Liquidity Constraints and Real-Time Adaptation to Extreme Heat: Evidence from Gig Workers*

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First version: December 2025
This version: March 2026

Abstract

Extreme heat reduces labor supply and worsens health for workers exposed to outdoor conditions. We study whether short-term liquidity facilitates adaptation to heat shocks. We evaluate a randomized intervention that provides small, forecast-triggered payments to gig delivery workers during heatwaves. Access to liquidity attenuates productivity losses and mitigates heat-related health symptoms by enabling costly avoidance behaviors, including rescheduling work to cooler hours and resting in cooled locations. Machine-learning-based heterogeneity analysis shows gains concentrate among workers facing rigid demand and output-linked pay. Despite ex-post benefits, workers display low ex-ante demand for heat-indexed insurance, highlighting liquidity constraints as a barrier to adaptation.

Keywords: Heatwaves, Climate Adaptation, Liquidity Constraints, Worker Health, Gig Economy, Labor Productivity

JEL codes: J22, J81, O12, Q54

*We thank the Department of Economics at the University of Virginia and the University of Texas at Arlington for financial Support. We are grateful to participants at the 2025 North Texas Economics Conference at UT Arlington and the 2026 Pacific Conference for Development Economics at UC Davis for their helpful comments. We are grateful to Shan Aman-Rana, Valentina Brailovskaya, David Wu, Shoada Wang, and anonymous reviewers for their suggestions. This study was approved by the Institutional Review Board of the University of Virginia (6832). This RCT was registered as AEARCTR-0015839 (Sekhri, 2025). All errors are our own.

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1 Introduction

As climate change intensifies, heatwaves are becoming more frequent, severe, and prolonged worldwide. Global temperatures had risen by 1.3°C above the 1951-1980 average as of 2024,[1] with further warming projected in the coming decades (Perkins-Kirkpatrick and Lewis, 2020; Thompson et al., 2023). Beyond their public-health consequences, heatwaves impose substantial economic costs, especially in sectors reliant on outdoor labor. Existing evidence suggests that extreme heat reduces worker productivity and generates direct income losses of $41-90 per worker in sectors such as agriculture and construction (Orlov et al., 2019). Yet many communities in low- and middle-income countries remain underprepared, with limited access to adaptive resources and formal social protection. Even when information on heat risk and basic public cooling infrastructure is available, workers may still be unable to adjust their behavior if avoiding heat entails immediate earnings losses and requires reallocating time away from household production.

We study whether short-run liquidity can facilitate adaptation to extreme heat among informal urban workers. In this context, liquidity constraints reflect limited ability to smooth short-run cash needs and time demands, rather than the lack of access to formal credit. We conducted our study in India, where the rapidly expanding gig economy provides a natural setting for this question.[2] Urban gig workers, particularly those engaged in food delivery, grocery delivery, and ride-hailing, face high exposure to outdoor heat while remaining largely excluded from formal labor protections. Compensation is typically task-based, with earnings tied directly to hours worked and deliveries completed, and few workers have access to paid sick leave, health insurance, or regulated work hours (Adhvaryu et al., 2026). Despite growing evidence of the health and productivity costs of heat exposure, there is limited causal evidence on interventions that enable informal service-sector workers to adapt to extreme heat without sacrificing earnings.

To examine how short-run liquidity affects adaptation to extreme heat, we implemented a randomized intervention among gig delivery workers in two metropolitan areas of India. Participants were randomly assigned to receive either heat-risk information only or the same information bundled with a heatwave-indexed cash transfer. Heatwave episodes were identified using official meteorological forecasts, and all participants received advance notifications at the onset of each episode. In addition to the notification,

[1] Statistics are from the National Aeronautics and Space Administration (NASA).

[2] Owing to its tropical geography and high urban density, India is among the countries most vulnerable to extreme heat events. The summer of 2024 was particularly severe: prolonged heatwaves between March and June were associated with more than 40,000 suspected cases of heat stroke and over 700 heat-related deaths. Source: *Down To Earth* news article.

treated workers received a small mobile payment at the start of each episode, whereas control workers received only the warning. This design isolates the causal effect of short-run liquidity provision while keeping heat-risk information constant between groups.

Our results show that heatwave exposure leads to substantial reductions in labor supply and productivity among gig delivery workers, with effects that persist beyond the heatwave period. Workers in the control group significantly reduce days worked, hours supplied, and deliveries completed during heatwaves, implying a 34% decline in weekly deliveries.[3] In contrast, access to heatwave-indexed liquidity markedly attenuates these declines. Compared to control participants, treated workers maintain higher work participation and productivity during heatwaves and exhibit persistent gains in the post-heatwave period, indicating that short-run liquidity cushions the adverse labor-market effects of extreme heat. Heatwaves also worsen workers' health, increasing the incidence of heat-related symptoms such as headaches and fatigue; these effects are largely offset among treated workers. Evidence on adaptive behaviors suggests that liquidity enables heat-avoidance strategies, including rescheduling work to cooler hours and resting in cooled locations, while reducing reliance on some other costly coping responses, such as buying extra water.

These average effects mask substantial heterogeneity in responses. We complement the experimental analysis with machine-learning-based heterogeneity methods to characterize which workers benefit most from liquidity. We show that cash benefits are concentrated among workers facing high short-run income risk, particularly those in time-sensitive, commission-only jobs. The gains from rescheduling work to cooler hours are concentrated among workers with more adults and fewer children at home. This pattern suggests that, while rescheduling may appear costless in monetary terms, it is not frictionless in practice: shifting work to cooler hours may require reallocating household production or caregiving responsibilities. In this setting, timely liquidity could help workers absorb the immediate financial costs of adaptation and, where feasible, substitute away from household production through other household members or market-based alternatives. Together, these findings indicate that short-run liquidity relaxes binding constraints on real-time adaptation.

We also examine workers' valuation of ex ante financial protection against heatwaves using contingent valuation questions. Despite the substantial ex post benefits of heatwave-indexed liquidity, workers exhibit limited demand for insurance-like protection purchased

[3] This number (34%) is computed from the statistics in Table 3 as $\frac{(6.14-0.817)\times(37.75-9.158)-6.14\times37.75}{6.14\times37.75}$. Under the simplifying assumption that the piece rate remains constant, this would translate into an approximately 34% decline in income. This magnitude is similar to the 40% decline in net earnings during heatwaves reported by Das and Somanathan (2024) for informal-sector workers in Delhi in 2019.

in advance. Exposure to the cash-transfer intervention does not increase stated willingness to pay or willingness to accept such products on average. However, the results mask significant heterogeneity. Workers facing more rigid demand and output-linked pay, who benefit most from ex post transfers according to our heterogeneity analysis, remain less willing to commit to ex ante protection. Follow-up evidence further shows that treated workers report better understanding of the hypothetical insurance product and greater trust in a government-provided version, while reporting similar expectations about future heatwave risk. These patterns make it difficult to attribute the weak demand for ex ante protection, particularly among the workers who benefited most from the transfers, solely to misunderstanding, mistrust, or divergent beliefs. Instead, they point to the importance of timing and short-run financial constraints in shaping the demand for formal heat-protection tools. This also strengthens the interpretation that the benefits of cash transfers primarily operate through the relaxation of liquidity constraints rather than through a pure income effect.

Our study makes three primary contributions to the literature. First, we contribute to the literature on climate change and labor markets by providing causal evidence on the effects of heatwaves—defined as prolonged periods of extreme heat—on productivity, health, and adaptive behavior in the urban service sector. While prior work documents the adverse impacts of high temperatures on labor supply and health, existing evidence has focused largely on agriculture and manufacturing, where heat exposure is salient and more readily measured (e.g., Graff Zivin and Neidell, 2014; Kjellstrom et al., 2016; Chen and Yang, 2019; Somanathan et al., 2021). However, many urban service jobs also involve substantial outdoor exposure and limited scope for heat avoidance. This is especially true for gig delivery workers, who spend long hours outdoors. Evidence for these urban service and gig settings remains limited.[4] We extend this literature by focusing explicitly on heatwaves rather than isolated hot days and by documenting their effects on labor supply, health, and behavioral adaptation among informal urban workers.

Second, we contribute to the literature on climate adaptation tools by evaluating a real-time, forecast-indexed financial intervention. A growing body of work shows that cash transfers and credit can help households manage weather-related shocks such as floods and droughts (e.g., Gertler et al., 2012; Macours et al., 2022; Lane, 2024; Pople et al., 2024), yet little causal evidence exists on whether financial instruments can mitigate productivity losses from heat exposure, particularly in informal urban labor markets. Using

[4] LoPalo (2023) shows reduced productivity on hot days among survey interviewers, while Das and Somanathan (2024) document substantial earnings losses during heatwaves among informal-sector workers in Delhi. In platform setting, Ge et al. (2024) show that high temperatures reduce courier efficiency and increase delays, even as orders and consumer spending rise.

a randomized controlled trial, we show that small payments delivered at the onset of extended extreme heat substantially attenuate declines in labor supply and improve health outcomes. We further document that liquidity relaxes time-use constraints by enabling substitution away from household production, particularly cooking, thereby facilitating shifts to cooler working hours. Unlike traditional workfare, insurance, or ex post relief, the intervention delivers liquidity precisely when heat-related income losses are most salient, highlighting the importance of timing in climate adaptation policy.

Third, our findings contribute to the literature documenting low willingness to pay for preventive or adaptive technologies, even when returns are high. Consistent with prior evidence from health, environmental, and energy contexts showing limited demand for products with large private and social benefits (e.g., Ashraf et al., 2010; Cohen and Dupas, 2010; Berry et al., 2020; Berkouwer and Dean, 2022), we find that workers exhibit low ex-ante demand for insurance-like protection against heat risk despite substantial ex-post gains from liquidity provision. This contrast underscores the role of liquidity constraints and related frictions in shaping demand for climate-risk mitigation tools, and suggests that real-time liquidity provision may be more effective than insurance-based approaches in supporting adaptation among informal workers.

The rest of the paper is organized as follows. Section 2 provides the context of the experimental setting in India. Section 3 describes the experimental design and the data. Section 4 outlines our empirical strategy. Section 5 presents the impacts of heatwave-indexed cash transfers on gig delivery workers. Section 6 examines heterogeneity in treatment effects. Section 7 analyzes workers' valuation of financial protection against heatwaves. Section 8 discusses whether the estimated effects are more consistent with liquidity relief or with a pure income effect. Section 9 considers additional concerns and external validity. Section 10 reports robustness checks. Section 11 concludes.

2 Study Context

2.1 Heatwaves in India

Unlike occasional hot days, heatwaves are prolonged periods of abnormally high temperatures that persist over multiple days. The India Meteorological Department (IMD) defines a heatwave as a period when the maximum temperature exceeds the normal by at least 4.5°C for two or more consecutive days. Prolonged exposure to such extreme temperatures poses serious health risks, including heat cramps, dizziness, fatigue, headaches, vomiting, and heat stroke. Beyond these direct health risks, heatwaves also contribute to

reduced labor productivity, particularly among outdoor workers who have limited capacity to avoid exposure during peak heat hours.

India is among the countries most vulnerable to extreme heat, with global warming intensifying the frequency, duration, and severity of heatwaves (Martinez-Villalobos et al., 2025). Coleman (2022) shows that climate change has made record-breaking temperatures in India 30 times more likely.[5] In response to the growing risks posed by extreme heat, several Indian cities and states have implemented Heat Action Plans (HAPs) over the past decade. Ahmedabad introduced the first HAP in 2013, followed by cities and states such as Nagpur (2016), Telangana (2017), Haryana (2017), and Delhi (April 2025). These HAPs include graded heat alerts via SMS, social media, and traditional media, along with public cooling spaces, drinking water stations, and improved medical preparedness. Residents of Delhi and Gurgaon also receive regular heatwave updates through multiple channels, ensuring broad public awareness.

Figure 1 presents daily maximum and minimum temperatures in Delhi during May and June 2025 alongside the corresponding 10-year historical averages for 2014–2023. The horizontal gray dashed lines indicate the average temperature between May 1 and June 30 over this historical period. As shown in Figure 1, daily maximum and minimum temperatures in 2025 broadly followed recent historical patterns.[6] Accordingly, our 2025 experiment evaluates the effects of forecasted heatwave events under relatively typical May–June conditions, providing a useful benchmark for average years.

2.2 Gig Delivery Workers in India

A large and growing share of gig work in India is concentrated in urban delivery services, including food delivery, grocery delivery, ride-hailing, and parcel services. The gig economy employed an estimated 7.7 million workers in 2020-21, or about 1.5% of the total workforce, and this number is projected to nearly triple by 2029-30.[7] Within this broader sector, approximately 3.3 million workers are estimated to be engaged on delivery platforms such as Ola, Swiggy, and Zomato (Raman et al., 2021). Gig delivery workers provide a useful setting for studying adaptation to heat because they face high direct

[5] For example, the summer of 2024 was particularly severe, with over 40,000 reported cases of heat stroke and 733 heat-related deaths between March and June across 17 states in India. Statistics are from the HeatWatch.

[6] Appendix Figure E1 presents the corresponding temperature series for May-June 2024. Relative to 2025, temperatures in 2024 were consistently higher than the 10-year average, with multiple extreme spikes exceeding 45°C. This comparison highlights that substantially more severe seasons can occur and may become increasingly relevant under climate change.

[7] Statistics are drawn from the report *India's Booming Gig and Platform Economy: Perspectives and Recommendations on the Future of Work*, published by NITI Aayog in June 2022 and available at this website.

exposure, strong dependence of earnings on current labor supply, and limited access to formal protections.

Despite the rapid growth of delivery platforms, gig delivery workers in India remain largely excluded from formal labor protections, making them particularly vulnerable to economic and environmental shocks. They lack access to paid leave, health insurance, or social security benefits. Gig delivery workers are typically compensated on a piece-rate basis, which fluctuates with platform algorithms, seasonal demand, and incentive structures. A nationwide survey finds that 75% of delivery workers work more than 10 hours per day outdoors, and 60% report struggling to cover their monthly expenses, reflecting high levels of economic instability.[8]

A 2024 survey of delivery workers in Hyderabad further illustrates the occupational risks associated with extreme heat. Conducted by the Telangana Gig & Platform Workers Union and HeatWatch among 166 delivery workers, the survey found that more than 50% reported heat exhaustion, 30% reported heat stroke, and 27% reported dehydration, while 36% experienced at least one heat-related symptom per month.[9] Together, these features make gig delivery workers a natural population in which to study whether forecast-indexed transfers can ease short-run constraints that limit adaptation to heat stress.

3 Experimental Design

This section describes the experiment conducted to evaluate the impact of heatwave-indexed cash transfers on the labor supply, health, and adaptive behaviors of gig deliverdy workers in Delhi and Gurgaon, India. The experiment took place during the peak summer period between May 19 and June 30, 2025, and the study window included one major heatwave spell (June 7-14).

3.1 Sample and Randomization

In April-May 2025, we recruited participants using snowball sampling at 10 rest points in Delhi and Gurgaon (4 in Delhi and 6 in Gurgaon), where gig workers commonly wait and/or take breaks between deliveries. The enumerators approached the workers at these sites, obtained informed consent, and interviewed those who agreed to participate. The respondents worked for several major online delivery platforms, including Zomato,

[8]Statistics are drawn from this news article published by *Etv Bharat*. Consistent with this evidence, our baseline survey shows that, on average, delivery workers in our sample work 10.3 hours per day and 6.4 days per week.

[9]The survey report can be accessed at this website.

Swiggy, Zepto, Porter, Uber (bike and courier), Blue Dart, and DTDC. Both Delhi and Gurgaon have large gig-worker populations and high volumes of delivery activity.

In total, 276 gig delivery workers were recruited. Approximately 70% of participants (193 out of 276) worked in food delivery, grocery delivery, and ride-hailing services, which are characterized by relatively time-sensitive and inflexible demand, while the remaining 83 participants were engaged in more flexible services such as courier and porter work.[10] To ensure balance across industry groups, we applied stratified randomization based on industry type using a computer-generated randomization procedure in Stata. A total of 137 participants were assigned to the treatment group, including 97 from inflexible-demand industries, while the remaining 139 participants formed the control group, including 96 from inflexible-demand industries. All participants were followed using the same survey schedule and questionnaire, and the outcome data was collected under identical protocols for the treatment and control workers, which limits the scope of differential prompting between groups.

3.2 Treatment & Timing

The treatment combines publicly available heatwave warnings with forecast-triggered cash transfers. Specifically, all participants received the same text notification whenever IMD forecasts indicated upcoming heatwave conditions, while participants in the treatment group additionally received a cash transfer of ₹200 via mobile payment on the first day of each forecasted heatwave episode. Participants in the control group received only text notifications. The design therefore holds information constant across groups and varies access to real-time liquidity.

To determine heatwave status, we monitored the Daily Impact-Based Heatwave Warning Bulletin issued by the National Weather Forecasting Centre (Appendix Figure E2) and the Daily Weather Report and Forecast Bulletin from the Regional Meteorological Centre, New Delhi (Appendix Figure E3), both under the IMD, Ministry of Earth Sciences.[11] IMD heatwave outlooks and warnings are widely reported in mainstream media and disseminated through multiple channels. To ensure consistency, and given that Gurgaon is adjacent to Delhi, we rely on Delhi forecast data throughout. Appendix Figure E4 shows that temperature patterns in Gurgaon closely track those in Delhi.

