers' work persistence, measured by the maximum consecutive driving hours in a day. We estimate that an additional hour above 33 °C leads to a 0.23 hours reduction in maximum continuous driving. Panel (c) reports similar declines in productivity, with the number of completed trips falling significantly with more exposure to high temperatures.

These findings are broadly consistent with previous studies documenting adverse effects of high temperatures on labor supply across a variety of contexts (Zivin et al., 2014; Garg et al., 2020; Somanathan et al., 2021; Rode et al., 2022), although the magnitude of the effects is difficult to compare directly due to differences in data, occupation, and climate, our results align with the general pattern. In contrast to the literature, we do not find evidence that cold temperatures affect labor supply in our setting. This likely reflects the subtropical climate of Guangdong province, where the average daily temperature is 23 °C during the sample period. Therefore, exposure to cold weather is relatively rare, and very few days fall below the temperature thresholds at which cold-related reductions in labor supply have been documented in other settings (e.g., 0 °C in Garg et al., 2020).

5.1.2. Work schedule adjustments and task intensity

When temperatures are high, drivers may shift work hours toward the later part of the day to avoid peak mid-day heat. To examine this, we test whether drivers are more likely to start work later than usual on hotter days. Panel (a) of Fig. 4 shows that high temperatures significantly increase the probability of a delayed start. Exposure to temperatures above 33 °C raises the likelihood of starting work late by about 0.7 percentage points, or 1.5% relative to the mean.

Such adjustments are more feasible when the job allows greater scheduling flexibility. Panel (b) explores heterogeneity by total driving distance, which we use as a proxy for task intensity. We find that the delayed-start response is concentrated among short-distance trips (less than 300 km), where drivers likely have greater discretion over when to begin work. For long-distance trips (more than 300 km), where workloads are heavier and scheduling is less flexible, the effect is small and statistically insignificant. These results suggest that drivers adapt to extreme heat by rescheduling work, but only when task demands permit.

5.1.3. Interday substitution

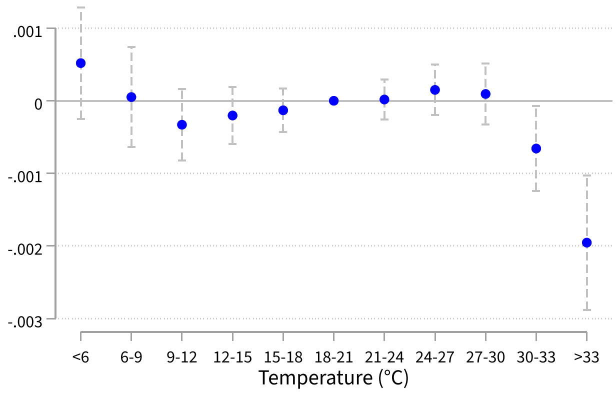
So far, we have focused on the contemporaneous effect of temperature on labor supply. To examine whether drivers shift labor across days in response to extreme heat, we estimate a distributed lag model:

$$Y_{it} = \rho H_{it}(> 30\,°\mathrm{C}) + \beta H_{it-1}(> 30\,°\mathrm{C}) + \gamma' \mathbf{X}it + \alpha_i + \delta_t + \varepsilon_{it}, \tag{4}$$

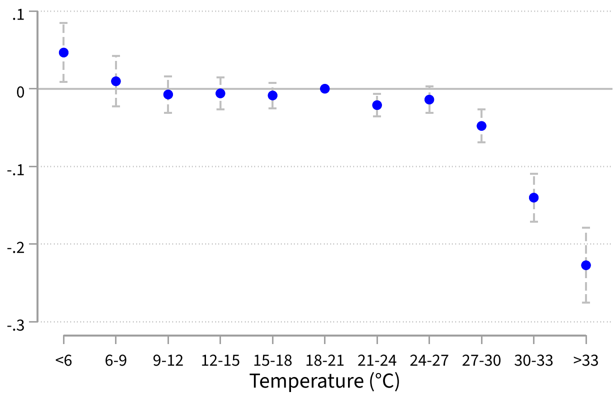
where $H_{it}(> 30\,°\mathrm{C})$ and $H_{it-1}(> 30\,°\mathrm{C})$ denote hours above 30 °C on the current and previous day, respectively. The specification follows Zivin et al. (2014) but uses fewer temperature bins. The coefficient ρ captures the contemporaneous effect of extreme heat on labor supply, while β captures the lagged effect from the prior day.

Table 2 reports the results. For work participation and completed trips, extreme heat reduces labor supply on the current day, with part of the reduction offset by increased labor the following day. For example, an additional hour above 30 °C reduces the probability of working on the same day by 0.02 percentage points but raises it the next day by 0.01 percentage points, recovering nearly half of the immediate loss. The bottom row reports the cumulative effect, $\rho + \beta$, capturing the net impact over a two-day window. Accounting for interday substitution, the net cumulative effects are attenuated relative to the contemporaneous estimates. For work participation and completed trips, the cumulative effects are no longer statistically significant.