[10] We classify food delivery, grocery delivery, and ride-hailing as relatively time-sensitive and inflexible-demand services because demand is tied to immediate consumption or transport needs. This feature is particularly salient in the growing "quick-commerce" segment, where speed is central to the business model.

[11] We focus on the subsequent three-day forecast horizon because forecast precision deteriorates rapidly beyond this window; see Appendix Figure E2.

Whenever the forecast indicated "Hot & Humid" and/or "Heatwave" conditions, both of which advise precautionary action, we sent a text message to all participants.[12] For the purpose of the experiment, we define every three consecutive days with heatwave warnings as a single heatwave episode.[13] We notified participants in both groups on the first day of each episode. For example, on June 10, 2025, participants received the following message: *This message is to inform you that a heatwave is expected in your city from June 10 to June 12.*

Table 1 summarizes the implementation of heatwave warnings and cash transfers during the study period. There were no heatwave warnings during the first two weeks of the experiment. During the study window, official heatwave warnings occurred continuously in a single spell spanning June 7 to June 14, after which temperatures declined starting June 15.[14] In total, we issued three heatwave warnings on June 7, June 10, and June 13 to all participants and disbursed ₹200 to treated participants on each of these dates. Hence, the experiment features three forecast-triggered transfer dates within a single major heatwave spell rather than a single one-time payment.[15]

3.3 Timeline & Data Collection

We conducted the baseline survey in April and early May 2025. The survey was administered in person and collected detailed information on participants' demographic characteristics (e.g., age, gender, education, marital status, and number of dependents), housing conditions (e.g., home ownership status and household assets such as access to air conditioning), financial situation (e.g., outstanding loans or debt obligations and health insurance coverage), work sector, and baseline labor supply (e.g., number of work days per week, average work hours per day, and average number of pieces delivered per working day).[16]

[12] In our pre-analysis plan registered at the AEA RCT Registry, we stated that a heatwave would be defined as a period in which temperatures exceed 43°C for at least two consecutive days. In implementation, however, we relied on official IMD heatwave warnings in order to align the intervention with the information environment faced by workers and to maintain consistency with publicly available advisories.

[13] If a heatwave warning persists for 2 to 4 consecutive days, it is treated as one episode; if it lasts for 5 to 7 consecutive days, it is counted as two episodes, and so on.

[14] See this news article for additional details on the decline in temperatures after June 15.

[15] The average commission per piece delivered in our baseline survey is ₹22, which falls within the ₹15-₹50 range reported in a *Times of India* news article. The average number of pieces delivered per day is 42. Thus, ₹200 represents about 22% of a delivery worker's average daily earnings.

[16] We do not have access to platform administrative records. However, workers can view completed deliveries in their platform dashboards on their phones, which provides a contemporaneous reference for reporting, and enumerators conducted random spot checks of these records during in-person surveys to verify delivery reports.

Following the baseline, participants completed six weekly phone surveys during the treatment period, from May 19 to June 30, 2025. These surveys collected consistent information on the paper's main outcomes, including labor supply and self-reported health symptoms. Labor-supply measures are based on respondents' reports of weekly work activity, while health outcomes are based on self-reported recent symptoms. Specifically, each weekly survey included the following four questions:

1. *How many days did you work in the week of [reference week]?*
2. *What were your average working hours per working day over the week of [reference week]?*
3. *On average, how many pieces did you deliver per working day in the week of [reference week]?*
4. *In the week of [reference week], did you experience any of the following symptoms: headache, stomachache, vomiting, or tiredness?*

During weeks in which a heatwave was forecast, participants were also asked about adaptation behaviors. This question was administered only in heatwave weeks, both to ensure the relevance of the responses and to limit respondent burden:

5. *In the week of [reference week], did you take any of the following actions to cope with the heat: avoided afternoon work and shifted to early morning or late evening hours ("Adjust Schedule"); bought extra water ("Buy Extra Water"); bought ice ("Buy Ice"); wore full-sleeve T-shirts ("Full-sleeve"); consumed glucose or oral rehydration salts ("Take ORS"); or rested at rest points equipped with coolers or air conditioning ("Rest AC").*

Because these weekly outcomes are self-reported, reporting error and experimenter-demand effects cannot be fully ruled out. This concern is mitigated by the randomized design and the use of identical survey protocols for treatment and control participants.

A comprehensive endline survey was conducted in late August and early September 2025. In addition to collecting data on labor supply and health outcomes, the endline introduced a module designed to assess workers' valuation of financial protection against prolonged extreme heat. This module presented two hypothetical products: a heatwave-indexed insurance product and an alternative job contract with built-in heatwave benefits. The insurance scenario elicited respondents' willingness to pay (WTP) a fixed premium before the onset of the hot season in exchange for receiving ₹200 for each heatwave episode occurring between March and July. The alternative contract offered the same heatwave-contingent payments but financed them through a lower per-delivery commission during March-July, thereby eliciting workers' willingness to accept (WTA) lower earnings in return for guaranteed support during heatwaves. This module allows us to study the perceived value of ex ante financial protection and to compare it with

the revealed benefits of real-time transfers. We provide additional details on the survey instrument and the calculation of expected payouts in Appendix A.

In February 2026, we conducted a short follow-up phone survey to collect additional information on workers' time use and constraints on schedule adjustment. We successfully re-interviewed 140 workers in the original sample. Appendix Table F1 shows that the re-interviewed sample is similar to the full baseline sample across observable characteristics, and the joint F-test of equality is not statistically significant. [17]

In total, our data consist of 2,348 observations (276 participants $\times$ 8 survey rounds + 140). The primary analysis focuses on the six weekly surveys during the treatment period, resulting in 1,656 observations (276 participants $\times$ 6 rounds). For the analysis of adaptive behaviors, which was restricted to the two weeks when heatwave events occurred, we use 552 observations (276 participants $\times$ 2 rounds). These weekly observations allow us to capture short-term responses to heatwave events in real time.[18]

3.4 Balance

Table 2 presents descriptive statistics and balance tests for key baseline characteristics across treatment and control groups. Overall, the sample consists primarily of young male gig workers, with an average age of 27.6 years. About 44% of participants are based in Delhi, and 62% are married. The majority have attained at least an undergraduate education, with only 2.5% having completed high school or below. Household characteristics, including the number of dependents, home ownership, and asset ownership, are broadly similar between the two groups. Approximately 16% of participants own their homes, while the vast majority rent. In terms of household assets, 95% own a bike, 31% have a cooler, and 15% have a fridge, while ownership of air conditioning units and cars is rare. Financial characteristics are also comparable, with approximately 40% reporting outstanding loans. Most participants lack health insurance coverage, with only 16% enrolled in any form of health insurance, either independently or through their employer. Regarding payment structure, about 18% of participants receive a base salary plus commission, 80% rely solely on commission, and 2% receive a fixed salary. In terms of labor supply outcomes, we find no statistically significant differences in work days per week, work hours per day, or pieces delivered per day. We further conduct a joint F-test of all baseline variables, which yields a p-value of 0.68, indicating no systematic differences

[17] We conducted this survey to bolster our mechanism on the suggestion of anonymous referees.

[18] Since we do not have access to platform administrative records, we do not have measures for earnings per delivery, trip-level characteristics (e.g., distance or delivery time), platform incentives, or within-day time use.

between the treatment and control groups.

3.5 Representativeness

To assess how our survey sample compares with the broader gig-delivery workforce, we benchmark baseline characteristics against two external sources.[19] The first is the National Council of Applied Economic Research (2023), which surveyed 924 food-delivery workers from a major platform across 28 Indian cities in April-May 2022. The second is the IDinsight report (Brailovskaya et al., 2025), which also surveyed food-delivery drivers from a major platform in India in February-May 2024; because our sample consists of workers with high work intensity, we compare it with the full-time active-driver subsample in the latter study.

As shown in Appendix Table F2, our sample is similar to both benchmark samples along several core dimensions. All three samples are overwhelmingly male (99.3% in our data, 99.0% in the NCAER survey, and 99% in the IDinsight full-time subsample). Average age is also very similar across datasets (27.6 in our data, 29.1 in NCAER, and 29.2 in IDinsight), as is average household size (4.5, 4.8, and 4.7, respectively). Work intensity is likewise comparable: our respondents work 10.3 hours per day and 6.4 days per week on average, closely matching the long-shift workers in NCAER (10.8 hours and 6.4 days) and the full-time subsample in IDinsight, which averages 65.5 hours per week compared with 65.9 hours in our sample. At the same time, some differences remain. Our sample has a higher marriage rate (61.6%) than either the NCAER sample (50.2%) or the IDinsight full-time subsample (53%), and lower home ownership (16.3%) than the NCAER sample (44.9%). These differences may reflect the geographic focus of our study on Delhi and Gurgaon, where housing markets and migration patterns differ from the broader multi-city samples used in the external reports, as well as differences in platform mix and work segments.

Overall, these comparisons suggest that our sample is broadly similar to other urban delivery-worker samples in India on observable demographics and work intensity, especially when compared to workers with similarly high levels of labor supply. We interpret these comparisons as descriptive benchmarks rather than evidence of statistical representativeness.

[19] We are not aware of any nationally representative census or administrative dataset on India's urban delivery workforce. We therefore rely on these survey-based benchmarks as the best available comparison points and interpret the results as suggestive evidence on similarity in observable characteristics rather than a definitive population match.

4 Empirical Strategy

This section outlines the empirical strategy used to estimate the causal effects of heatwave-indexed cash transfers on labor supply, health outcomes, and adaptive behaviors. We first examine how workers' labor supply and health respond to heatwave exposure and whether these responses differ by treatment status. We then estimate the effect of treatment on coping strategies adopted during heatwave weeks.

First, to estimate the impact of the intervention on labor supply and health outcomes, we employ the following regression specification:

$$\begin{aligned} Y_{it} = \alpha_i + \beta_0 Heatwave_t + \beta_1 (Treat_i \times Heatwave_t) \\ + \beta_2 PostHeat_t + \beta_3 (Treat_i \times PostHeat_t) + \epsilon_{it} \end{aligned} \tag{1}$$

where Y_{it} denotes the outcome variable for individual i in week t; $Treat_i$ is a binary indicator equal to one if individual i was assigned to the treatment group (i.e., receive a cash transfer when there is an episode of heatwave) and zero otherwise; $Heatwave_t$ is an indicator equal to one if any day within week t is covered by an official heatwave warning, as described in Section 3.2, corresponding to the third and fourth weeks of the experiment; and $PostHeat_t$ is an indicator equal to one if week t falls after the heatwave period, namely, the fifth and sixth weeks of the experiment. We include individual fixed effects, α_i, to control for time-invariant individual characteristics, including fixed differences associated with baseline recruitment at sampled rest points.

In this specification, β_0 captures the average effect of heatwave exposure on the control group. β_1 is our coefficient of interest, which measures the causal impact of receiving a cash transfer during heatwave weeks. The sum $\beta_0 + \beta_1$ represents the total effect of heatwave exposure on the treatment group. β_2 captures the average post-heatwave effects on the control group, while β_3 reflects potential lasting impacts of the cash transfer on treated individuals after the heatwave period. The sum $\beta_2 + \beta_3$ is the total post-heatwave effect for treated individuals. Standard errors are clustered at the individual level.

Second, for outcomes related to adaptive behaviors, which are only collected during heatwave weeks (i.e., the third and fourth weeks of the experiment), we employ the following regression specification:

$$Y_{it} = \beta \; Treat_i + X_i + \epsilon_{it}, \tag{2}$$

where Y_{it} denotes the adaptive behavior outcome, defined as a binary variable equal to one if individual i engaged in a specific adaptive behavior during week t, and zero other-

wise. X_i is a vector of baseline control variables, including key demographic and socioeconomic characteristics as reported in Table 2. The parameter of interest, β, captures the causal effect of receiving a cash transfer on adaptive behaviors during heatwave periods.

5 Average Treatment Effects

In this section, we present the average effects of heatwaves and heatwave-indexed cash transfers on gig delivery workers. We first examine labor-supply responses, then turn to health outcomes, and finally study changes in coping behaviors during heatwave weeks.

5.1 Labor Supply

Table 3 shows that heatwaves substantially reduce labor supply and productivity, while access to heatwave-indexed liquidity attenuates these declines. Labor supply is measured using three main outcomes: days worked per week, hours worked per working day, and pieces delivered per working day. We also construct an hourly productivity measure, pieces delivered per working hour, defined as pieces delivered per working day divided by hours worked per day.[20]

We find statistically significant negative effects of heatwave exposure on labor supply among delivery workers, with these reductions persisting even after the heatwave period at similar levels. On average, workers in the control group reduced their working days by 0.8 days per week (a 13.3% decline relative to the control mean in weeks 1-2), cut 1.2 working hours per day (12.1%), and delivered 9 fewer deliveries per day (24.3%), implying an overall 34% decline in weekly deliveries. Hourly productivity also declines by 0.56 pieces per hour (15.1%). In contrast, treated workers increased their number of working days by 0.5 days relative to the control group during heatwave weeks. Although they reduced their working hours by an additional 0.5 hours per day, they delivered 5.5 more deliveries per day, translating into 0.8 more pieces per hour than the control group.[21] Notably, even after the heatwave period, when treated workers no longer received cash transfers, we observe persistent positive effects on their labor supply in terms of the number of work days per week and the number of pieces delivered per day and thus hourly productivity.

[20] The number of observations for this constructed outcome is smaller than for the other labor outcomes because some respondents reported zero pieces delivered and zero hours worked in some weeks, making the ratio undefined.

[21] For treated workers, the combined effect on days worked and deliveries per working day implies an approximately 14% decline in weekly deliveries during heatwave weeks, 20 percentage points smaller than the decline for control workers.

We also report the total effect of heatwave exposure for treated workers, $\hat{\beta}_0 + \hat{\beta}_1$, which remains negative but is significantly smaller in magnitude compared to the control group for days worked and pieces delivered. Similarly, the total post-heatwave effect, $\hat{\beta}_2 + \hat{\beta}_3$, is less negative for treated individuals, suggesting cash transfers not only mitigate immediate labor supply reductions but also help post-heatwave recovery. These findings indicate that while heatwaves substantially reduce labor supply among gig workers, heatwave-indexed cash transfers help cushion these adverse effects, especially on work participation and productivity.

5.2 Health

Next, we examine the effects of heatwaves and cash transfers on self-reported health outcomes. The results are reported in Table 4. We observe significant negative health impacts of heatwaves among delivery workers in the control group, particularly with regard to headaches and fatigue. Specifically, heatwaves increase the likelihood of experiencing headaches by 17.3 percentage points for the control group (a 144% increase relative to the control mean), tiredness by 36.0 percentage points (a 62% relative increase), and any of the four symptoms by 28.4 percentage points (a 43% relative increase). These adverse health effects are consistent with the observed reductions in labor supply, as worsening health likely constrains workers' ability to maintain regular working days, hours, and productivity.

In contrast, cash transfers significantly mitigate these negative health effects: treated workers experience a 13.1 percentage point reduction in headaches and a 35.5 percentage point reduction in tiredness during the two heatwave weeks. These effects remain statistically significant after Holm adjustment for multiple testing across the four individual symptom outcomes, with adjusted p-values of 0.02 for headaches and 0.00 for tiredness. By contrast, the treatment interactions for stomachache and vomit remain statistically insignificant both before and after adjustment. As a result, the total effects of heatwave exposure among treated workers ($\hat{\beta}_0 + \hat{\beta}_1$) are economically small and statistically insignificant for these health outcomes, suggesting the cash transfer effectively offsets the adverse health effects of an extended period of extreme heat. These improvements in health likely contribute to the smaller reduction in labor supply observed among treated workers, as shown in Table 3.

In addition to the immediate effects, we also observe persistent adverse health impacts in the post-heatwave period among the control group. Apart from headache and tiredness, delivery workers in the control group are 7.2 percentage points (a 120% relative

increase) more likely to experience stomachaches during the two post-heatwave weeks. In contrast, treated workers do not exhibit statistically significant negative health outcomes ($\hat{\beta}_2 + \hat{\beta}_3$) after the heatwave period, suggesting a sustained protective effect of the cash transfer intervention.

5.3 Adaptive Behaviors

We now shift our focus to adaptive behaviors, examining how cash transfers affect workers' coping strategies during heatwaves, with potential implications for sustained productivity and improved health. These measures are informative about mechanisms as they capture both avoidance-based responses (e.g., shifting work away from the hottest hours and resting in cooled locations) and spending-related responses (e.g., purchasing extra water, ice, or ORS). Table 5 presents the results.

We find that treated workers are 13.8 percentage points (a 37.3% increase relative to the control group) more likely to adjust their work schedules by avoiding afternoon work and shifting to early morning or late evening hours, and 14.6 percentage points more likely to rest at rest points equipped with coolers or air conditioning (AC). These effects remain statistically significant after Holm adjustment for multiple testing across the six adaptive behaviors, with adjusted p-values of 0.02 and 0.00, respectively.

At the same time, we do not observe broad increases in the specific spending-related coping behaviors measured in the weekly survey. Treated workers are 45.4 percentage points less likely to report buying extra water,[22] and we find no evidence of increased purchases of ice or glucose. This pattern suggests substitution toward avoidance-based strategies rather than greater spending on the protective inputs captured in the weekly survey.[23] Additionally, we observe a 70.1 percentage point reduction in the likelihood of wearing full-sleeve T-shirts. While protective clothing could reduce sunburn, it can be burdensome in extreme heat, potentially amplifying discomfort, and may be avoided when workers can reduce exposure. Follow-up survey evidence further suggests that some treated workers used the June 2025 transfer for cold drinks other than water (Appendix Figure E6), indicating that part of the spending response may have taken the form of immediate consumption-based relief not directly captured by the weekly adaptive-behavior measures.

[22] This measure does not capture cold drinks other than water.

[23] These patterns are more consistent with substitution across coping margins than with uniform increases in all reported behaviors, and therefore suggest real adjustments in behavior rather than broad changes in awareness or reporting.

5.4 A Simple Model of Heat Exposure, Time Allocation, and Liquidity

To organize the empirical patterns, we develop a simple framework in which workers allocate time across periods and household production subject to short-run liquidity constraints. The purpose of the model is to clarify how timely cash support can relax short-run time allocation constraints during heatwaves and thereby facilitates shifts toward cooler working hours.

Setup Time is divided into discrete periods $t \in \{m, a, e\}$ corresponding to morning, afternoon, and evening. Let $h_t \in [0, 1]$ denote hours worked in period t, and let ℓ_t denote leisure. In addition, the worker must allocate time to household production, denoted by s_t, such as cooking or caregiving. Total time in each period is normalized to one:

$$h_t + \ell_t + s_t = 1 \quad \forall t.$$

Heat exposure varies across periods, with the afternoon being the hottest. Let θ_t denote heat intensity, with $\theta_a > \theta_m, \theta_e$. A worker derives utility from consumption c and leisure and experiences disutility from working in hotter periods:

$$U = u(c) + \sum_t v(\ell_t) - \sum_t \theta_t \cdot h_t,$$

where $u'(\cdot) > 0$, $u''(\cdot) < 0$, $v'(\cdot) > 0$, and $v''(\cdot) < 0$.

Household Production The worker must meet a minimum household-production requirement in the morning and evening:

$$s_t + \phi x_t \geq \bar{s}_t \qquad \text{for } t \in \{m, e\},$$

where $x_t \geq 0$ denotes market expenditure that substitutes for household production in period t—for example, purchasing prepared food or other goods and services that reduce time-intensive household tasks—and $\phi > 0$ captures the efficiency of that substitution.

Earnings, Budget, and Liquidity Earnings depend on hours worked:

$$y = \sum_t w_t h_t,$$

where wages w_t may vary across periods (e.g., higher during peak demand hours). Consumption and market expenditure must satisfy

$$c + \sum_{t \in \{m,e\}} x_t \leq y + T,$$

where $T \geq 0$ is the heatwave-indexed transfer. In addition, the worker faces a short-run liquidity constraint that limits the ability to finance market expenditures at the time the heat shock occurs:

$$\sum_{t \in \{m,e\}} x_t \leq L + T,$$

where $L \geq 0$ denotes liquid cash-on-hand available before the transfer, which may be low even when overall resources are sufficient. The budget constraint captures overall affordability, while the liquidity constraint captures immediate spending capacity at the moment the shock occurs. The liquidity constraint is relevant when some desired short-run adaptation expenditure would otherwise exceed pre-transfer cash-on-hand.

Adaptation & Liquidity Avoiding heat requires reducing work in the hottest period, the afternoon, and shifting work toward cooler morning or evening hours. However, those cooler hours are also used for household production. Reallocating work toward cooler hours therefore requires lowering s_t in those periods, which in turn may require higher expenditure x_t on market substitutes. The transfer T relaxes both the budget constraint and the liquidity constraint, allowing higher x. This enables substitution away from time-intensive household production and frees up cooler periods for work. Timely cash support can therefore facilitate adaptation by lowering heat exposure (lower h_a) and shifting labor toward cooler hours, while attenuating the resulting short-run earnings losses.

Implications For $t \in \{m, e\}$, the household-production constraint implies $s_t \geq \bar{s}_t - \phi x_t$. Substituting this into the time constraint yields

$$h_t + \ell_t \leq 1 - \bar{s}_t + \phi x_t.$$

Thus, market expenditure relaxes the time-allocation constraint in cooler periods by reducing required household production. A higher transfer T expands the feasible set for $\{x_t\}$ through both the budget and liquidity margins, but the liquidity margin is especially

important here because adaptation requires immediate spending at the time of the heat shock. When the liquidity constraint binds, timely cash support increases the worker's ability to substitute away from household production in cooler periods and reallocate labor away from peak heat.

This framework yields three empirical predictions. First, because heat disutility is highest in the afternoon at the time of a heat shock ($\theta_a > \theta_m, \theta_e$), relaxing the liquidity constraint makes it feasible to reallocate labor away from the hottest hours and toward cooler morning and evening periods. Thus, timely cash support should increase schedule adjustment away from afternoon work, which is consistent with the adaptation patterns documented in Section 5.3. Second, the gains from this relaxation should be larger when avoiding peak-heat work entails greater immediate earnings losses, such as in time-sensitive or commission-based jobs. In such settings, the marginal value of additional cash-on-hand is greater because it helps smooth the short-run income cost of adaptation. Third, the effects should be larger when ϕ is higher, that is, when household production is more easily substitutable through expenditure or intra-household reallocation. Empirically, one source of such variation is household composition: household production (such as child care) for workers with more children may not be easily substituted with market services despite cash transfers, given thin markets and low-quality childcare in developing countries. On the other hand, having more co-residing adults may complement cash transfers by making it easier to use market services to outsource household production (for example, by having someone else go to the market to buy food or groceries).

The model highlights that adaptation requires reallocating time away from household production, which may in turn require substitution toward market purchases. In the subsequent sections, we examine these implications using heterogeneity in treatment effects together with descriptive evidence on time use and spending.

6 Heterogeneous Treatment Effects

In this section, we examine which workers benefit most from heatwave-indexed transfers and whether those patterns align with the adaptation mechanisms emphasized above. The average treatment effects mask substantial heterogeneity in workers' responses to timely cash support during heatwaves. Although the pre-specified subgroup analyses reported in Appendix C.1 already indicate larger effects among workers in time-sensitive and commission-based segments of the gig economy, those dimensions alone do not provide a comprehensive characterization of heterogeneity in exposure and responsiveness. We therefore use a machine-learning-based procedure as a structured way to organize

heterogeneity across a rich set of baseline characteristics and to identify which workers benefit most from the transfer.

Data Construction and Training Features We examine heterogeneity along two key outcomes: labor productivity and schedule adjustment. For labor productivity, we construct an individual-level change-in-output measure by comparing each worker's average number of pieces delivered per working day during heatwave weeks (weeks 3-4) to that in pre-heatwave weeks (weeks 1-2). For adaptive behavior, we compute each worker's average schedule-adjustment indicator during weeks 3-4. Schedule adjustment is defined as a binary indicator equal to one if the worker avoids afternoon work and instead shifts activity to early-morning or late-evening hours in a given week. The machine-learning models are trained using a rich set of pre-treatment characteristics, including demographics, education, household composition, housing ownership, ownership of cooling assets, loan and insurance indicators, compensation structure, and sector of work. Full details on outcome construction and training features are provided in Appendix C.5.

Method We estimate heterogeneous treatment effects using the Generic Machine Learning (GenericML) framework (Chernozhukov et al., 2025). The procedure repeatedly splits the sample into training and estimation subsamples and uses machine-learning learners to predict untreated potential outcomes and individualized treatment effects. We summarize heterogeneity using Group Average Treatment Effects (GATES), which show how treatment effects vary across groups ranked by predicted responsiveness, and Classification Analysis (CLAN), which describes how observable baseline characteristics differ between workers predicted to benefit the most and the least. Appendix C.5 provides additional methodological details, including the full implementation and supporting results.

Distribution of Treatment Effects: GATES To visualize how treatment effects vary across the distribution of predicted responsiveness, we next compute GATES. Workers are partitioned into four equally sized groups, and average treatment effects are estimated within each group. Group assignments are outcome-specific, as the heterogeneity score is estimated separately for productivity and schedule adjustment.

Figure 2 plots the resulting estimates and 95% confidence intervals. For productivity (Figure 2a), treatment effects increase monotonically across groups, from near zero in the lowest quartile to more than 11 additional deliveries per day in the highest quartile. The average treatment effect lies between these extremes, masking substantial dispersion. A

similarly monotonic pattern emerges for schedule adjustment (Figure 2b): workers in the most responsive quartile are 35 percentage points more likely to shift work away from afternoon hours, while those in the lowest-response quartile are 28 percentage points less likely to adjust their schedules during heatwaves in response to the transfer. hese patterns suggest that treatment effects are uneven across workers, with the largest gains concentrated among those most responsive to the transfer.

Characterizing High- and Low-response Workers: CLAN We next use CLAN to describe how observable baseline characteristics differ between treated workers who benefit the most relative to those who benefit the least. The results for productivity and schedule adjustment are reported in Tables 6 and 7. We find evidence consistent with the implications of the conceptual model in Section 5.4.

CLAN Results Re-enforcing Liquidity Mechanism First, workers who gain the most in terms of productivity are disproportionately commission-paid and employed in inflexible-demand industries such as food delivery, grocery delivery, and ride-hailing (Table 6). They are also less likely to own cooling or refrigeration assets—patterns consistent with greater heat exposure and limited capacity to mitigate it at home. In contrast, workers who benefit the least are more likely to operate in flexible-demand sectors, receive a base salary plus commissions, and own cooling assets. These patterns are consistent with the idea that liquidity is especially valuable for workers facing high short-run income risk and limited private means of heat avoidance.

Second, Table 7 shows that workers most likely to adjust their schedules tend to be younger, more likely to be commission-paid, and more likely to work in relatively inflexible-demand sectors. They also tend to live in households with more adults and fewer children. This pattern is consistent with the time-use mechanism underlying liquidity constraints. In this setting, shifting work to cooler hours requires reallocating time away from household production, particularly cooking. Liquidity enables substitution away from these time-intensive activities, for example through the purchase of prepared food, thereby freeing up time for work during cooler periods. In contrast, childcare is less easily substituted through market purchases, given the limited availability of formal options and the size of the transfer. As a result, workers with fewer children are better able to adjust their schedules in response to the transfer.

Overall, the GenericML results align closely with the pre-specified subgroup analyses reported in Appendix C.2-C.4 and with the mechanism evidence presented above. While heatwave-indexed cash transfers generate sizable average improvements in productiv-

ity, the gains are concentrated among workers facing high short-run income risk, rigid labor demand, and limited access to private cooling. At the same time, the schedule-adjustment results suggest that the benefits of liquidity also depend on whether workers can reallocate time away from household production and toward cooler working hours. These findings underscore the role of liquidity constraints in shaping adaptation to heatwaves and highlight the importance of targeting adaptation policies toward workers who are both highly exposed to climate-related income risk and well positioned to translate timely support into effective heat avoidance.

7 Valuation of Ex-Ante Heatwave Protection

The heterogeneity results indicate that heatwave-indexed transfers generate substantial productivity and health benefits for a specific subset of workers—those facing rigid demand, output-linked pay, and limited capacity to mitigate heat exposure. We next examine whether these same workers express demand for ex ante financial protection against heatwaves. This comparison helps assess whether insurance-style instruments can serve as effective adaptation tools for informal workers or whether liquidity support is primarily valued when delivered in real time. We therefore interpret this exercise as informative about the role of short-run financial constraints and the timing of support, rather than as a full decomposition of insurance demand.

Elicitation of Valuation We elicit workers' WTP for a hypothetical heatwave-indexed insurance product that provides a payment of ₹200 for each officially declared heatwave day between March and July. We also elicit workers' WTA a reduction in per-delivery commissions in exchange for an otherwise equivalent built-in benefit. These elicitation methods mirror the structure of the experimental transfer while shifting the timing from ex post liquidity to ex ante coverage. We administer both questions to workers in the treatment and control groups.[24]

Average Valuation Figure 3 plots the inverse demand curve for a heatwave-indexed insurance product. WTP declines sharply with price, with take-up falling below 20 percent at premiums that would cover expected payouts. Exposure to transfer does not increase the stated demand for ex ante insurance on average (column 1 of Panel A of Table 8). This

[24]Because these products are hypothetical, stated WTP may be biased. Our objective is not to recover market demand for insurance, but to compare valuation patterns across treated and control workers and across worker types.

contrasts sharply with the large ex post productivity and health gains from timely cash support, suggesting that workers may value support differently when it must be purchased in advance than when it is delivered at the time of the shock. Similarly, although a majority of workers are willing to accept a small per-delivery commission reduction that could, in principle, finance the expected payout (Appendix Figure B1), only 22% prefer a job offer that embeds such protection when asked to choose between alternatives. As shown in columns 2-3 of Panel A of Table 8, treated and control workers report similar WTP and WTA, indicating that the observed benefits of liquidity during heatwaves do not, on average, translate into greater stated demand for similar ex ante protection. This average pattern should be interpreted cautiously, as stated valuation may reflect not only liquidity constraints but also beliefs about payout likelihood, trust, product understanding, and risk preferences (Cole et al., 2014; Fezzi et al., 2021).

Heterogeneity in Valuation by Realized Benefits The average results mask substantial heterogeneity in WTP and WTA. As shown in Panels B and C of Table 8, treated workers in flexible-demand sectors and those with fixed or mixed compensation (base salary plus commission) exhibit significantly higher WTP for ex ante protection, whereas workers in time-sensitive, commission-only roles—who experienced the largest productivity gains from ex post liquidity—display weaker demand for insurance-style products. In Panel B, treated workers in flexible-demand sectors are willing to pay ₹91 more ($p < 0.10$, 18.9% of the control mean) relative to control workers. Yet, the interaction term implies that workers in inflexible-demand sectors are willing to pay ₹100 less ($p < 0.10$), effectively offsetting this effect. A similar pattern emerges by payment structure in Panel C. Treated workers with fixed or mixed pay exhibit a large increase in WTP of ₹180 ($p < 0.01$, 37.3% of the control mean), while commission-only workers are willing to pay ₹211 less ($p < 0.01$), again offsetting the effect.

This heterogeneity is consistent with the conceptual framework. Workers facing greater short-run income risk appear to benefit most from support delivered when the heat shock occurs, yet they are less willing to pay for protection that requires advance payment or commitment. This pattern is also consistent with the distinction between time and state in insurance discussed by Casaburi and Willis (2018): workers who value support ex post need not place high value on products that must be purchased ex ante.

Understanding, Trust, and Beliefs The February 2026 follow-up survey provides descriptive evidence on several factors that may shape demand for ex ante heatwave insurance. Relative to the control group, treated workers are more likely to report under-

standing how the hypothetical heatwave-indexed insurance product works (Appendix Figure E7a) and to express trust in a government-provided insurance product for gig workers (Appendix Figure E7b). By contrast, the two groups report similar expectations about the number of heatwave episodes in the coming summer (Appendix Figure E7c). In addition, all participants in both the treatment and control groups received identical real-time SMS alerts based on official IMD forecasts, so differential access to heatwave information was held constant by construction. Taken together, these patterns make it less likely that weak demand for ex ante protection, particularly among workers who benefited most from the transfers, is primarily driven by differences in product understanding, trust, or beliefs about future heat risk. Instead, they are more consistent with the importance of timing and short-run financial constraints in shaping demand.

Interpretation The valuation results reveal an important asymmetry: workers appear to benefit substantially from timely financial support during heatwaves, yet they show comparatively weak willingness to pay in advance for formal state-contingent protection. This divergence is especially pronounced among workers in commission-only and inflexible-demand jobs, who experienced the largest ex post gains from real-time liquidity but display the weakest ex ante demand. While the broader index-insurance literature emphasizes trust, beliefs, and preferences as important determinants of take-up (Cole et al., 2014; Fezzi et al., 2021), the follow-up evidence makes it harder to attribute either the lack of an average treatment-control difference or the especially low WTP among the largest beneficiaries to misunderstanding, mistrust, or divergent beliefs alone. Overall, the results are more consistent with a setting in which support is highly valued when delivered at the moment of need, but advance payment or commitment remains difficult. From a policy perspective, this suggests that interventions delivering liquidity in response to realized environmental shocks may be more effective than ex ante insurance in supporting adaptation among high-risk informal workers.

8 Liquidity Constraints versus Pure Income Effects

In this section, we assess whether the effects of the heatwave-indexed transfers are more consistent with the relaxation of liquidity constraints or with a pure income effect. A pure income effect would predict broadly similar behavioral responses across workers and limited dependence on the timing of transfers. In contrast, a liquidity-based explanation implies that the timing of cash on hand matters, particularly when workers face short-run trade-offs between earnings, time use, and exposure to heat.