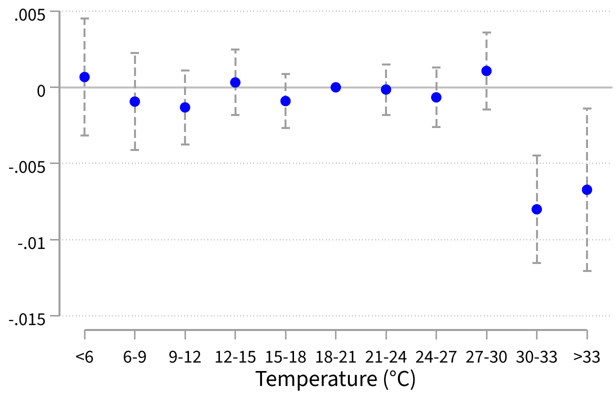
For maximum consecutive driving hours, however, the cumulative effect remains negative and statistically significant, with no evidence of interday substitution. This divergence likely reflects differences in flexibility across labor supply margins. Maximum consecutive driving hours, a measure of work persistence, are more tightly bound to same-day conditions: once a driver begins work,



(a) If Driving on a Day



(b) Maximum Consecutive Driving Hours

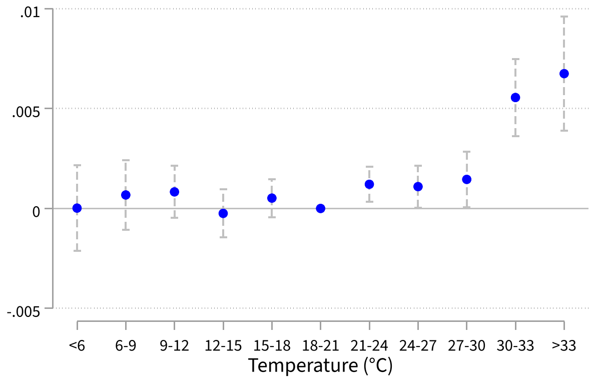


(c) Number of Completed Trips

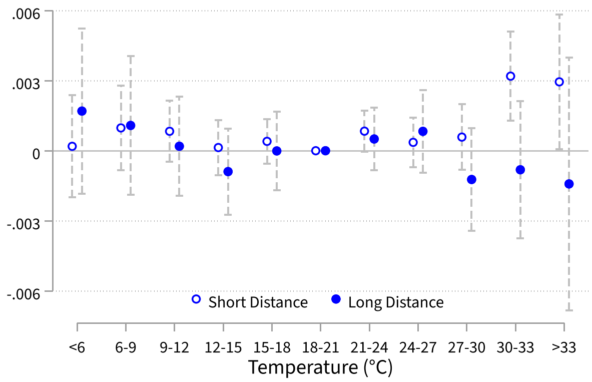
Fig. 3. The effect of temperature on labor Supply. *Notes*: This figure plots the estimated effects of temperature exposure on truck drivers' labor supply, including the probability of driving on a day (Panel a), the maximum consecutive driving hours in a day (Panel b), and the number of completed trips in a day (Panel c). Blue dots represent point estimates, and gray vertical lines denote 95% confidence intervals. All regressions control for other weather conditions, air quality, and geographic characteristics, and include driver fixed effects and date fixed effects. The temperature range of 18–21 °C is the reference category. Standard errors are two-way clustered by driver and date. (For interpretation of the references to colour in this figure legend, the reader is referred to the web Version of this article.)

the duration of continuous driving can be difficult to defer. Decisions about whether to work on a given day or how many trips to complete are more plannable, giving drivers room to shift activity away from extremely hot days.

Appendix Figure S3 presents estimates using the full set of temperature bins for both the current and prior day, and the patterns are consistent with those in Table 2.



(a) Whole Sample



(b) Heterogeneity by Total Distance of Transportation Task

Fig. 4. Temperature, work Load, and work Schedule. *Notes*: This figure presents the estimated effects of temperature on the likelihood that a driver starts work later than their usual start time. Panel (a) shows results for the full sample. Panel (b) examines heterogeneity by the total distance of transportation tasks, with separate estimates for days when the total distance is above or below 300 km. Blue dots represent point estimates, and gray lines indicate 95% confidence intervals. All regressions control for other weather conditions, air quality, and geographic characteristics, and include driver fixed effects and date fixed effects. The temperature range of 18–21 °C is the reference category. Standard errors are two-way clustered by driver and date. (For interpretation of the references to colour in this figure legend, the reader is referred to the web Version of this article.)

5.2. *Effects on on-duty driving safety*

5.2.1. *Baseline results*

We next examine whether extreme heat compromises drivers' on-duty performance by increasing unsafe driving episodes. Fig. 5 presents estimated effects of temperature exposure on the number of accident-risk warnings per 100 km of driving. High temperatures significantly increase unsafe driving behaviors: the intensity of warnings begins to rise at temperatures above 27 °C and increases sharply under extreme heat. Specifically, an additional hour of exposure above 33 °C is associated with 0.17 more accident-risk warnings per 100 km, relative to the 18–21 °C reference range, corresponding to a 2.5% increase over the sample mean.

The findings add to a growing body of evidence that extreme temperatures impair cognitive and physical functioning, raising the incidence of errors, risky behaviors, and workplace accidents (e.g., Park et al., 2021; Ireland et al., 2023; Drescher and Janzen, 2025). In our context, heavy-duty trucking demands sustained attention and precision, and performance deterioration carries risks not only for drivers but also for other road users.