Time-Use Constraints and Substitution A first piece of evidence comes from the role of time-use constraints. In our setting, the cooler early morning and evening hours are also commonly used for household production, particularly cooking (Appendix Figure E5). As a result, shifting work to cooler hours is not costless, as it requires reallocating time away from these activities. Consistent with this, we find that treated workers are significantly more likely to adjust their schedules and work during cooler periods.

Descriptive evidence from the February 2026 follow-up survey supports this mechanism. Workers report using early morning hours for cooking, and treated workers who switched to working during cooler hours report using transfers primarily for food and groceries (Appendix Figure E6). These patterns suggest substitution away from time-intensive household production through market purchases, thereby freeing up time that can be reallocated toward work in cooler periods.

Together, these findings indicate that liquidity relaxes both short-run budget constraints and time-use constraints. This mechanism is difficult to reconcile with a pure income effect alone, which would not predict systematic changes in how workers allocate time between market work and household production.[25] Importantly, the costs of reallocating time away from household production are small in absolute terms but binding at high frequency. Even modest expenditures, such as purchasing prepared food, may not be feasible without immediate cash-on-hand at the time of the heat shock. This makes liquidity, rather than overall income, the relevant constraint.

Heterogeneity in Treatment Effects A second piece of evidence comes from heterogeneity in treatment effects. Workers who benefit most from the transfers are disproportionately those facing high short-run income risk, including commission-paid workers and those in time-sensitive, inflexible-demand sectors. These workers are more exposed to immediate earnings losses when reducing heat exposure and are therefore more likely to face constraints in adjusting their behavior without additional liquidity. We also find that schedule adjustment is more pronounced among workers with fewer children, consistent with the idea that childcare-related time constraints are less easily relaxed through market substitution than other time-intensive household activities (e.g., cooking). This evidence align with the second and the third predictions of our model.

Ex Post Benefits versus Ex Ante Valuation Finally, we observe a divergence between ex post benefits and ex ante valuation. While the transfers generate substantial improve-

[25] We also do not find consistent evidence that treatment effects vary systematically with baseline loan status (see also Table 7). This suggests that the relevant friction operates through the availability of immediate cash on hand at the time of the heat shock, rather than through access to formal credit.

ments in productivity and health, workers exhibit low TWP for insurance that would provide similar payouts in advance. Moreover, the workers who benefit most from ex post liquidity are the least willing to pay for ex ante protection. This pattern is consistent with the importance of timing: support is most valuable when delivered at the moment workers face trade-offs between income, time use, and exposure. A pure income effect would not naturally predict this disconnect between realized benefits and WTP in advance.

To summarize, these findings indicate that the effects of the transfers are better understood as operating through the relaxation of short-run liquidity constraints that shape both financial and time-use decisions. By enabling workers to substitute away from time-intensive household production and to absorb short-run income losses, timely liquidity facilitates real-time adaptation to extreme heat.

9 Additional Concerns & External Validity

In this section, we address several additional issues relevant to the interpretation and scope of our results. We first consider whether spillovers or interference across treated and control workers could contaminate the experimental comparison. We then discuss the extent to which the estimated effects should be understood as partial-equilibrium responses and how they might differ under larger-scale implementation. Lastly, we consider the external validity of the findings.

9.1 Spillovers and Interference

A potential concern is that treated workers' schedule adjustments could shift delivery demand toward control workers, thereby contaminating the comparison between the two groups. This type of interference would tend to attenuate treatment effects if control workers benefited from demand reallocation during peak heat hours. If anything, we would be picking up the lower bound. But we do not believe this interference operates in our context. First, we observe that deliveries decline for both treated and control workers during heatwaves, with a smaller decline among treated workers. If schedule adjustments by treated workers substantially shifted demand toward the control group, we would expect deliveries among control workers to rise or stay the same rather than fall. In addition, gig workers in our sample operate across large metropolitan areas in Delhi and Gurgaon and often work on multiple platforms, making it unlikely that schedule changes by a subset of treated workers would generate meaningful demand reallocation

to control workers. These considerations suggest that spillovers are unlikely to be a major driver of our main results.

9.2 General Equilibrium and Scale

Another concern is that if many workers shift labor supply toward cooler hours, platform pricing may adjust, increasing compensation during peak-heat periods and partially offsetting the behavioral response. Our experimental design identifies the partial-equilibrium effect of relaxing liquidity constraints among a relatively small subset of workers and is therefore unlikely to affect market-level pricing. At larger scale, however, such equilibrium adjustments are plausible.

We do not expect these responses to fully offset the effects we document for several reasons. First, adaptation operates along multiple margins, not only through shifting work toward cooler hours but also through greater use of cooled rest locations. These behaviors reduce heat exposure and improve worker health, and would remain beneficial even if relative prices change. Second, shifting labor to cooler hours is constrained by competing demands on workers' time. In our setting, early morning and evening hours are commonly used for household production (Appendix Figure E5). Timely cash may ease these constraints by enabling substitution away from time-intensive household tasks, for example through market purchases, thereby allowing workers to reallocate labor to cooler periods. These time-use constraints imply that labor supply may not fully revert even if peak-hour prices rise. Third, the behavioral responses we document also improve worker health, with treated workers reporting fewer heat-related symptoms even after the heatwave period. To the extent that workers value the health benefits of reduced heat exposure, they may continue to avoid peak-heat hours even if short-run financial incentives shift.

To further assess the potential magnitude of such attenuation, Appendix G presents a simple calibration. The exercise suggests that equilibrium responses would likely dampen, but not fully eliminate, the behavioral effects documented in Table 5. Taking the estimated 13.8 percentage point increase in schedule adjustment as a proxy for the direct reduction in afternoon labor supply under universal rollout, the calibration implies an equilibrium reduction in afternoon labor supply of roughly 6.9-12.5 percentage points, so that about 9% to 50% of the initial effect is dampened by equilibrium feedback.[26] Attenuation is greater when afternoon demand is less elastic or when workers are more responsive to higher peak-hour compensation

[26]The numbers should be interpreted cautiously since schedule adjustment is a binary measure in our setting.

9.3 External Validity

Our findings are most relevant for urban informal and gig workers in low- and middle-income countries who face substantial outdoor heat exposure, depend on daily or output-linked earnings, and have limited access to formal labor protections or savings. In these settings, reducing heat exposure is often costly because it requires foregoing work during peak earning hours or reallocating time away from household production. Recent cross-country evidence from India, Indonesia, and Kenya shows that platform work commonly serves both as a primary source of income and as a fallback source of earnings, underscoring the broader relevance of our setting for informal urban labor markets (Adhvaryu et al., 2026).[27]

More broadly, the results are likely to generalize to environments in which workers face similar short-run liquidity and time-allocation constraints. In our setting, the early morning and evening hours when temperatures are lower are also used for household production, particularly cooking. As a result, adaptation requires both cash-on-hand and the ability to substitute away from time-intensive activities. Settings in which these constraints are less binding—for example, where workers have access to savings, formal insurance, or employer-provided protections—may exhibit smaller effects.

At the same time, our estimates are most applicable to contexts where heat-risk information is already available or can be communicated at low cost. In our experiment, both treatment and control workers received the same heatwave warnings, so the estimated treatment effect isolates the role of timely liquidity rather than improved access to information. In settings where workers lack access to reliable heat-risk information, the effects of combined information and liquidity interventions may differ.

As heatwaves become more frequent and severe, and as informal urban service work is widespread in many developing countries, our findings suggest that adaptation policy should not rely on information provision alone. Even when warnings are salient, workers may still be unable to protect their health if doing so entails immediate income losses. In such contexts, small and timely transfers may be an important complement to heat alerts, cooling infrastructure, and other workplace protections.

[27] The underlying mechanism may extend beyond gig delivery workers to other heat-exposed informal workers, such as launderers, street vendors, and petty traders. For example, Das and Somanathan (2024) show that heat substantially reduces work attendance and earnings among informal workers in Delhi, with net earnings about 40% lower during heatwave periods. This suggests that the economic risks highlighted in our setting are not unique to platform-based work.

10 Robustness Checks

In this section, we conduct three checks to examine the robustness of our main results reported in Section 5. First, in the main analysis, we include individual fixed effects in equation (1) and a vector of individual control variables in equation (2). Here, we relax the individual fixed effect to test if our results are sensitive to unobserved, time-invariant individual heterogeneity. The results are presented in Appendix Table D1-Table D3. As shown, the estimated coefficients are both economically and statistically similar to those reported in Table 3-Table 5.

Next, we examine whether our estimates are robust to the inclusion of week fixed effects which would account for any common shocks or temporal trends such as weather fluctuations. We report the results in Appendix Table D4-Table D6. Again, the results are similar to those reported Table 3-Table 5 in both magnitude and significance. Together, the above two checks indicate that our findings are not sensitive to alternative fixed-effects specifications and are unaffected by potential unobserved individual or time-specific confounders.

Lastly, we expand the analysis sample to include the post-hot-season endline round conducted in late August and early September 2025. We examine how this inclusion affects the estimated treatment effects on labor supply (Appendix Table D7) and health outcomes (Appendix Table D8). This exercise allows us to test whether appending the endline observations alters our estimates of treatment effects in the post-heatwave period ($Treat \times PostHeat$). As expected, the positive treatment effect on labor supply following the heatwave period attenuates slightly once the endline round is added, likely reflecting the seasonal slowdown in delivery demand and partial convergence between treatment and control groups after the experiment concluded. Meanwhile, individuals who received cash transfers during the heatwave period continue to exhibit a reduced likelihood of experiencing any heat-related symptom. The estimated coefficient becomes larger in magnitude (–0.149 vs. –0.086) and statistically significant at the 1% level, suggesting a sustained health benefit of the cash transfer intervention that extends from June through early September.

11 Conclusion

We examine whether small, heatwave-indexed cash transfers can help gig delivery workers in India adapt to prolonged extreme heat, using a randomized controlled trial conducted in two metropolitan cities in India, a setting where climate-related risks are rapidly

intensifying. We find that heatwave exposure substantially reduces labor supply and worsens health outcomes, while timely cash transfers effectively mitigate these adverse effects. These improvements likely arise because treated workers were more likely to adjust their schedules to cooler hours and take rest at air-conditioned rest points, suggesting that liquidity support enabled them to absorb short-term income losses while protecting their health. The benefits are most pronounced among workers in time-sensitive, commission-based sectors, where long-time exposure to extreme heat directly constrains earnings potential and work flexibility. Despite the clear ex-post benefits of the cash transfers, we find limited ex-ante demand for formal financial protection. Workers' willingness to pay for heatwave-indexed insurance or to accept small commission reductions for equivalent protection remained low.

These findings highlight the potential of small, timely cash transfers as a scalable tool to enhance resilience among outdoor gig workers during climate shocks. As heatwaves become more frequent and severe, policymakers should consider integrating heat-indexed cash assistance into urban heat action plans, alongside investments in cooling infrastructure and workplace protections. Targeted and flexible support of this kind can complement existing measures and provide an essential buffer for workers in the gig economy and informal sectors, who often lack formal labor protections yet remain highly exposed to climate risks.

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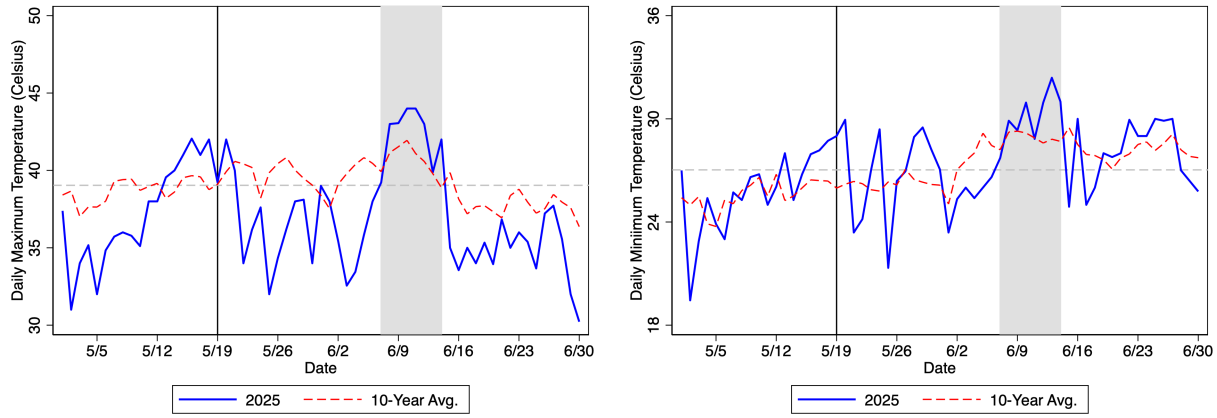
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Figures

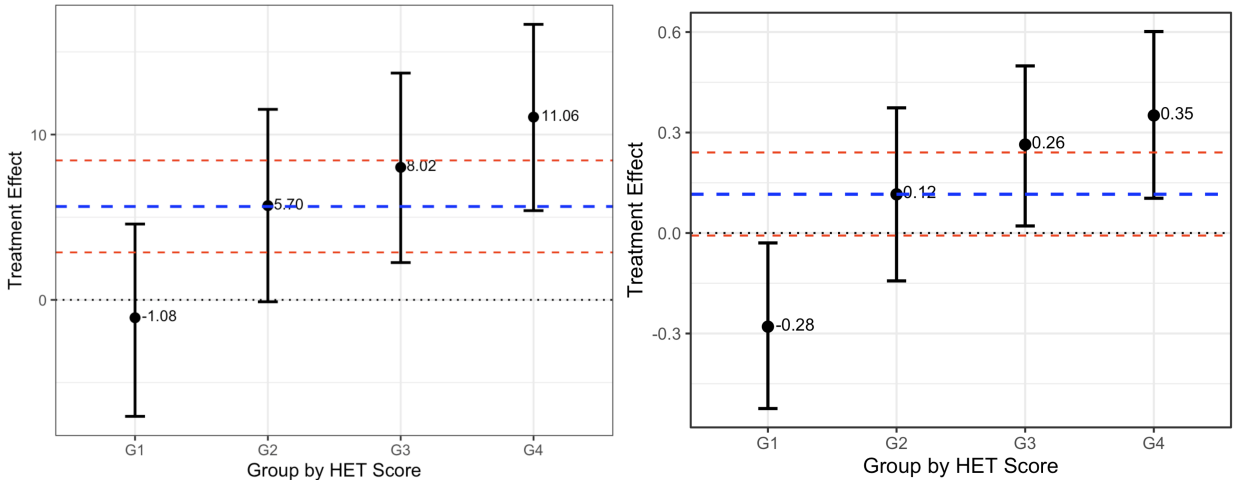
FIGURE 1: Historical Daily Maximum and Minimum Temperatures (°C) in Delhi



(a) 2025 vs. 10-Year Average, Maximum (b) 2025 vs. 10-Year Average, Minimum

Notes: This figure compares daily maximum (Panel a) and minimum (Panel b) temperatures in Delhi during May and June of 2025 with the corresponding 10-year historical average. The solid blue line shows the observed daily maximum and minimum temperatures in 2025, respectively, while the red dashed line represents the 10-year average maximum and minimum temperature for each corresponding calendar date, calculated over the period 2014–2023. The horizontal gray dashed line indicates the average daily maximum temperature (39.0°C) between May 1 and June 30 during the same 10-year period in Panel a, and the average daily minimum temperature (27.0°C) in Panel b. The vertical black line indicates the start date of our randomized control trial (May 19, 2025). The shaded area from June 7 to June 14 indicates the period during which a heatwave warning was issued by the India Meteorological Department. Historical temperature data for Delhi are obtained from Visual Crossing and are accessible via this website.

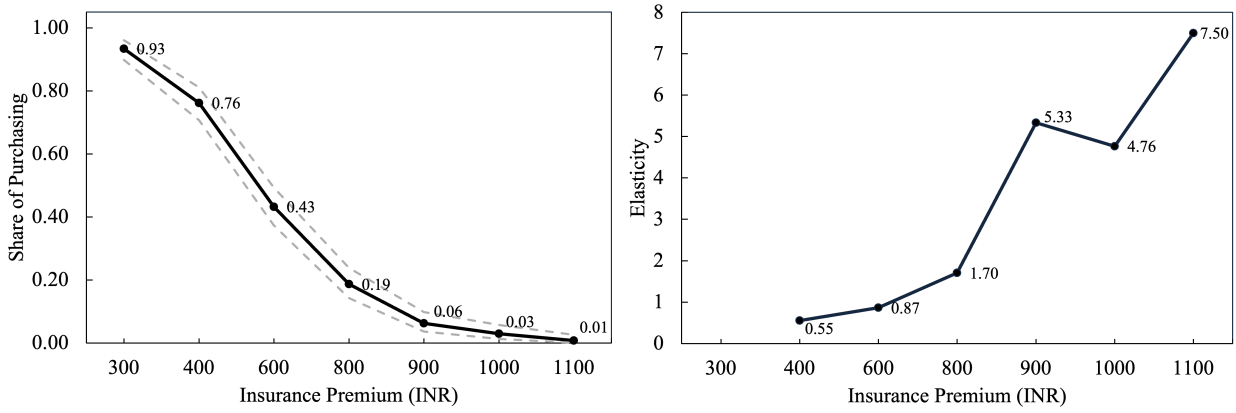
FIGURE 2: GATES Estimates: Effects of Heatwave-Indexed Cash Transfers on Daily Productivity & Schedule Adjustment



(a) Changes in Daily Productivity (b) Schedule Adjustment

Notes: The figures report GATES estimates computed using GenericML (Chernozhukov et al., 2025) with 100 repeated 50/50 sample splits. In Figure 2a, the outcome is the change in the average number of pieces delivered per working day between the heatwave weeks (weeks 3-4) and the pre-heatwave weeks (weeks 1-2). In Figure 2b, the outcome is schedule adjustment, defined as a binary indicator equal to one if an individual avoids afternoon work and instead shifts to early-morning or late-evening hours. The best learner selected for GATES is a ridge-regression model for Figure 2a and an elastic-net model for Figure 2b. Workers are partitioned into quartiles (G1-G4) based on their predicted heterogeneous treatment-effect (HET) scores for each outcome. Higher groups correspond to workers predicted to benefit more from cash transfers—either in terms of productivity gains (Figure 2a) or a greater likelihood of adjusting work schedules (Figure 2b). Dots represent estimated treatment effects, and vertical bars indicate 95% confidence intervals. The blue dashed line shows the average treatment effect (ATE) from the BLP estimator, with red dashed lines marking its 95% confidence interval.

FIGURE 3: Demand and Price Elasticity of Heatwave-Indexed Insurance



(a) Inverse Demand Curve (b) Price Elasticity of Demand

Notes: Figure 3a displays the inverse demand curve for heatwave-indexed insurance at seven price points (INR 300, 400, 600, 800, 900, 1,000, and 1,100). This is a one-time premium paid before the onset of the heat season, entitling participants to receive ₹200 for each episode of heatwave occurring between March and July. The curve shows the cumulative share of respondents who chose to purchase the insurance product at each price. Dashed gray lines indicate 95% confidence intervals. Figure 3b presents the corresponding price elasticity of demand, calculated between adjacent price points. Both panels are based on 273 observations.

Tables

TABLE 1: Experiment Calendar (May–June 2025)

Week 1	5/19	5/20	5/21	5/22	5/23	5/24	5/25
Heatwave Forecast Status	None	None	None	None	None	None	None
Forecasted Max. Temp.	38-40	38-40	38-40	39-41	36-38	37-39	37-39
Actual Max. Temp.	39	42	40	35	36	38	32
Cash Transfer Issued	No	No	No	No	No	No	No
Week 2	5/26	5/27	5/28	5/29	5/30	5/31	6/1
Heatwave Forecast Status	None	None	None	None	None	None	None
Forecasted Max. Temp.	38-40	39-41	38-40	38-40	36-38	36-38	37-39
Actual Max. Temp.	34	36	38	38	34	39	38
Cash Transfer Issued	No	No	No	No	No	No	No
Week 3	6/2	6/3	6/4	6/5	6/6	**6/7**	6/8
Heatwave Forecast Status	None	None	None	None	None	Hot & Humid	Heatwave
Forecasted Max. Temp.	36-38	35-37	33-35	35-37	38-40	39-41	40-42
Actual Max. Temp.	36	33	33	36	38	39	43
Cash Transfer Issued	No	No	No	No	No	**Yes**	-
Week 4	6/9	**6/10**	6/11	6/12	**6/13**	6/14	6/15
Heatwave Forecast Status	Heatwave	Heatwave	Heatwave	Heatwave	Heatwave	Heatwave	None
Forecasted Max. Temp.	43-45	43-45	44-46	43-45	41-43	39-41	39-41
Actual Max. Temp.	43	44	44	43	40	42	35
Cash Transfer Issued	-	**Yes**	-	-	**Yes**	-	No
Week 5	6/16	6/17	6/18	6/19	6/20	6/21	6/22
Heatwave Forecast Status	None	None	None	None	None	None	None
Forecasted Max. Temp.	35-37	35-37	33-35	35-37	36-38	35-37	34-36
Actual Max. Temp.	34	35	34	35	34	37	35
Cash Transfer Issued	No	No	No	No	No	No	No
Week 6	6/23	6/24	6/25	6/26	6/27	6/28	6/29
Heatwave Forecast Status	None	None	None	None	None	None	None
Forecasted Max. Temp.	33-35	34-36	33-35	33-35	36-38	35-37	35-37
Actual Max. Temp.	36	35	34	37	38	36	32
Cash Transfer Issued	No	No	No	No	No	No	No
	6/30						
Heatwave Forecast Status	None						
Forecasted Max. Temp.	31-33						
Actual Max. Temp.	30						
Cash Transfer Issued	No						

Notes: We present daily information on heatwave forecast status, forecasted and actual maximum temperatures (in °C), and the implementation of cash transfers between May 19 and June 30, 2025. Heatwave status is determined based on predictions from the Daily Impact-Based Heatwave Warning Bulletin issued by the National Weather Forecasting Centre and the Daily Weather Report and Forecast Bulletin from the Regional Meteorological Centre, New Delhi. The categories "Hot & Humid" and "Heatwave" indicate days when an official warning was issued, both of which advise individuals to take precautionary action, while "None" denotes the absence of any warning. Forecasted maximum temperatures for Delhi are drawn from the Daily Weather Report and Forecast Bulletin issued on the preceding day, whereas actual maximum temperatures are obtained from Visual Crossing. The table also records the implementation of cash transfers to the treatment group in accordance with the experimental protocol. Specifically, we define every three consecutive days with a heatwave warning as a single "wave" of heatwave and issue the cash transfer on the first day of each new episode.

TABLE 2: Summary Statistics: Control vs. Treated Groups

Variable	(1) Control (139) Mean/SD	(2) Treated (137) Mean/SD	(3) Total (276) Mean/SD	t-test Difference (1)-(2)
Delhi	0.424	0.445	0.435	-0.021
	(0.496)	(0.499)	(0.497)	
Age	27.259	27.847	27.551	-0.588
	(5.490)	(6.190)	(5.845)	
Male	0.993	0.993	0.993	0.000
	(0.085)	(0.085)	(0.085)	
Married	0.568	0.664	0.616	-0.096
	(0.497)	(0.474)	(0.487)	
Education Level				
High school and below	0.022	0.029	0.025	-0.008
	(0.146)	(0.169)	(0.158)	
Undergraduate	0.791	0.847	0.819	-0.055
	(0.408)	(0.362)	(0.386)	
Graduate and above	0.187	0.124	0.156	0.063
	(0.391)	(0.331)	(0.363)	
Household Members				
Number of non-child dependents	2.583	2.686	2.634	-0.103
	(1.273)	(1.270)	(1.271)	
Number of dependents: Children	0.806	0.978	0.891	-0.172
	(1.021)	(1.018)	(1.021)	
Home Ownership				
Own house	0.158	0.168	0.163	-0.010
	(0.366)	(0.375)	(0.370)	
Rented House	0.842	0.825	0.833	0.017
	(0.366)	(0.382)	(0.373)	
Household Assets				
Has a bike	0.957	0.949	0.953	0.008
	(0.204)	(0.221)	(0.212)	
Has a cooler	0.331	0.285	0.308	0.046
	(0.472)	(0.453)	(0.462)	
Has a fridge	0.165	0.131	0.149	0.034
	(0.373)	(0.339)	(0.356)	
Has an A/C	0.014	0.007	0.011	0.007
	(0.120)	(0.085)	(0.104)	
Has a car	0.007	0.007	0.007	-0.000
	(0.085)	(0.085)	(0.085)	
Financial Situation				
Has a loan	0.388	0.401	0.395	-0.013
	(0.489)	(0.492)	(0.490)	
Amount of loan (₹)	2304.712	2236.752	2270.978	67.960
	(3692.600)	(3191.240)	(3446.745)	
Has a health insurance	0.173	0.146	0.159	0.027
	(0.379)	(0.354)	(0.367)	
Payment Structure				
Commission only	0.799	0.818	0.808	-0.019
	(0.403)	(0.388)	(0.395)	
Base salary + Commission	0.180	0.146	0.163	0.034
	(0.385)	(0.354)	(0.370)	

Table 2 continued from previous page

Variable	(1) Control (139) Mean/SD	(2) Treated (137) Mean/SD	(3) Total (276) Mean/SD	t-test Difference (1)-(2)
Fix salary	0.022	0.036	0.029	-0.015
	(0.146)	(0.188)	(0.168)	
Labor Supply				
Work days per week	6.309	6.394	6.351	-0.085
	(0.509)	(0.520)	(0.515)	
Work hours per day	10.302	10.328	10.315	-0.026
	(1.423)	(1.491)	(1.454)	
Deliveries per day	42.827	41.803	42.319	1.024
	(10.172)	(9.545)	(9.862)	
Joint test (all differences = 0)	$F(23, 252) = 0.84$		$p = 0.68$	

Notes: This table reports descriptive statistics and balance tests for baseline characteristics across treatment and control groups. Column (1) presents the overall mean and standard error (in parentheses) for the full sample of 276 participants. Columns (2) and (3) report means and standard errors separately for the control group (139 participants) and the treatment group (137 participants), respectively. Column (4) shows the mean differences between the treatment and control groups. Baseline characteristics include demographic information, educational attainment, household composition, housing ownership status, asset ownership, financial situation, and payment structure. Non-child dependents include parents, siblings, grandparents, and other adult dependents. There are no statistically significant differences between treatment and control groups across any of the baseline variables at the 10% level. The p-value for the joint test of equality across all baseline characteristics is 0.68.

TABLE 3: Impact on Labor Supply

VARIABLES	(1) Days per week	(2) Hours per day	(3) Deliveries per day	(4) Deliveries per hour
Heatwave ($\hat{\beta}_0$)	-0.817***	-1.234***	-9.158***	-0.562***
	(0.109)	(0.181)	(0.872)	(0.065)
Treat $\times$ Heatwave ($\hat{\beta}_1$)	0.533***	-0.493**	5.512***	0.841***
	(0.174)	(0.246)	(1.115)	(0.088)
PostHeat ($\hat{\beta}_2$)	-0.838***	-1.604***	-8.597***	-0.384***
	(0.124)	(0.224)	(1.129)	(0.077)
Treat $\times$ PostHeat ($\hat{\beta}_3$)	0.637***	0.066	6.323***	0.785***
	(0.172)	(0.271)	(1.329)	(0.099)
$\hat{\beta}_0 + \hat{\beta}_1$	-0.283**	-1.727***	-3.646***	0.279***
p-value	(0.038)	(0.000)	(0.000)	(0.000)
$\hat{\beta}_2 + \hat{\beta}_3$	-0.201*	-1.539***	-2.274***	0.401***
p-value	(0.092)	(0.000)	(0.001)	(0.000)
Individual FE	Yes	Yes	Yes	Yes
Control Mean	6.14	10.18	37.75	3.73
R^2	0.39	0.45	0.66	0.77
Observations	1,631	1,631	1,631	1,582

Notes: "Days per week" = Number of days worked in a week. "Hours per day" = Average number of hours worked per day in a week. "Deliveries per day" = Average number of pieces delivered per working day in a week. "Deliveries per hour" = A derived measure equal to deliveries per day divided by hours per day (i.e., the average number of pieces delivered per hour). "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. All regressions include individual fixed effects. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 4: Impact on Health Outcomes

VARIABLES	(1) Headache	(2) Stomachache	(3) Vomit	(4) Tiredness	(5) Any
Heatwave ($\hat{\beta}_0$)	0.173***	0.014	0.011	0.360***	0.284***
	(0.036)	(0.021)	(0.017)	(0.035)	(0.036)
Treat × Heatwave ($\hat{\beta}_1$)	-0.131***	-0.007	0.000	-0.355***	-0.242***
	(0.049)	(0.033)	(0.028)	(0.062)	(0.061)
PostHeat ($\hat{\beta}_2$)	0.147***	0.072**	0.018	0.169***	0.151***
	(0.037)	(0.028)	(0.019)	(0.040)	(0.040)
Treat × PostHeat ($\hat{\beta}_3$)	-0.144***	-0.042	-0.044*	-0.104	-0.086
	(0.047)	(0.040)	(0.026)	(0.064)	(0.060)
Holm-adjusted p-value ($\hat{\beta}_1$)	[0.022]	[1.000]	[1.000]	[0.000]	
$\hat{\beta}_0 + \hat{\beta}_1$	0.041	0.008	0.011	0.005	0.042
p-value	(0.210)	(0.768)	(0.624)	(0.929)	(0.397)
$\hat{\beta}_2 + \hat{\beta}_3$	0.004	0.030	-0.026	0.065	0.065
p-value	(0.899)	(0.294)	(0.161)	(0.188)	(0.143)
Individual FE	Yes	Yes	Yes	Yes	Yes
Control Mean	0.12	0.06	0.03	0.58	0.66
R^2	0.23	0.28	0.17	0.28	0.26
Observations	1,631	1,631	1,631	1,631	1,631

Notes: "Headache" = A binary indicator equal to one if an individual experienced a headache during the week, and zero otherwise. "Stomachache" = A binary indicator equal to one if an individual experienced a stomachache during the week, and zero otherwise. "Vomit" = A binary indicator equal to one if an individual experienced vomiting during the week, and zero otherwise. "Tiredness" = A binary indicator equal to one if an individual experienced tiredness during the week, and zero otherwise. "Any" = A binary indicator equal to one if an individual experienced any of the four symptoms during the week, and zero otherwise. "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. Holm-adjusted p-values for "Treat × Heatwave" are reported in square brackets for the first four columns to account for multiple hypothesis testing within this family of related outcomes. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. All regressions include individual fixed effects. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01.

TABLE 5: Impact on Adaptive Behaviors

VARIABLES	(1) Adjust Schedule	(2) Buy Extra Water	(3) Buy Ice	(4) Full-sleeve	(5) Take ORS	(6) Rest AC
Treat	0.138***	-0.454***	0.007	-0.701***	-0.014	0.146***
	(0.049)	(0.041)	(0.021)	(0.034)	(0.039)	(0.034)
Holm-adjusted p-value	[0.016]	[0.000]	[1.000]	[0.000]	[1.000]	[0.000]
Ind.-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.37	0.77	0.04	0.86	0.21	0.06
R^2	0.12	0.24	0.05	0.52	0.02	0.10
Observations	544	544	544	544	544	544

Notes: "Adjust schedule" = A binary indicator equal to one if an individual avoids afternoon work and shifts to early morning or late evening hours. "Buy Extra Water" = A binary indicator equal to one if an individual buys extra water. "Buy Ice" = A binary indicator equal to one if an individual buys ice. "Full-sleeve" = A binary indicator equal to one if an individual wears full-sleeve T-shirts. "Take ORS" = A binary indicator equal to one if an individual consumes glucose or oral rehydration salts. "Rest AC" = A binary indicator equal to one if an individual rests at rest points equipped with coolers or air conditioning. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. Holm-adjusted p-values for "Treat" are reported in square brackets to account for multiple hypothesis testing within this family of related outcomes. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the third and fourth weeks of the experiment. All regressions include individual-level baseline characteristics, including location, age, gender, marital status, educational attainment (measured using dummy variables), number of dependents, asset ownership (house, bike, cooler, refrigerator, air conditioner, and car), loan status and loan amount, health insurance coverage, and payment structure. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01.