5.2.2. *Potential mechanisms*

Disruption of off-duty rest. One potential explanation for the performance decline is that high temperatures disrupt drivers' off-duty rest. Sleep deprivation impairs cognitive functioning, reduces alertness, and slows reaction times (Lim and Dinges, 2010; Belenky et al., 2003)—consequences that are particularly significant in an occupation requiring sustained attention and split-second judgment. A large body of literature links adequate rest to labor productivity and task performance more broadly (Hafner et al., 2017; Gibson and Shrader, 2018; Bessone et al., 2021), and recent work establishes that extreme heat directly curtails sleep duration (Bigler and Janzen, 2024). If heat leaves drivers under-rested, the resulting fatigue could translate directly into the unsafe driving behaviors we document.

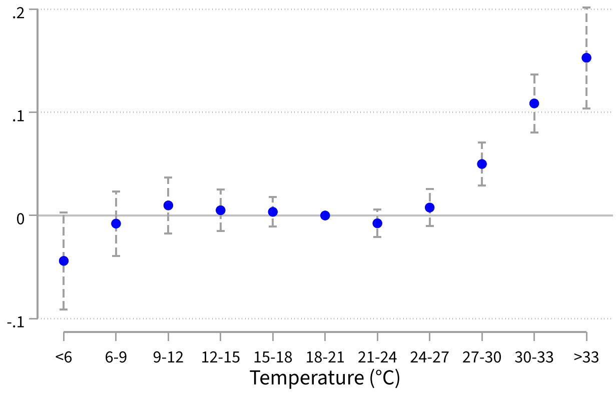


Fig. 5. The effect of temperature on unsafe driving Behaviors. *Notes*: This figure plots the estimated effects of temperature exposure on unsafe driving behaviors, measured by the number of accident-risk warnings per 100 km of driving. Blue dots represent point estimates, and gray lines indicate 95% confidence intervals. The regression model controls for other weather conditions, air quality, and geographic characteristics, and includes driver fixed effects and date fixed effects. The temperature range of 18–21 °C is the reference category. Standard errors are two-way clustered by driver and date. (For interpretation of the references to colour in this figure legend, the reader is referred to the web Version of this article.)

We test this mechanism using two outcomes: off-duty rest duration and yawning intensity while driving. The first captures whether drivers are getting less recovery time on hot days; the second provides a behavioral signal of fatigue. Yawning events are recorded via in-cabin cameras and detected through computer vision algorithms. We normalize by distance driven to construct yawns per 100 km. Fig. 6 presents the results. Panel (a) shows that off-duty rest hours decline significantly at higher temperatures. Panel (b) shows that yawning intensity rises sharply under extreme heat.

On-duty heat stress. In addition to disrupted off-duty rest, performance may deteriorate through direct exposure to high temperatures during active driving. To examine how unsafe driving behaviors relate to temperature exposure realized during driving versus resting periods, we estimate:

$$Y_{it} = \sum_{k \in \mathcal{B}} \rho_k^D \, H_{it}^D(k) + \sum_{k \in \mathcal{B}} \rho_k^R \, H_{it}^R(k) + \gamma' \mathbf{X}_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{5}$$

where $H_{it}^D(k)$ and $H_{it}^R(k)$ denote hours in temperature bin k during driving and resting periods, respectively. Resting hours include both on-duty idle time and off-duty rest. Total driving hours enter as a control in $\mathbf{X}_{it}$. Importantly, we include total driving hours as part of the control vector $\mathbf{X}_{it}$.

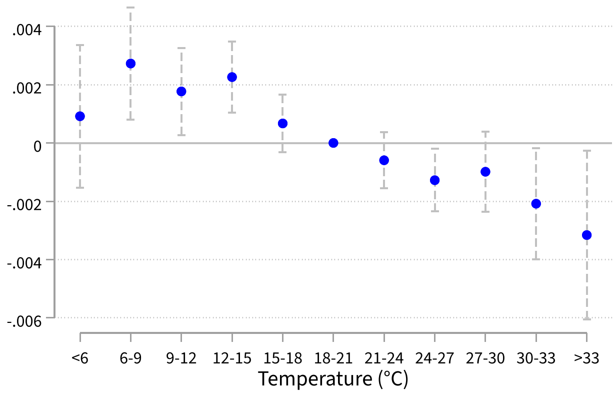
Fig. 7 plots the estimated coefficients for driving (ρ_k^D) and resting (ρ_k^R) temperature exposure. We find that high temperatures during driving are more strongly associated with elevated unsafe driving behaviors. Specifically, an additional hour above 33 °C while driving is associated with 0.25 more accident-risk warnings per 100 km, a 3.8% increase over the sample mean. Exposure during resting periods generates a smaller response. The stronger response to driving-period exposure is consistent with evidence that heat stress directly impairs physical and cognitive functioning (Park et al., 2020; Sexton et al., 2022). In heavy-duty trucking, real-time heat exposure may diminish alertness, slow reaction times, and impair judgment—each raising the likelihood of unsafe driving episodes.

Because drivers can adjust when they drive and rest in response to temperature and operational constraints, the allocation of exposure between driving and resting periods may be endogenous. Drivers may shift driving toward cooler hours and rest during peak heat. Our specification addresses this by jointly including temperature exposure during both driving and resting periods alongside total driving hours and a rich set of controls. Identification of the driving exposure effect comes from within-driver variation in the temperature composition of driving time across days with identical total driving hours, conditional on the temperature composition of resting time (and vice versa for identification of the resting exposure). The remaining confounding concern becomes more restrictive.[18] Robustness checks that add controls for traffic conditions and route characteristics leave the patterns unchanged (Appendix Figure S4). Since drivers may respond to heat along margins that are difficult to observe, we interpret the estimates as characterizing the association between unsafe driving and realized temperature exposure under equilibrium behavioral adjustments, rather than as isolating a physiological effect of heat with behavior held fixed.

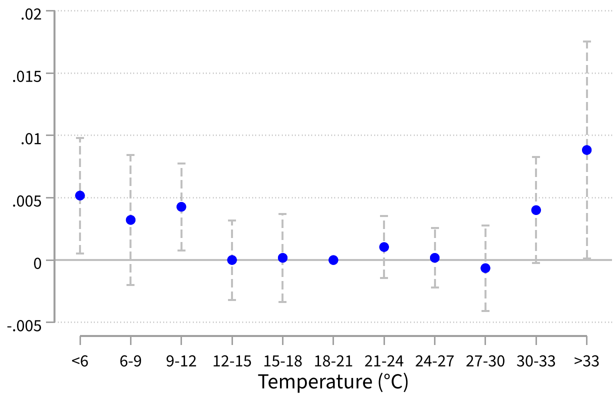
5.2.3. Lagged effects

Beyond the immediate impact of heat, unsafe driving may worsen with sustained exposure over preceding days as physiological and cognitive stress accumulate. We examine this using the distributed lag model in Eq. (4), including same-day and lagged temperature exposure over varying measurement windows.

[18] Specifically, bias would require an unobserved driver–day shock that affects unsafe driving outcomes and simultaneously shifts the temperature composition of driving time, for the same driver across days with the same total driving hours, even after conditioning on the temperature composition of resting periods.



(a) Duration of Off-Duty Rest



(b) Intensity of Yawning while Driving

Fig. 6. The effect of temperature on Off-Duty rest and yawning Intensity. *Notes*: This figure plots the estimated effects of temperature exposure on truck drivers' off-duty rest duration and yawning intensity. In Panel (a), off-duty rest duration is measured as the logarithm of total off-duty rest hours in a day. In Panel (b), the intensity of yawning is measured using the number of yawns per 100 km of driving. Yawning events are detected using in-cabin camera footage processed through computer vision algorithms. Blue dots represent point estimates, and gray lines indicate 95% confidence intervals. All regressions control for other weather conditions, air quality, and geographic characteristics, and include driver fixed effects and date fixed effects. The temperature range of 18–21 °C is the reference category. Standard errors are two-way clustered by driver and date. (For interpretation of the references to colour in this figure legend, the reader is referred to the web Version of this article.)

Table 1 reports the results. The three columns include lagged exposure averaged over the past 1, 3, and 7 days, respectively. The bottom row reports the cumulative effect, calculated as the sum of the coefficients for contemporaneous and lagged exposure. We find that lagged temperature exposure significantly elevates unsafe driving on the current day. In Column (1), one additional hour of exposure above 30 °C on the previous day raises accident-risk warnings by 0.03 units, a 0.4% increase over the sample mean. The effect grows with the exposure window. As Column (3) shows, an additional hour of average daily exposure over the prior week raises warnings by 0.07 units, comparable in magnitude to the same-day effect.

Appendix Figure S5 estimates the distributed lag model using the full set of temperature bins for both current and prior days, with results consistent with the simplified specification.

5.2.4. Heterogeneity by driver characteristics

We next examine whether the effect of extreme heat on unsafe driving varies by driver characteristics and experience. Because our administrative driving records do not include individual-level demographic information, we conducted an online survey with a randomly selected subset of 190 drivers from our sample. The survey collected information on basic demographics and driving history. The heterogeneity analysis here is restricted to this subsample.

Fig. 8 presents the results. Panel (a) shows that the adverse effect of high temperatures is more pronounced among older drivers (above age 40). In contrast, the relationship between temperature and unsafe driving is flatter for younger drivers. Panel (b) compares drivers with fewer than 10 years of experience to those with more. We do not find systematic differences in temperature sensitivity across these two groups. While the point estimates during extreme heat (e.g., >33 °C) are somewhat smaller for more experienced drivers, the differences are not statistically significant. Panel (c) explores heterogeneity based on whether the driver had any prior accident-related experience, including being personally involved in, witnessing, or knowing someone involved in a road accident.