TABLE 6: Classification Analysis (CLAN) on *Daily Productivity*: Baseline Characteristics of Workers With the Highest and Lowest Predicted Treatment Effects

	(1) 25% Most (G4) [95% CI]	(2) 25% Least (G1) [95% CI]	(3) Difference (G4-G1) [95% CI]
Delhi	0.118	0.765	-0.618***
	[0.008, 0.228]	[0.620, 0.909]	[-0.806, -0.435]
Age	28.319	29.044	-0.515
	[26.269, 30.338]	[27.051, 30.965]	[-3.371, 2.399]
Married	0.765	0.706	0.048
	[0.620, 0.909]	[0.550, 0.861]	[-0.171, 0.251]
Education Level			
High school and below	0.029	0.029	0.000
	[-0.009, 0.087]	[-0.009, 0.087]	[-0.054, 0.080]
Undergraduate	0.941	0.706	0.223**
	[0.861, 1.009]	[0.550, 0.861]	[0.050, 0.400]
Household Members			
Number of non-child dependents	2.706	2.500	0.235
	[2.247, 3.176]	[2.127, 2.854]	[-0.320, 0.814]
Number of dependents: Children	1.257	1.029	0.235
	[0.876, 1.626]	[0.693, 1.333]	[-0.263, 0.730]
Home Ownership			
Own house	0.059	0.176	-0.118
	[-0.009, 0.139]	[0.046, 0.307]	[-0.268, 0.033]
Household Assets			
Has a cooler	0.059	0.412	-0.338***
	[0.000, 0.139]	[0.244, 0.580]	[-0.517, -0.151]
Has a fridge	0.029	0.206	-0.176**
	[0.000, 0.087]	[0.068, 0.344]	[-0.326, -0.027]
Financial Situation			
Has a loan	0.254	0.412	-0.162
	[0.110, 0.393]	[0.244, 0.580]	[-0.377, 0.054]
Has a health insurance	0.176	0.265	-0.088
	[0.046, 0.307]	[0.114, 0.415]	[-0.299, 0.100]
Payment Structure			
Commission only	1.000	0.324	0.676***
	[1.000, 1.000]	[0.164, 0.483]	[0.517, 0.836]
Demand Flexibility			
Inflexible-demand	1.000	0.029	0.971***
	[1.000, 1.000]	[0.000, 0.087]	[0.91, 1.000]

Notes: The outcome variable is the change in the average number of pieces delivered per working day between the heatwave weeks (week 3-4) and the pre-heatwave weeks (weeks 1-2). This table reports the Classification Analysis (CLAN) estimates comparing baseline characteristics of workers in the top (G4) and bottom (G1) 25 percent of the predicted treatment-effect distribution. Estimates are obtained using the GenericML algorithm with 100 sample-splits. Columns (1) and (2) show predictions for the most-affected and least-affected subgroups, respectively. Column (3) reports the difference between these groups. 95% confidence intervals are shown in brackets. The characteristics shown correspond to the baseline covariates used in the GenericML estimation. "Inflexible-demand" = An indicator equal to one for workers engaged in food delivery, grocery delivery, or ride-hailing services, and zero for those working in courier or parcel delivery. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 7: Classification Analysis (CLAN) on *Schedule Adjustment*: Baseline Characteristics of Workers With the Highest and Lowest Predicted Treatment Effects

	(1) 25% Most (G4) [95% CI]	(2) 25% Least (G1) [95% CI]	(3) Difference (G4-G1) [95% CI]
Delhi	0.353	0.706	-0.354***
	[0.202, 0.502]	[0.550, 0.861]	[-0.572, -0.132]
Age	26.456	29.735	-3.108**
	[24.847, 27.896]	[27.636, 31.797]	[-5.709, -0.419]
Married	0.531	0.765	-0.206*
	[0.386, 0.700]	[0.620, 0.909]	[-0.433, 0.005]
Education Level			
High school and below	0.026	0.029	-0.001
	[-0.016, 0.074]	[-0.022, 0.087]	[-0.082, 0.065]
Undergraduate	0.866	0.735	0.147
	[0.766, 0.974]	[0.585, 0.886]	[-0.050, 0.336]
Household Members			
Number of non-child dependents	2.985	2.412	0.567**
	[2.570, 3.404]	[2.060, 2.753]	[0.013, 1.138]
Number of dependents: Children	0.696	1.147	-0.536**
	[0.395, 1.014]	[0.836, 1.479]	[-0.970, -0.089]
Home Ownership			
Own house	0.059	0.176	-0.118
	[-0.009, 0.139]	[0.046, 0.307]	[-0.268, 0.033]
Household Assets			
Has a cooler	0.206	0.412	-0.215**
	[0.068, 0.331]	[0.244, 0.580]	[-0.427, -0.008]
Has a fridge	0.000	0.235	-0.233***
	[0.000, 0.000]	[0.091, 0.380]	[-0.380, -0.070]
Financial Situation			
Has a loan	0.412	0.382	0.007
	[0.244, 0.567]	[0.217, 0.548]	[-0.212, 0.241]
Has a health insurance	0.059	0.353	-0.294***
	[-0.008, 0.139]	[0.190, 0.516]	[-0.476, -0.124]
Payment Structure			
Commission only	1.000	0.239	0.761***
	[1.000, 1.000]	[0.094, 0.387]	[0.613, 0.906]
Demand Flexibility			
Inflexible-demand	1.000	0.000	1.000***
	[1.000, 1.000]	[0.000, 0.000]	[1.000, 1.000]

Notes: The outcome variable is schedule adjustment, defined as a binary indicator equal to one if an individual avoids afternoon work and instead shifts to early-morning or late-evening hours. This table reports the Classification Analysis (CLAN) estimates comparing baseline characteristics of workers in the top (G4) and bottom (G1) 25 percent of the predicted treatment-effect distribution. Estimates are obtained using the GenericML algorithm with 100 sample-splits. Columns (1) and (2) show predictions for the most-affected and least-affected subgroups, respectively. Column (3) reports the difference between these groups. 95% confidence intervals are shown in brackets. The characteristics shown correspond to the baseline covariates used in the GenericML estimation. "Inflexible-demand" = An indicator equal to one for workers engaged in food delivery, grocery delivery, or ride-hailing services, and zero for those working in courier or parcel delivery. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 8: Impact on Demand for Insurance and Alternative Job Offers

	(1) Insurance Interest	(2) WTP for Insurance	(3) Max Cut per Delivery
Panel A. Main			
Treat	-0.025	22.385	0.017
	(0.062)	(29.030)	(0.011)
R^2	0.08	0.13	0.09
Panel B. By Flexibility			
Treat	0.094	91.063*	0.054**
	(0.110)	(48.727)	(0.022)
Treat × Inflexible Demand	-0.171	-99.836*	-0.054**
	(0.132)	(60.393)	(0.026)
R^2	0.08	0.14	0.11
Panel C. By Payment Structure			
Treat	0.206*	179.729***	0.097***
	(0.116)	(48.484)	(0.021)
Treat × Commission Only	-0.307**	-211.052***	-0.107***
	(0.137)	(59.021)	(0.025)
R^2	0.10	0.16	0.15
Ind.-level Controls	Yes	Yes	Yes
Control Mean	0.68	481.88	0.18
Observations	259	273	273

Notes: "Insurance Interest" = A binary indicator equal to one if an individual is interested in purchasing the heatwave-index insurance product, and zero otherwise. "WTP for Insurance" = The maximum premium amount (in ₹) an individual is willing to pay for a heatwave-index insurance product that pays ₹200 per episode of heatwave. "Max Cut per Delivery" = The maximum reduction in per-delivery commission an individual is willing to accept in exchange for receiving ₹200 per episode of heatwave. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the endline survey. All regressions include individual-level baseline characteristics, including location, age, gender, marital status, educational attainment (measured using dummy variables), number of dependents, asset ownership (house, bike, cooler, refrigerator, air conditioner, and car), loan status and loan amount, health insurance coverage, and payment structure. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

ONLINE APPENDIX

Liquidity Constraints and Real-Time Adaptation to Extreme Heat: Evidence from Gig Workers

Yutong Chen Md Amzad Hossain Sheetal Sekhri

A Survey Module on Insurance and Job Contract

In this section, we describe the design of a module in the endline survey that assesses participants' valuations of two financial protection products against heatwaves. We first present the script used in the survey and then discuss how the price points are selected.

A.1 Script

We would like to ask you a few questions about a potential new insurance product that might be offered in the future. These questions are for research purposes only—you are not being asked to purchase anything at the moment. Your responses can help design a good insurance product that a well-established and reputable insurance company could offer.

How it works:

Under this program, you would pay a one-time fixed amount before March. Then, during the hot season (March–July), you would automatically receive ₹200 each time an episode of heatwave occurs, based on official alerts issued by the India Meteorological Department (IMD). You would receive this payout as long as you are working as a delivery worker during that time, even if you do not work on the specific heatwave days.

What counts as an episode of heatwave?

- According to the IMD, a heatwave is declared when the daily maximum temperature is 4.5°C or more above normal, depending on local norms and humidity.
- For the purpose of this product, an episode of heatwave is defined as at least two consecutive days of IMD-issued heatwave alerts.
- Every 3 consecutive days with alerts is considered one episode (e.g., 1-4 days = 1 episode, 5 -7 days = 2 episodes, 8-10 days = 3 episodes).

Example

If the IMD issues heatwave alerts from May 11 to May 15, this would count as two episodes:

- Episode 1 = May 11–13
- Episode 2 = May 14–15

If you are working as a delivery worker during that time and purchase the insurance product, you would receive ₹200 for each episode, for a total of ₹400.

Now we want to ask:

1. Suppose this insurance would cost ₹1,100 for the entire March–July season. If it were offered in the future, would you be willing to pay this amount?

   A. Yes $->$ [Skip to Question 8]

   B. No $->$ [Continue to Question 2]

2. Suppose this insurance would cost ₹1,000 for the entire March–July season. If it were offered in the future, would you be willing to pay this amount?

   A. Yes $->$ [Skip to Question 8]

   B. No $->$ [Continue to Question 3]

3. Suppose this insurance would cost ₹900 for the entire March–July season. If it were offered in the future, would you be willing to pay this amount?

   A. Yes $->$ [Skip to Question 8]

   B. No $->$ [Continue to Question 4]

4. Suppose this insurance would cost ₹800 for the entire March–July season. If it were offered in the future, would you be willing to pay this amount?

   A. Yes $->$ [Skip to Question 8]

   B. No $->$ [Continue to Question 5]

5. Suppose this insurance would cost ₹600 for the entire March–July season. If it were offered in the future, would you be willing to pay this amount?

   A. Yes $->$ [Skip to Question 8]

   B. No $->$ [Continue to Question 6]

6. Suppose this insurance would cost ₹400 for the entire March–July season. If it were offered in the future, would you be willing to pay this amount?

   A. Yes $->$ [Skip to Question 8]

   B. No $->$ [Continue to Question 7]

7. Suppose this insurance would cost ₹300 for the entire March–July season. If it were offered in the future, would you be willing to pay this amount?

   A. Yes

   B. No

Now we want to ask about a hypothetical job offer that includes a built-in heatwave benefit.

Suppose you are offered a new work contract where you automatically receive ₹200 each time there is an episode of heatwave between March and July. The ₹200 payment is guaranteed based on official heatwave alerts. You are eligible for this payout as long as you are working as a delivery worker during this period, even if you do not work on the specific heatwave days. However, to fund this benefit, your per-delivery payment will be slightly reduced from March to July.

8. If the per-delivery payment is reduced by ₹0.4, would you accept this job offer with the heatwave benefit?

   A. Yes $->$ [End]

   B. No $->$ [Continue to Question 9]

9. If the per-delivery payment is reduced by ₹0.3, would you accept this job offer with the heatwave benefit?

   A. Yes $->$ [End]

   B. No $->$ [Continue to Question 10]

10. If the per-delivery payment is reduced by ₹0.2, would you accept this job offer with the heatwave benefit?

    A. Yes $->$ [End]

    B. No $->$ [Continue to Question 11]

11. If the per-delivery payment is reduced by ₹0.1, would you accept this job offer with the heatwave benefit?

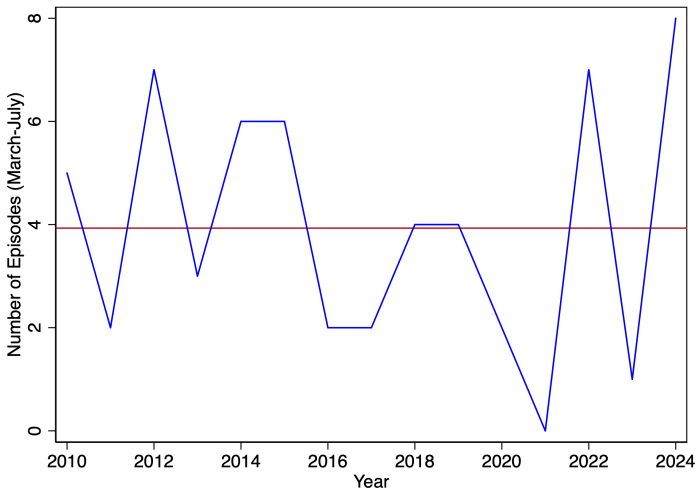
    A. Yes

    B. No

A.2 Price Design

To determine appropriate price points for the insurance product shown in Appendix A.1, we use historical daily maximum temperature data for Delhi from March to July between 2010 and 2024. As we do not have access to official historical IMD heatwave alert data, we approximate the number of heatwave episodes by defining a heatwave event as two or more consecutive days with maximum temperatures exceeding 43°C. This threshold-based method allows us to estimate the number of heatwave episodes for illustrative purposes. Between 2010 and 2024, Delhi experienced an average of 3.9 heatwave episodes during the March–July period. Figure A1 shows the annual number of heatwave episodes in Delhi during this period. The expected payout under the insurance product is approximately ₹780 per worker. Accordingly, we select a range of fixed premium amounts—from ₹300 to ₹1,100—to elicit demand curves.

FIGURE A1: Annual Number of Heatwave Episodes in Delhi, March-July (2010-2024)



Notes: This figure shows the number of heatwave episodes per year in Delhi between March and July, based on historical daily maximum temperature data from 2010 to 2024. A heatwave episode is defined as two or more consecutive days with maximum temperatures exceeding 43°C. If the duration of consecutive heatwave days is longer, we count a new episode every three days (e.g., 5–7 consecutive days = 2 episodes). The red horizontal line represents the average (3.9 episodes per year) over this 15-year period. Historical temperature data for Delhi are obtained from Visual Crossing and are accessible via this website

For the alternative job contract, we calculate how much the average per-delivery commission would need to be reduced to fund the equivalent heatwave payout of ₹200 per

episode. In our baseline survey, the average commission per piece delivered is ₹22, the average number of pieces delivered per day is 42, and the average number of workdays per week is 6.4. This amounts to 5,376 deliveries per worker from March to July (calculated as 42 pieces $\times$ 6.4 workdays $\times$ 4 weeks $\times$ 5 months). To fund an expected total payout of ₹780 during this period, the per-delivery commission would need to be reduced by at least ₹0.15 (calculated as ₹780 $\div$ 5376 deliveries). To examine participants' willingness to accept this trade-off, we presented them with hypothetical job offers involving small absolute reductions in per-delivery commission—₹0.4, ₹0.3, ₹0.2, and ₹0.1—in exchange for receiving ₹200 per heatwave episode. These reductions correspond to average total earnings losses of ₹2,150, ₹1,613, ₹1,075, and ₹538, respectively, over the five-month period.

B Inverse Demand for Heatwave-Indexed Financial Products

This section presents inverse demand curves for the two financial products considered in the valuation exercise: a heatwave-indexed insurance product with a one-time premium, and an alternative job contract that embeds heatwave protection through a per-delivery commission reduction. The figures summarize stated demand across price points and illustrate how willingness to pay varies with the timing and structure of financial protection. By comparing demand for ex ante insurance with demand for protection embedded in ongoing compensation, this section provides descriptive evidence on workers' valuation of heatwave risk coverage and complements the heterogeneity and interpretation results discussed in the main text.

B.1 Heatwave-Indexed Insurance Product

Figure 3a presents the inverse demand curve for the heatwave-indexed insurance product. The figure plots the share of respondents willing to purchase the product at each of seven one-time premium levels: ₹300, ₹400, ₹600, ₹800, ₹900, ₹1,000, and ₹1,100. Willingness to pay is high at low premiums: 95% of respondents report willingness to pay at least ₹300. However, stated demand declines sharply as the premium increases. Overall willingness to pay is low relative to the expected payout of the product. The median willingness to pay is ₹400, which corresponds to approximately 51% of the expected payout of ₹780 over the March–July heat season. This expected payout is based on an average of 3.9 officially declared heatwave episodes per year between 2010 and 2024, with a payment of ₹200 per episode.[28]

Figure 3b summarizes the corresponding changes in demand across premium levels: demand is relatively flat at lower premiums but declines rapidly once the premium exceeds ₹800, indicating limited willingness to pay for insurance coverage at prices that would fully cover expected payouts.

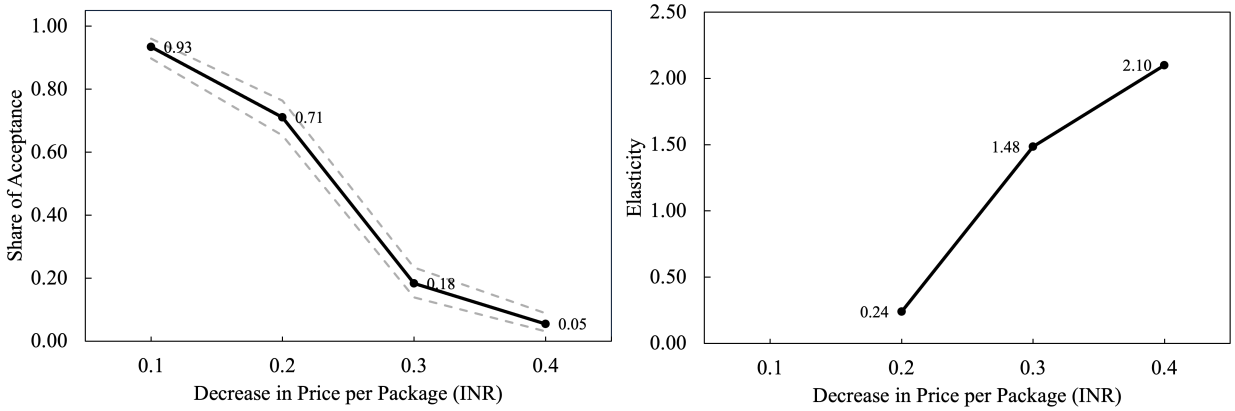
B.2 Alternative Job Contract with Embedded Protection

Figure B1 presents the inverse demand curve for an alternative job contract that provides ₹200 per heatwave episode in exchange for a reduction in the per-delivery commission during the March–July period. Figure B1a plots the share of respondents willing to accept

[28] See Appendix A.2 for details on the pricing and payout design.

the contract at four commission reduction levels—₹0.10, ₹0.20, ₹0.30, and ₹0.40 per delivery. Acceptance rates decline steeply as the commission reduction increases: while 93% of respondents are willing to accept a reduction of ₹0.10 per delivery, acceptance falls to 71% at ₹0.20 and to 18% at ₹0.30. Consistent with this pattern, Figure B1b shows that demand is relatively insensitive at the lowest reduction levels but becomes sharply responsive as the implied income loss increases.