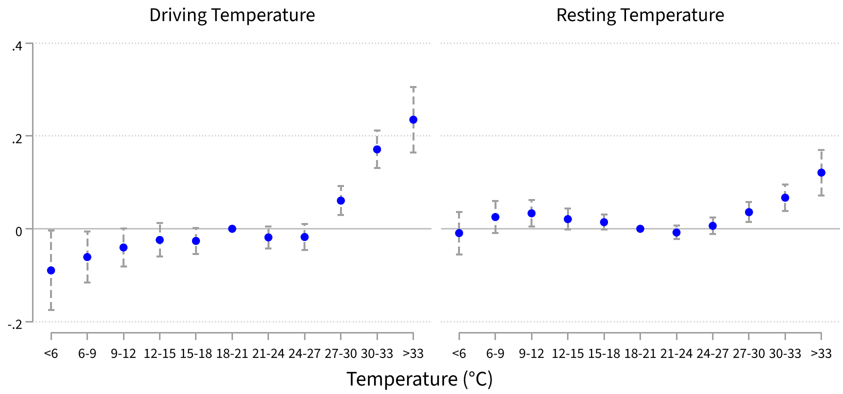


Fig. 7. Heterogeneous effects on unsafe driving behaviors by driving vs resting temperature Exposure. *Notes*: This figure presents the estimated effects of temperature exposure during driving and resting periods on unsafe driving behavior, measured by the number of accident-risk warnings per 100 km of driving. Resting periods include both on-duty idle and off-duty rest. The estimates are obtained from a single regression model that includes temperature exposure separately for driving hours and non-driving (resting) hours, with the number of hours spent in each temperature bin used as the key explanatory variables. Blue dots represent point estimates, and gray lines indicate 95% confidence intervals. The regression controls for total driving hours, other weather conditions, air quality, and geographic characteristics, and includes driver fixed effects and date fixed effects. The temperature range of 18–21 °C is the reference category. Standard errors are two-way clustered by driver and date. (For interpretation of the references to colour in this figure legend, the reader is referred to the web Version of this article.)

Table 1
Lagged effect of temperature exposure on unsafe driving behaviors.

Dep. var.:	Intensity of accident-risk warnings		
	(1)	(2)	(3)
Current Day: # Hours (T > 30 °C)	0.0742***	0.0708***	0.0699***
	(0.0101)	(0.0097)	(0.0096)
Past 1 Day: # Hours (T > 30 °C)	0.0308***		
	(0.0089)		
Past 3 Days: # Hours (T > 30 °C)		0.0532***	
		(0.0138)	
Past 7 Days: # Hours (T > 30 °C)			0.0704***
			(0.0178)
Cumulative Effect	0.1051***	0.1239***	0.1403***
	(0.0152)	(0.0189)	(0.0224)
N	3,015,191	3,093,440	3,115,887

Notes: This table reports estimates from distributed lag models examining the effect of extreme temperature exposure on unsafe driving behaviors, measured by the number of accident-risk warnings per 100 km of driving. The key explanatory variables are the number of hours with temperature above 30 °C on the current day and the average number of hours above 30 °C over the past 1, 3, or 7 days, depending on the specification. The lagged exposure variables represent the average intensity of extreme heat over the specified period. The cumulative effect is calculated as the sum of the coefficients on current and lagged exposure variables, capturing the total impact over the corresponding window. All regressions control for other weather conditions, air quality, and geographic characteristics, and include driver fixed effects and date fixed effects. Standard errors are two-way clustered by driver and date. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Drivers with such experience show a smaller increase in unsafe driving behaviors under extreme heat, though again the difference is not statistically significant.

5.3. Heterogeneity by high-temperature subsidy provision

Adapting to extreme heat requires costly behavioral and financial adjustments. In high-temperature work environments, individual workers typically bear the cost of adaptation—through schedule changes or cooling investments—while the benefits may spill over to employers and third parties. These externalities are particularly relevant in heavy-duty trucking, where heat-induced performance impairments pose public safety risks beyond the worker.

One firm-level feature that may foster adaptation is whether employers provide formal heat compensation. High-temperature subsidies may help correct underinvestment in adaptation by better aligning private and social incentives. By offsetting discomfort or enabling more effective coping strategies, they may support sustained labor participation and reduce heat-related productivity losses and safety risks.

Table 2
Interday substitution of labor supply.

	(1) If driving on a day	(2) Max. consecutive driving hours	(3) Number of completed trips
Current Day: # Hours (T > 30 °C)	−0.0002***	−0.0629***	−0.0076***
	(0.0000)	(0.0081)	(0.0014)
Past 1 Day: # Hours (T > 30 °C)	0.0001***	−0.0294***	0.0072***
	(0.0000)	(0.0079)	(0.0012)
Cumulative Effect	−0.0001	−0.0923***	−0.0003
	(0.0001)	(0.0111)	(0.0017)
N	3,015,191	3,015,191	3,015,191

Notes: This table reports estimates from a distributed lag model examining the effect of extreme temperature exposure on labor supply. The cumulative effect is the sum of the coefficients on current and lagged exposure, representing the total impact over the two-day period. The key explanatory variables are the number of hours with temperatures exceeding 30 °C on the current day and on the previous day. The outcome variables include (1) an indicator for whether the driver worked on a given day, (2) the maximum consecutive driving hours in a day, and (3) the number of completed trips. All regressions control for other weather conditions, air quality, and geographic characteristics, and include driver fixed effects and date fixed effects. Standard errors are two-way clustered by driver and date. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In China, national regulations entitle workers exposed to high temperatures to employer-provided heat subsidies, but implementation is delegated to provincial and municipal governments.[19] Many local authorities have issued guidelines requiring employers to compensate workers in outdoor or high-temperature indoor settings during summer months, typically through monthly or daily payments, but the standards and enforcement vary considerably across regions and firms. Guangdong province, for instance, mandates subsidies between June and October at 300 RMB per month as of 2021. In practice, enforcement is uneven, potentially due to job-site mobility, limited administrative oversight, and compliance monitoring challenges. As a result, many eligible workers do not receive full compensation.

To examine whether drivers employed by subsidy-providing firms respond differently to heat, we conducted a phone survey of transportation companies in our sample and collected information on heat compensation practices. Based on survey responses, we estimate:

$$Y_{it} = \rho H_{it}(> 30\,°\mathrm{C}) + \phi H_{it}(> 30\,°\mathrm{C}) \times I[\text{Heat Subsidy}]_{j(i)} + \gamma' \mathbf{X}_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{6}$$

where $H_{it}(> 30\,°\mathrm{C})$ is daily hours with temperatures above 30 °C and $I[\text{Heat Subsidy}]_{j(i)}$ indicates whether driver i's employer provides a heat subsidy. The coefficient ρ captures the temperature effect for drivers employed by non-subsidy firms, while ϕ captures the difference in that temperature effect for drivers employed by subsidy-providing firms. Because subsidy provision is determined at the firm level, the comparison in temperature effects across these two groups should be interpreted as descriptive rather than causal.[20]

Table 3 reports the results. Across all outcomes, the estimated temperature effects are smaller in magnitude for drivers employed by firms that offer heat subsidies. For example, an additional hour above 30 °C reduces completed trips by 0.0167 among drivers employed by firms without subsidies. The interaction coefficient implies that the temperature effect for drivers employed by firms that offer subsidies is a decline of 0.0084 trips, which is much smaller in magnitude. The same pattern holds for unsafe driving behaviors, work participation, and start-time delays.

We also conduct robustness checks by estimating a model similar to Eq. (6), but replacing the indicator for hours above 30 °C with the full set of temperature bins and their interactions with the high-temperature subsidy indicator. Appendix Figure S6 presents the results, with patterns consistent with Table 3.

The mechanisms behind these differences are difficult to disentangle. One possibility is that subsidies provide resources or flexibility that make it easier for workers to cope with hot conditions. Another is that firms offering heat subsidies also adopt broader heat-management practices, such as better vehicle cooling, greater schedule flexibility, or more supportive rest arrangements. Subsidy provision may therefore proxy for a wider set of firm characteristics related to worker protection. Our analysis cannot distinguish among these explanations. We therefore view these results as suggestive and useful for motivating future work on firm-level adaptation and worker protection, rather than as a causal evaluation of subsidy effectiveness.

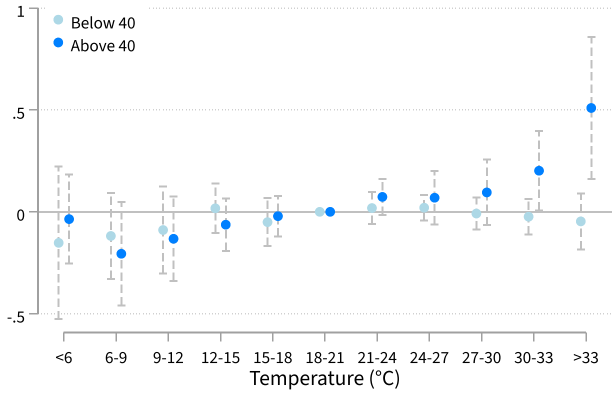
5.4. Robustness checks

Alternative temperature exposure measures. To address potential endogeneity in realized temperature exposure arising from drivers' schedule adjustments, we estimate the model using two alternative exposure measures: average temperature exposure and predicted temperature exposure.[21]

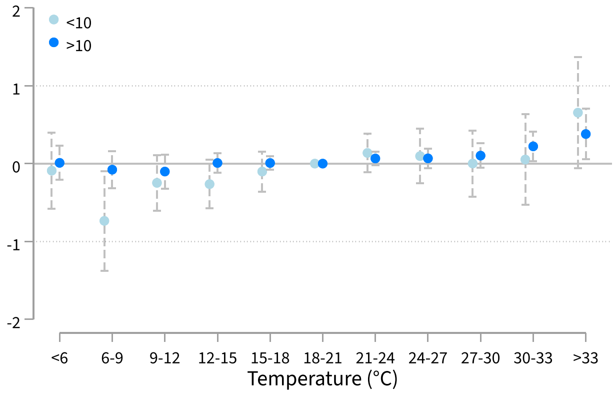
[19] We provide more details about high-temperature subsidies in China in Appendix A.

[20] Firms that offer high-temperature subsidies may differ systematically from other firms along dimensions such as safety culture, management practices, or compliance with labor regulations, which we cannot observe. If these firm characteristics also affect workers' labor outcomes or their sensitivity to heat, then the interaction term may capture broader cross-firm differences rather than the effect of subsidy provision itself. A causal interpretation would therefore require the strong assumption that, conditional on our controls and fixed effects, subsidy provision is uncorrelated with other firm-level factors that shape worker outcomes under high temperatures.

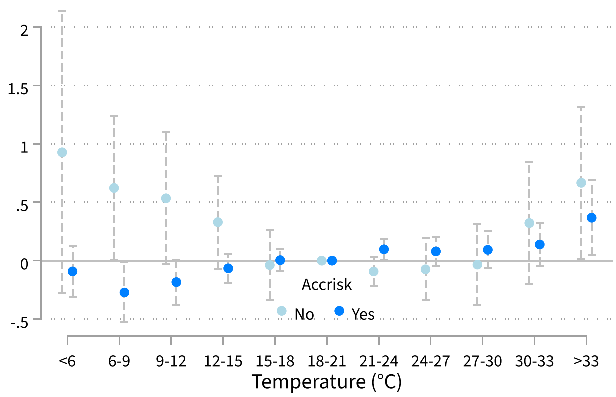
[21] Details on the construction of these measures are provided in Section 4.2.