FIGURE B1: Demand and Price Elasticity of Alternative Job Offer



(a) Inverse Demand Curve (b) Price Elasticity of Demand

Notes: Figure B1a displays the inverse demand curve for the alternative job offer, which involves reducing per-package commissions between March and July in exchange for a ₹200 payment per heatwave episode. The figure plots the cumulative share of respondents willing to accept the offer at four reduction levels: ₹0.10, ₹0.20, ₹0.30, and ₹0.40. Dashed gray lines indicate 95% confidence intervals. Figure B1b presents the corresponding price elasticity of demand, calculated between adjacent price points. Both panels are based on 273 observations.

B.3 Comparison Across Financial Products

Overall, the figures indicate that demand for both financial products is relatively inelastic at low price points but declines sharply beyond modest premiums or commission reductions. While 76% of respondents are willing to pay a one-time premium of ₹400 for the insurance product, this amount is insufficient to cover the expected payout of ₹780 over the heat season. By contrast, a ₹0.20 reduction in per-delivery commission—corresponding to an average income loss of approximately ₹1,075 over the same period—achieves a 71% acceptance rate and would generate sufficient revenue to finance the expected payout. Taken together, these patterns underscore the limited demand for ex ante heatwave protection at prices that fully internalize expected costs, and illustrate how alternative contract structures differ in perceived affordability and acceptance, even when they offer equivalent expected benefits.

C Heterogeneity

C.1 Pre-Specified Heterogeneity Analyses

This section reports heterogeneity analyses that were pre-specified in our AEA RCT registry prior to data collection. These analyses examine variation in treatment effects by industry type (time-sensitive versus flexible-demand sectors), payment structure (base or mixed pay versus commission-only), and city (Delhi, a water-stressed area, versus Gurgaon, which is less water-stressed). Because these dimensions are highly correlated with one another and with other baseline characteristics, we present these results as consistency checks rather than as the primary heterogeneity analysis.

Accordingly, the main text relies on a machine-learning-based framework to characterize treatment effect heterogeneity across correlated baseline features in a more systematic and informative manner. The pre-specified subgroup results reported here closely align with the ML-based findings and reinforce the interpretation that liquidity provision is most effective for workers facing high short-run income risk and rigid labor demand.

C.2 By Payment Structure

TABLE C1: Impact on Labor Supply by Payment Structure

	(1) Days per week	(2) Hours per day	(3) Deliveries per day	(4) Deliveries per hour
Heatwave	-0.893***	-0.536	0.571	0.263**
	(0.216)	(0.356)	(1.967)	(0.120)
Heatwave × Commission Only	0.096	-0.874**	-12.184***	-1.037***
	(0.249)	(0.411)	(2.133)	(0.134)
Treat × Heatwave	1.018***	-0.360	-1.488	0.026
	(0.339)	(0.525)	(2.512)	(0.155)
Treat × Heatwave × Commission Only	-0.594	-0.140	8.851***	1.024***
	(0.393)	(0.592)	(2.752)	(0.180)
PostHeat	-0.357**	0.143	5.786***	0.570***
	(0.141)	(0.273)	(1.924)	(0.115)
PostHeat × Commission Only	-0.602***	-2.188***	-18.011***	-1.204***
	(0.205)	(0.374)	(2.208)	(0.138)
Treat × PostHeat	0.461*	-0.893**	-6.015**	-0.257
	(0.250)	(0.431)	(2.590)	(0.186)
Treat × PostHeat × Commission Only	0.230	1.225**	15.514***	1.311***
	(0.322)	(0.528)	(2.909)	(0.212)
Individual FE	Yes	Yes	Yes	Yes
Control Mean	6.14	10.18	37.75	3.73
R^2	0.39	0.47	0.69	0.79
Observations	1,631	1,631	1,631	1,582

Notes: "Days per week" = Number of days worked in a week. "Hours per day" = Average number of hours worked per day in a week. "Deliveries per day" = Average number of pieces delivered per working day in a week. "Deliveries per hour" = A derived measure equal to deliveries per day divided by hours per day (i.e., the average number of pieces delivered per hour). "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Commission Only" = A binary indicator equal to one if an individual receives only commission, and zero if the individual receives either a fixed salary or a base salary plus commission. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. All regressions include individual fixed effects. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C2: Impact on Health Outcomes by Payment Structure

VARIABLES	(1) Headache	(2) Stomachache	(3) Vomit	(4) Tiredness	(5) Any
Heatwave	0.161*	-0.036	-0.036	0.446***	0.321***
	(0.084)	(0.043)	(0.043)	(0.078)	(0.073)
Heatwave × Commission Only	0.015	0.063	0.058	-0.109	-0.047
	(0.093)	(0.050)	(0.047)	(0.087)	(0.083)
Treat × Heatwave	-0.140	-0.006	-0.006	-0.446***	-0.426***
	(0.121)	(0.060)	(0.067)	(0.138)	(0.139)
Treat × Heatwave × Commission Only	0.010	-0.003	0.006	0.114	0.225
	(0.132)	(0.071)	(0.073)	(0.155)	(0.155)
PostHeat	0.071	0.071	-0.018	0.321***	0.250***
	(0.083)	(0.075)	(0.047)	(0.099)	(0.093)
PostHeat × Commission Only	0.095	0.001	0.045	-0.191*	-0.124
	(0.092)	(0.080)	(0.051)	(0.108)	(0.103)
Treat × PostHeat	-0.071	-0.030	-0.024	-0.217	-0.188
	(0.106)	(0.104)	(0.069)	(0.162)	(0.133)
Treat × PostHeat × Commission Only	-0.091	-0.015	-0.026	0.143	0.127
	(0.119)	(0.112)	(0.075)	(0.176)	(0.149)
Individual FE	Yes	Yes	Yes	Yes	Yes
Control Mean	0.12	0.06	0.03	0.58	0.66
R^2	0.23	0.28	0.17	0.28	0.26
Observations	1,631	1,631	1,631	1,631	1,631

Notes: "Headache" = A binary indicator equal to one if an individual experienced a headache during the week, and zero otherwise. "Stomachache" = A binary indicator equal to one if an individual experienced a stomachache during the week, and zero otherwise. "Vomit" = A binary indicator equal to one if an individual experienced vomiting during the week, and zero otherwise. "Tiredness" = A binary indicator equal to one if an individual experienced tiredness during the week, and zero otherwise. "Any" = A binary indicator equal to one if an individual experienced any of the four symptoms during the week, and zero otherwise. "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Commission Only" = A binary indicator equal to one if an individual receives only commission, and zero if the individual receives either a fixed salary or a base salary plus commission. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. All regressions include individual fixed effects. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C3: Impact on Adaptive Behaviors by Payment Structure

VARIABLES	(1) Adjust Schedule	(2) Buy Extra Water	(3) Buy Ice	(4) Full-sleeve	(5) Take ORS	(6) Rest AC
Treat	-0.370***	-0.428***	0.030	-0.839***	-0.112	0.100
	(0.099)	(0.098)	(0.048)	(0.065)	(0.082)	(0.078)
Treat × Commission Only	0.620***	-0.031	-0.029	0.168**	0.119	0.056
	(0.110)	(0.108)	(0.052)	(0.076)	(0.093)	(0.084)
Individual-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.37	0.77	0.04	0.86	0.21	0.06
R^2	0.17	0.24	0.05	0.53	0.03	0.10
Observations	544	544	544	544	544	544

Notes: "Adjust schedule" = A binary indicator equal to one if an individual avoids afternoon work and shifts to early morning or late evening hours. "Buy Extra Water" = A binary indicator equal to one if an individual buys extra water. "Buy Ice" = A binary indicator equal to one if an individual buys ice. "Full-sleeve" = A binary indicator equal to one if an individual wears full-sleeve T-shirts. "Take ORS" = A binary indicator equal to one if an individual consumes glucose or oral rehydration salts. "Rest AC" = A binary indicator equal to one if an individual rests at rest points equipped with coolers or air conditioning. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "Commission Only" = A binary indicator equal to one if an individual receives only commission, and zero if the individual receives either a fixed salary or a base salary plus commission. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the third and fourth weeks of the experiment. All regressions include individual-level baseline characteristics, including location, age, gender, marital status, educational attainment (measured using dummy variables), number of dependents, asset ownership (house, bike, cooler, refrigerator, air conditioner, and car), loan status and loan amount, health insurance coverage, and payment structure. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.3 By Demand Flexibility

TABLE C4: Impact on Labor Supply by Demand Flexibility

	(1) Days per week	(2) Hours per day	(3) Deliveries per day	(4) Deliveries per hour
Heatwave	-0.667***	-0.512**	-0.143	0.170*
	(0.153)	(0.254)	(1.448)	(0.102)
Heatwave × Inflexible Demand	-0.215	-1.034***	-12.919***	-1.059***
	(0.208)	(0.342)	(1.657)	(0.115)
Treat × Heatwave	0.627**	-0.674*	-2.045	0.058
	(0.252)	(0.392)	(1.889)	(0.130)
Treat × Heatwave × Inflexible Demand	-0.132	0.263	10.838***	1.131***
	(0.337)	(0.494)	(2.218)	(0.161)
PostHeat	-0.417***	-0.381	2.357	0.394***
	(0.134)	(0.258)	(1.696)	(0.120)
PostHeat × Inflexible Demand	-0.604***	-1.753***	-15.697***	-1.129***
	(0.212)	(0.384)	(2.046)	(0.140)
Treat × PostHeat	0.489**	-0.605*	-3.670*	-0.125
	(0.201)	(0.352)	(2.085)	(0.158)
Treat × PostHeat × Inflexible Demand	0.214	0.965*	14.327***	1.319***
	(0.303)	(0.491)	(2.527)	(0.190)
Individual FE	Yes	Yes	Yes	Yes
Control Mean	6.14	10.18	37.75	3.73
R^2	0.39	0.47	0.70	0.79
Observations	1,631	1,631	1,631	1,582

Notes: "Days per week" = Number of days worked in a week. "Hours per day" = Average number of hours worked per day in a week. "Deliveries per day" = Average number of pieces delivered per working day in a week. "Deliveries per hour" = A derived measure equal to deliveries per day divided by hours per day (i.e., the average number of pieces delivered per hour). "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Inflexible Demand" = A binary indicator equal to one if an individual works in food delivery, grocery delivery, or ride-hailing, and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. All regressions include individual fixed effects. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C5: Impact on Health Outcomes by Demand Flexibility

VARIABLES	(1) Headache	(2) Stomachache	(3) Vomit	(4) Tiredness	(5) Any
Heatwave	0.214***	-0.024	-0.024	0.452***	0.357***
	(0.061)	(0.034)	(0.029)	(0.061)	(0.059)
Heatwave × Inflexible Demand	-0.060	0.055	0.050	-0.133*	-0.105
	(0.075)	(0.043)	(0.035)	(0.074)	(0.074)
Treat × Heatwave	-0.177**	-0.001	-0.027	-0.425***	-0.405***
	(0.084)	(0.055)	(0.045)	(0.107)	(0.110)
Treat × Heatwave × Inflexible Demand	0.065	-0.008	0.038	0.100	0.233*
	(0.103)	(0.069)	(0.057)	(0.131)	(0.132)
PostHeat	0.131*	0.083	0.012	0.345***	0.298***
	(0.074)	(0.056)	(0.036)	(0.075)	(0.070)
PostHeat × Inflexible Demand	0.024	-0.016	0.009	-0.252***	-0.210**
	(0.085)	(0.064)	(0.042)	(0.088)	(0.084)
Treat × PostHeat	-0.131	-0.071	-0.050	-0.343***	-0.346***
	(0.088)	(0.076)	(0.052)	(0.123)	(0.110)
Treat × PostHeat × Inflexible Demand	-0.018	0.042	0.008	0.341**	0.371***
	(0.104)	(0.090)	(0.060)	(0.143)	(0.130)
Individual FE	Yes	Yes	Yes	Yes	Yes
Control Mean	0.12	0.06	0.03	0.58	0.66
R^2	0.23	0.28	0.17	0.29	0.26
Observations	1,631	1,631	1,631	1,631	1,631

Notes: "Headache" = A binary indicator equal to one if an individual experienced a headache during the week, and zero otherwise. "Stomachache" = A binary indicator equal to one if an individual experienced a stomachache during the week, and zero otherwise. "Vomit" = A binary indicator equal to one if an individual experienced vomiting during the week, and zero otherwise. "Tiredness" = A binary indicator equal to one if an individual experienced tiredness during the week, and zero otherwise. "Any" = A binary indicator equal to one if an individual experienced any of the four symptoms during the week, and zero otherwise. "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Inflexible Demand" = A binary indicator equal to one if an individual works in food delivery, grocery delivery, or ride-hailing, and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. All regressions include individual fixed effects. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C6: Impact on Adaptive Behaviors by Demand Flexibility

VARIABLES	(1) Adjust Schedule	(2) Buy Extra Water	(3) Buy Ice	(4) Full-sleeve	(5) Take ORS	(6) Rest AC
Treat	-0.244***	-0.489***	0.028	-0.795***	-0.054	0.191***
	(0.087)	(0.073)	(0.035)	(0.056)	(0.062)	(0.065)
Treat × Inflexible Demand	0.536***	0.048	-0.030	0.132*	0.061	-0.068
	(0.100)	(0.088)	(0.042)	(0.072)	(0.079)	(0.074)
Individual-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.37	0.77	0.04	0.86	0.21	0.06
R^2	0.20	0.24	0.05	0.53	0.04	0.11
Observations	544	544	544	544	544	544

Notes: "Adjust schedule" = A binary indicator equal to one if an individual avoids afternoon work and shifts to early morning or late evening hours. "Buy Extra Water" = A binary indicator equal to one if an individual buys extra water. "Buy Ice" = A binary indicator equal to one if an individual buys ice. "Full-sleeve" = A binary indicator equal to one if an individual wears full-sleeve T-shirts. "Take ORS" = A binary indicator equal to one if an individual consumes glucose or oral rehydration salts. "Rest AC" = A binary indicator equal to one if an individual rests at rest points equipped with coolers or air conditioning. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "Inflexible Demand" = A binary indicator equal to one if an individual works in food delivery, grocery delivery, or ride-hailing, and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the third and fourth weeks of the experiment. All regressions include individual-level baseline characteristics, including location, age, gender, marital status, educational attainment (measured using dummy variables), number of dependents, asset ownership (house, bike, cooler, refrigerator, air conditioner, and car), loan status and loan amount, health insurance coverage, and payment structure. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.4 By City

TABLE C7: Impact on Labor Supply by City

	(1) Days per week	(2) Hours per day	(3) Deliveries per day	(4) Deliveries per hour
Heatwave	-0.938***	-1.369***	-11.506***	-0.767***
	(0.157)	(0.252)	(1.037)	(0.077)
Heatwave × Delhi	0.285	0.318	5.532***	0.476***
	(0.211)	(0.358)	(1.740)	(0.125)
Treat × Heatwave	0.712***	-0.472	7.016***	1.009***
	(0.250)	(0.352)	(1.461)	(0.107)
Treat × Heatwave × Delhi	-0.415	-0.062	-3.635	-0.393**
	(0.341)	(0.484)	(2.202)	(0.175)
PostHeat	-0.956***	-1.913***	-11.256***	-0.561***
	(0.180)	(0.319)	(1.437)	(0.095)
PostHeat × Delhi	0.278	0.726*	6.265***	0.408***
	(0.240)	(0.434)	(2.231)	(0.153)
Treat × PostHeat	0.724***	0.309	8.388***	0.932***
	(0.244)	(0.383)	(1.779)	(0.129)
Treat × PostHeat × Delhi	-0.207	-0.580	-4.930*	-0.343*
	(0.337)	(0.532)	(2.615)	(0.197)
Individual FE	Yes	Yes	Yes	Yes
Control Mean	6.14	10.18	37.75	3.73
R^2	0.39	0.46	0.67	0.77
Observations	1,631	1,631	1,631	1,582

Notes: "Days per week" = Number of days worked in a week. "Hours per day" = Average number of hours worked per day in a week. "Deliveries per day" = Average number of pieces delivered per working day in a week. "Deliveries per hour" = A derived measure equal to deliveries per day divided by hours per day (i.e., the average number of pieces delivered per hour). "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Delhi" = A binary indicator equal to one if an individual works in Delhi, and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. All regressions include individual fixed effects. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C8: Impact on Health Outcomes by City