(a) By Age



(b) By Years of Driving Experience



(c) By Previous Accident Experience

Fig. 8. Heterogeneous effect of temperature on unsafe driving behaviors by driver Characteristics. *Notes*: This figure presents heterogeneous effects of temperature on unsafe driving behaviors, measured by the number of accident-risk warnings per 100 km of driving, across different groups of drivers. Panel (a) compares drivers aged below and above 40. Panel (b) splits the sample by driving experience: fewer than 10 years versus more than 10 years. Panel (c) compares drivers with and without a prior accident experience. Blue and gray dots represent point estimates, and gray lines indicate 95% confidence intervals. All regressions control for other weather conditions, air quality, and geographic characteristics, and include driver fixed effects and date fixed effects. The temperature range of 18–21 °C is the reference category. Standard errors are two-way clustered by driver and date. (For interpretation of the references to colour in this figure legend, the reader is referred to the web Version of this article.)

First, to address endogenous schedule adjustments (e.g., when drivers start working or take rest breaks), we eliminate hourly timing variation and construct the average temperature exposure measure based solely on inter-day temperature variation. For each

Table 3
Heterogeneous effect of temperature by provision of high-temperature subsidies.

Variables	(1) If driving on a day	(2) Max. consecutive driving hours	(3) Number of completed trips	(4) Start work late	(5) Intensity of accident-risk warnings
# Hours (T>30 °C)	−0.0020***	−0.1764***	−0.0167***	0.0083***	0.1015***
	(0.0005)	(0.0229)	(0.0024)	(0.0015)	(0.0239)
# Hours (T>30 °C) × I[Heat Subsidy]	0.0017***	0.1057***	0.0093***	−0.0060***	−0.0461*
	(0.0006)	(0.0269)	(0.0028)	(0.0018)	(0.0277)
N	1,611,854	1,611,854	1,611,854	1,611,854	1,611,854

Notes: This table reports heterogeneous effects of extreme temperature exposure on labor supply and unsafe driving behavior, by provision of high-temperature subsidies. The key explanatory variable is the number of hours in a day with temperature exceeding 30 °C. I[Heat Subsidy] is a binary indicator equal to 1 if the transportation company provides heat-related compensation to its drivers. The interaction term captures whether the effect of extreme heat differs for drivers whose companies offer such subsidies. All regressions control for other weather conditions, air quality, and geographic characteristics, and include driver fixed effects and date fixed effects. Standard errors are two-way clustered by driver and date. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

driver–day, we identify the ERA5 pixels overlapping the GPS trajectory and compute the average temperature distribution in a day across those pixels, ignoring the exact timing of travel. Under this construction, if a driver follows the same route on two days but starts at different times or takes breaks at different times or locations, variation in exposure arises only from inter-day temperature differences rather than endogenous scheduling decisions.

Second, to address potential endogeneity in the decision to work on a given day, we construct the predicted temperature exposure by imputing the route a driver would typically take if they worked. Because we observe each driver repeatedly over time, we define a typical route for each driver based on the trajectory most representative of their historical routes—intuitively, the route most similar to all other observed routes for that driver.[22] For non-driving days, we compute temperature exposure along this typical route using realized temperature in the overlapping ERA5 pixels on that day.

Figures S7 and S8 present the results using these alternative measures. The main findings remain robust, and the estimated temperature effects are generally larger in magnitude.

Self-selection in work participation. Since hot days reduce drivers' likelihood of working, one may be concerned that the estimated temperature effects could reflect compositional changes in the active driving sample. Two forms of selection may be relevant. Across drivers, those who stop working on hot days may differ from those who remain active, for example in risk preferences. Within the same driver, day-to-day participation may respond to time-varying factors correlated with heat, such as health conditions or accumulated fatigue.

To assess cross-driver selection, we classify drivers into high- and low-risk groups based on their average accident-risk warning intensity on mild days (daily average temperature below 24 °C) and test whether participation responses to heat differ between groups. Figure S9 shows no significant difference, indicating that hotter days do not disproportionately remove safer or riskier drivers from the working sample. We also examine heterogeneity by drivers' labor supply flexibility. We classify drivers by the number of non-working days observed over the sample period and re-estimate temperature effects on unsafe driving by group. Figure S10 shows similar effects across groups, providing further evidence that the main results are not driven by composition shifts among drivers with different work propensities.

To address within-driver selection across days, our baseline design treats work participation itself as an endogenous equilibrium response to temperature and estimates over the full driver-day sample, including non-driving days.[23] Under this framework, the estimated coefficients capture the reduced-form effect of temperature on realized labor and safety outcomes, incorporating both the performance response conditional on working and adjustment along the participation margin.

We assess sensitivity to alternative assumptions about counterfactual outcomes on non-driving days through a bounding exercise. For each non-driving day, we impute outcomes using the driver-specific historical maximum observed during the sample period for maximum consecutive driving hours, completed trips, and accident-risk warning intensity, and set the late-start indicator to zero. This imputation defines an extreme counterfactual in which drivers who chose not to work would, had they worked, have performed at the most intensive level ever observed for that driver. Figure S11 reports the resulting estimates. Bound 1 reproduces the baseline coding of non-driving days, whereas Bound 2 uses this alternative imputation. The two bounds bracket the estimates from the active driving sample under opposite extreme assumptions. We implement this exercise using both the baseline temperature exposure measure and

[22] Details of this construction are provided in Appendix B.

[23] As discussed in Section 2, labor outcomes on non-driving days are defined as follows. For labor-supply outcomes, we code non-driving days as the lowest feasible labor realization: zero driving hours, zero completed trips, and an indicator equal to one for starting work late. For unsafe-driving outcomes, accident-risk warnings are coded as zero on non-driving days, since no on-road unsafe driving can occur when the driver does not work.

the predicted temperature exposure measure. Estimated coefficients generally preserve their sign and qualitative interpretation across specifications.[24]

Alternative outcome constructions and model specifications for safety performance. Our baseline outcome is accident-risk warnings per 100 kilometers driven. This normalization may be sensitive to endogenous adjustments in driving speed and rest behavior, which can affect time on the road and traffic exposure per kilometer. To show that the results are not driven by this particular normalization, we consider three alternative specifications. First, we add average speed—defined as total driving distance divided by total driving hours—as an additional control variable. Second, we use the number of accident-risk warnings per driving hour as the outcome. Third, we estimate Poisson models for the count of accident-risk warnings, incorporating driving distance or driving hours as exposure offsets. Fig. 12 shows that estimated effects remain qualitatively similar across all specifications.

Traffic conditions. Traffic conditions may confound the estimated temperature effects on driver performance if hot days are associated with systematically different traffic patterns. We construct two proxies and include them as additional controls to test the robustness of our results for on-duty performance. First, we compute the average driving speed, defined as the total driving distance divided by total driving hours on a given day. Lower speeds may reflect heavier traffic or congestion. Second, we take advantage of the sensor-based warning system. In addition to the unsafe driving behaviors in our main outcomes, the system also detects blind-spot situations and issues alarms when objects remain in the vehicle's blind spot without driver response. The intensity of these warnings, measured per 100 kilometers, reflects surrounding vehicle or pedestrian density and serves as a proxy for local traffic conditions. Adding both proxies as controls leaves the estimated effects on maximum consecutive driving hours, completed trips, and accident-risk warnings largely unchanged (Figure S13).

6. Conclusion and discussion

As climate change increases the frequency and severity of extreme heat events, understanding their effects on labor supply and worker performance becomes increasingly important, particularly in sectors where physical presence and real-time decision-making are essential. This paper contributes to the growing literature on climate impacts and adaptation by providing new evidence from the heavy-duty trucking industry in China.

We document that extreme heat significantly affects both the extensive and intensive margins of labor supply, as well as on-duty driving performance. Drivers respond to heat by reducing work participation, shortening continuous driving hours, and completing fewer trips. These effects are partially offset through behavioral adaptations such as shifting work schedules and reallocating labor across days. Extreme heat also increases unsafe driving behaviors, and the evidence points to two complementary channels: real-time physiological stress during driving and cumulative fatigue from disrupted off-duty rest. We also examine heterogeneity by firms' provision of high-temperature subsidies. Drivers employed by firms that offer heat compensation exhibit smaller estimated temperature effects on labor participation and unsafe driving. These patterns may suggest that heat compensation or related firm practices are associated with greater resilience to heat exposure, though the cross-firm differences should be interpreted as descriptive rather than causal.

From a policy perspective, our findings point to firm-level adaptation as a practical margin for reducing the costs of heat exposure. In contrast to large-scale infrastructure investments or broader structural reforms, firm-level heat-protection measures may offer a comparatively practical margin along which workers' exposure and performance under extreme temperatures can differ. This resonates with recent policy efforts to address occupational heat risks. For example, in the United States, the Occupational Safety and Health Administration (OSHA) proposed a federal heat standard that would require employers to implement heat injury and illness prevention plans, including provisions for water, rest, shade, and training. In China, where heat protections are currently guided by fragmented local policies, our results highlight the potential relevance of firm-level heat protections and the need for future work to evaluate which specific measures are most effective.

Our findings should be interpreted in light of several limitations. First, drivers in our setting work substantially longer hours than those typically permitted in the United States and the European Union. Such long workdays may increase cumulative fatigue, which could amplify the impact of temperature on driver performance. Therefore, the magnitude of the estimated temperature effects may not transfer directly to more regulated settings. Second, although we document systematic differences in estimated temperature effects across firms with and without heat subsidies, our design cannot isolate the effect of subsidy provision from correlated firm characteristics, such as safety culture or management practices. Future research with richer firm-level data or quasi-experimental variation in subsidy provision could better identify the role of compensation in shaping worker adaptation and performance. More broadly, longer-run evidence is needed on how firms and workers dynamically adjust to rising heat risks, and whether compensation-based measures complement or crowd out broader investments in climate resilience.

[24] The only exception is the number of completed trips, for which the negative effect of heat reverses under the extreme imputation based on the driver-specific historical maximum. However, this case is intentionally conservative and likely unrealistic, as it assumes that drivers who do not work on hot days would have completed trips at their own peak observed level had they chosen to work.

CRediT authorship contribution statement

Wenzhi Dave Ding: Writing – review & editing, Writing – original draft, Resources, Project administration, Investigation, Funding acquisition, Data curation. **Xincheng Wang:** Writing – review & editing, Writing – original draft, Resources, Project administration, Investigation, Funding acquisition, Data curation, Conceptualization. **Yucheng Wang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Zhenxuan Wang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data for this article can be found online at doi:10.1016/j.jeem.2026.103338.

Data availability

The data used in this study are proprietary and were made available under a data usage agreement. Authors will provide information on data access upon request.

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