VARIABLES	(1) Headache	(2) Stomachache	(3) Vomit	(4) Tiredness	(5) Any
Heatwave	0.181***	-0.006	0.006	0.363***	0.275***
	(0.045)	(0.029)	(0.023)	(0.048)	(0.049)
Heatwave × Delhi	-0.020	0.049	0.011	-0.007	0.022
	(0.073)	(0.042)	(0.033)	(0.071)	(0.071)
Treat × Heatwave	-0.100	-0.000	0.007	-0.408***	-0.246***
	(0.062)	(0.044)	(0.035)	(0.081)	(0.082)
Treat × Heatwave × Delhi	-0.070	-0.017	-0.016	0.120	0.009
	(0.099)	(0.067)	(0.058)	(0.126)	(0.123)
PostHeat	0.156***	0.050	0.019	0.169***	0.131**
	(0.047)	(0.038)	(0.027)	(0.053)	(0.053)
PostHeat × Delhi	-0.021	0.052	-0.002	0.001	0.047
	(0.075)	(0.055)	(0.036)	(0.082)	(0.081)
Treat × PostHeat	-0.156**	-0.016	-0.032	-0.127	-0.049
	(0.062)	(0.054)	(0.035)	(0.084)	(0.080)
Treat × PostHeat × Delhi	0.029	-0.060	-0.027	0.051	-0.087
	(0.096)	(0.080)	(0.053)	(0.129)	(0.120)
Individual FE	Yes	Yes	Yes	Yes	Yes
Control Mean	0.12	0.06	0.03	0.58	0.66
R^2	0.24	0.28	0.17	0.28	0.26
Observations	1,631	1,631	1,631	1,631	1,631

Notes: "Headache" = A binary indicator equal to one if an individual experienced a headache during the week, and zero otherwise. "Stomachache" = A binary indicator equal to one if an individual experienced a stomachache during the week, and zero otherwise. "Vomit" = A binary indicator equal to one if an individual experienced vomiting during the week, and zero otherwise. "Tiredness" = A binary indicator equal to one if an individual experienced tiredness during the week, and zero otherwise. "Any" = A binary indicator equal to one if an individual experienced any of the four symptoms during the week, and zero otherwise. "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Delhi" = A binary indicator equal to one if an individual works in Delhi, and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. All regressions include individual fixed effects. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE C9: Impact on Adaptive Behaviors by City

VARIABLES	(1) Adjust Schedule	(2) Buy Extra Water	(3) Buy Ice	(4) Full-sleeve	(5) Take ORS	(6) Rest AC
Treat	0.194***	-0.362***	-0.001	-0.639***	0.005	0.161***
	(0.065)	(0.058)	(0.021)	(0.047)	(0.055)	(0.045)
Treat × Delhi	-0.127	-0.210**	0.017	-0.143**	-0.042	-0.035
	(0.096)	(0.082)	(0.038)	(0.067)	(0.075)	(0.067)
Individual-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.37	0.77	0.04	0.86	0.21	0.06
R^2	0.12	0.25	0.05	0.53	0.02	0.10
Observations	544	544	544	544	544	544

Notes: "Adjust schedule" = A binary indicator equal to one if an individual avoids afternoon work and shifts to early morning or late evening hours. "Buy Extra Water" = A binary indicator equal to one if an individual buys extra water. "Buy Ice" = A binary indicator equal to one if an individual buys ice. "Full-sleeve" = A binary indicator equal to one if an individual wears full-sleeve T-shirts. "Take ORS" = A binary indicator equal to one if an individual consumes glucose or oral rehydration salts. "Rest AC" = A binary indicator equal to one if an individual rests at rest points equipped with coolers or air conditioning. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "Delhi" = A binary indicator equal to one if an individual works in Delhi, and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the third and fourth weeks of the experiment. All regressions include individual-level baseline characteristics, including location, age, gender, marital status, educational attainment (measured using dummy variables), number of dependents, asset ownership (house, bike, cooler, refrigerator, air conditioner, and car), loan status and loan amount, health insurance coverage, and payment structure. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.5 Additional Details on GenericML Exercise

This appendix provides additional details on outcome construction, training features, estimation, and supporting heterogeneity results for the machine-learning analysis in Section 6.

Detailed Outcome Construction and Training Features We examine heterogeneity along two key outcomes: labor productivity and schedule adjustment. For labor productivity, we construct an individual-level change-in-output measure by comparing each worker's average number of pieces delivered per working day during heatwave weeks (weeks 3-4) to that in pre-heatwave weeks (weeks 1-2). For adaptive behavior, we compute each worker's average schedule-adjustment indicator during weeks 3-4. Schedule adjustment is defined as a binary indicator equal to one if the worker avoids afternoon work and instead shifts activity to early-morning or late-evening hours in a given week; the resulting variable therefore takes values of 0, 0.5, or 1.

The machine-learning models are trained using a rich set of pre-treatment characteristics, which serve solely as *training features*. These include demographics (age, marital status, and an indicator for Delhi), education, household composition, housing ownership, ownership of cooling assets (cooler and refrigerator), loan and insurance indicators, compensation structure (commission-only), and indicators for operating in food delivery, grocery delivery, or ride-hailing. Variables with little variation in the sample, such as vehicle ownership and air conditioning, are excluded (see Table 2). Importantly, these features are used to *predict* heterogeneity and are not interpreted as causal determinants of treatment effects.

Detailed Method We estimate heterogeneous treatment effects using the Generic Machine Learning (GenericML) framework of Chernozhukov et al. (2025). The procedure repeatedly splits the sample into training and estimation subsamples, and we apply six machine-learning learners—lasso, ridge regression, elastic net, random forest, single regression tree, and gradient boosting—to predict untreated potential outcomes and individualized treatment effects. Heterogeneity is summarized using three complementary objects: the Best Linear Predictor (BLP), Group Average Treatment Effects (GATES), and Classification Analysis (CLAN). For each object, GenericML evaluates all learners and selects the best-performing model based on out-of-sample predictive accuracy. In our application, the elastic-net learner is selected for the BLP, while ridge regression is selected for GATES and CLAN in the productivity analysis, and elastic net is selected for all three objects when the outcome is schedule adjustment.

To mitigate concerns about overfitting, the GenericML procedure relies on repeated sample splitting and cross-fitting: predictions of untreated outcomes and heterogeneous treatment effects are generated using models trained on disjoint subsamples from those used for estimation. Learners are selected based on out-of-sample predictive accuracy, and all reported treatment effect estimates use cross-fitted scores. As a result, the heterogeneity patterns documented below reflect stable, out-of-sample variation rather than in-sample fitting.

Evidence of Heterogeneity: BLP We begin by summarizing heterogeneity using the BLP, which relates treatment effects to the ML-predicted heterogeneity score. Specifically, we estimate

$$y_i = \alpha X_i + \beta_1 \text{Treat}_i + \beta_2 \text{Treat}_i \times S(Z_i) + \varepsilon_i, \tag{3}$$

where X_i denotes control variables, Treat_i is the treatment indicator, and $S(Z_i)$ is the ML heterogeneity score. The coefficient β_1 recovers the average treatment effect, while β_2 captures how treatment effects vary with the score.

As reported in Table C10, the average treatment effect estimates (β_1) for productivity are stable across learners and closely match the corresponding OLS estimates reported in Section 5. Turning to heterogeneity, the interaction coefficient β_2 is positive and statistically significant for both outcomes. These results provide strong evidence of economically meaningful heterogeneity in both productivity and adaptive behavior. Importantly, this heterogeneity is present despite stable average treatment effects across learners.

TABLE C10: Best Linear Predictor (BLP) Estimates Across Machine-Learning Learners

Learner	(1) ATE (β_1)	(2) 95% CI	(3) HET (β_2)	(4) 95% CI
Panel A. Outcome Variable = Changes in the average number of pieces delivered per working day				
LASSO	5.670	[2.764, 8.435]	0.882	[0.334, 1.455]
Ridge Regression	5.750	[2.841, 8.585]	0.909	[0.336, 1.492]
Elastic Net	5.648	[2.872, 8.435]	0.973	[0.349, 1.500]
Random Forest	5.650	[2.733, 8.518]	0.636	[0.035, 1.214]
Single Regression Tree	5.713	[2.857, 8.672]	0.524	[0.091, 0.950]
XGBoost	5.537	[2.470, 8.617]	0.211	[-0.088, 0.494]
Panel B. Outcome Variable = Adjust Schedule				
LASSO	0.117	[-0.007, 0.241]	0.993	[0.470, 1.517]
Ridge Regression	0.117	[-0.007, 0.247]	0.958	[0.443, 1.461]
Elastic Net	0.116	[-0.008, 0.240]	1.030	[0.499, 1.599]
Random Forest	0.115	[-0.011, 0.244]	0.788	[0.319, 1.268]
Single Regression Tree	0.117	[-0.011, 0.241]	0.577	[0.172, 0.956]
XGBoost	0.111	[-0.017, 0.241]	0.273	[0.001, 0.543]

Notes: This table reports the Best Linear Predictor (BLP) estimates obtained by applying each machine-learning learner separately within the GenericML framework (Chernozhukov et al., 2025). The outcome variable is the change in the average number of pieces delivered per working day between the heatwave weeks (weeks 3–4) and the pre-heatwave weeks (weeks 1–2) in Panel A. In Panel B, the outcome variable is schedule adjustment, defined as a binary indicator equal to one if an individual avoids afternoon work and instead shifts to early-morning or late-evening hours. Columns (1) and (3) present the coefficients for the projected average treatment effect (β_1) and the heterogeneity-scaling parameter (β_2), respectively. Columns (2) and (4) report the corresponding 95% confidence intervals based on repeated 50/50 sample splitting with 100 splits. Elastic Net ($\alpha = 0.5$) is the best-performing learner for the BLP object according to GenericML's cross-validated selection rule for both outcome variables.

D Robustness Checks

D.1 Without Individual Fixed Effects or Controls

TABLE D1: Impact on Labor Supply (Without Individual Fixed Effects)

VARIABLES	(1) Days per week	(2) Hours per day	(3) Deliveries per day	(4) Deliveries per hour
Heatwave	-0.817***	-1.234***	-9.158***	-0.550***
	(0.109)	(0.181)	(0.872)	(0.067)
Treat × Heatwave	0.535***	-0.499**	5.500***	0.853***
	(0.174)	(0.246)	(1.117)	(0.089)
PostHeat	-0.838***	-1.604***	-8.597***	-0.366***
	(0.124)	(0.224)	(1.129)	(0.079)
Treat × PostHeat	0.639***	0.059	6.311***	0.768***
	(0.171)	(0.272)	(1.331)	(0.101)
Individual FE	No	No	No	No
Control Mean	6.14	10.18	37.75	3.73
R^2	0.05	0.18	0.08	0.08
Observations	1,632	1,632	1,632	1,583

Notes: "Days per week" = Number of days worked in a week. "Hours per day" = Average number of hours worked per day in a week. "Deliveries per day" = Average number of pieces delivered per working day in a week. "Deliveries per hour" = A derived measure equal to deliveries per day divided by hours per day (i.e., the average number of pieces delivered per hour). "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. We do not control for individual fixed effects in all regressions. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D2: Impact on Health Outcomes (Without Individual Fixed Effects)

VARIABLES	(1) Headache	(2) Stomachache	(3) Vomit	(4) Tiredness	(5) Any
Heatwave	0.173***	0.014	0.011	0.360***	0.284***
	(0.036)	(0.021)	(0.017)	(0.035)	(0.036)
Treat × Heatwave	-0.131***	-0.007	0.000	-0.356***	-0.243***
	(0.049)	(0.033)	(0.028)	(0.062)	(0.061)
PostHeat	0.147***	0.072**	0.018	0.169***	0.151***
	(0.037)	(0.028)	(0.019)	(0.040)	(0.040)
Treat × PostHeat	-0.144***	-0.042	-0.044*	-0.105*	-0.087
	(0.047)	(0.040)	(0.026)	(0.063)	(0.060)
Individual FE	No	No	No	No	No
Control Mean	0.12	0.06	0.03	0.58	0.66
R^2	0.03	0.01	0.00	0.09	0.05
Observations	1,632	1,632	1,632	1,632	1,632

Notes: "Headache" = A binary indicator equal to one if an individual experienced a headache during the week, and zero otherwise. "Stomachache" = A binary indicator equal to one if an individual experienced a stomachache during the week, and zero otherwise. "Vomit" = A binary indicator equal to one if an individual experienced vomiting during the week, and zero otherwise. "Tiredness" = A binary indicator equal to one if an individual experienced tiredness during the week, and zero otherwise. "Any" = A binary indicator equal to one if an individual experienced any of the four symptoms during the week, and zero otherwise. "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. We do not control for individual fixed effects in all regressions. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D3: Impact on Adaptive Behaviors (Without Individual-Level Baseline Characteristics)

VARIABLES	(1) Adjust Schedule	(2) Buy Extra Water	(3) Buy Ice	(4) Full-sleeve	(5) Take ORS	(6) Rest AC
Treat	0.118**	-0.454***	0.006	-0.706***	-0.013	0.134***
	(0.050)	(0.041)	(0.020)	(0.033)	(0.038)	(0.033)
Ind.-level Controls	No	No	No	No	No	No
Control Mean	0.37	0.77	0.04	0.86	0.21	0.06
R^2	0.01	0.21	0.00	0.50	0.00	0.04
Observations	544	544	544	544	544	544

Notes: "Adjust schedule" = A binary indicator equal to one if an individual avoids afternoon work and shifts to early morning or late evening hours. "Buy Extra Water" = A binary indicator equal to one if an individual buys extra water. "Buy Ice" = A binary indicator equal to one if an individual buys ice. "Full-sleeve" = A binary indicator equal to one if an individual wears full-sleeve T-shirts. "Take ORS" = A binary indicator equal to one if an individual consumes glucose or oral rehydration salts. "Rest AC" = A binary indicator equal to one if an individual rests at rest points equipped with coolers or air conditioning. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the third and fourth weeks of the experiment. We do not control for individual-level baseline characteristics in all regression. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.2 Including Week Fixed Effects

TABLE D4: Impact on Labor Supply (With Week Fixed Effects)

VARIABLES	(1) Days per week	(2) Hours per day	(3) Deliveries per day	(4) Deliveries per hour
Treat × Heatwave	0.533***	-0.493**	5.507***	0.842***
	(0.174)	(0.246)	(1.116)	(0.088)
Treat × PostHeat	0.637***	0.065	6.318***	0.788***
	(0.172)	(0.272)	(1.330)	(0.099)
Individual FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Control Mean	6.14	10.18	37.75	3.73
R^2	0.39	0.46	0.66	0.77
Observations	1,631	1,631	1,631	1,582

Notes: "Days per week" = Number of days worked in a week. "Hours per day" = Average number of hours worked per day in a week. "Deliveries per day" = Average number of pieces delivered per working day in a week. "Deliveries per hour" = A derived measure equal to deliveries per day divided by hours per day (i.e., the average number of pieces delivered per hour). "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. All regressions include both individual and week fixed effects. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D5: Impact on Health Outcomes (With Week Fixed Effects)

VARIABLES	(1) Headache	(2) Stomachache	(3) Vomit	(4) Tiredness	(5) Any
Treat× Heatwave	-0.131***	-0.007	0.000	-0.355***	-0.242***
	(0.049)	(0.033)	(0.028)	(0.062)	(0.061)
Treat× PostHeat	-0.144***	-0.042	-0.044*	-0.104	-0.086
	(0.047)	(0.040)	(0.027)	(0.064)	(0.060)
Week FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Control Mean	0.12	0.06	0.03	0.58	0.66
R^2	0.24	0.28	0.17	0.29	0.26
Observations	1,631	1,631	1,631	1,631	1,631

Notes: "Headache" = A binary indicator equal to one if an individual experienced a headache during the week, and zero otherwise. "Stomachache" = A binary indicator equal to one if an individual experienced a stomachache during the week, and zero otherwise. "Vomit" = A binary indicator equal to one if an individual experienced vomiting during the week, and zero otherwise. "Tiredness" = A binary indicator equal to one if an individual experienced tiredness during the week, and zero otherwise. "Any" = A binary indicator equal to one if an individual experienced any of the four symptoms during the week, and zero otherwise. "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. All regressions include both individual and week fixed effects. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE D6: Impact on Adaptive Behaviors (With Week Fixed Effects)

VARIABLES	(1) Adjust Schedule	(2) Buy Extra Water	(3) Buy Ice	(4) Full-sleeve	(5) Take ORS	(6) Rest AC
Treat	0.138***	-0.454***	0.007	-0.701***	-0.014	0.146***
	(0.049)	(0.041)	(0.021)	(0.034)	(0.039)	(0.034)
Ind.-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.37	0.77	0.04	0.86	0.21	0.06
R^2	0.12	0.26	0.05	0.53	0.02	0.10
Observations	544	544	544	544	544	544

Notes: "Adjust schedule" = A binary indicator equal to one if an individual avoids afternoon work and shifts to early morning or late evening hours. "Buy Extra Water" = A binary indicator equal to one if an individual buys extra water. "Buy Ice" = A binary indicator equal to one if an individual buys ice. "Full-sleeve" = A binary indicator equal to one if an individual wears full-sleeve T-shirts. "Take ORS" = A binary indicator equal to one if an individual consumes glucose or oral rehydration salts. "Rest AC" = A binary indicator equal to one if an individual rests at rest points equipped with coolers or air conditioning. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the third and fourth weeks of the experiment. All regressions include both individual-level baseline characteristics and week fixed effects. The individual-level baseline characteristics include location, age, gender, marital status, educational attainment (measured using dummy variables), number of dependents, asset ownership (house, bike, cooler, refrigerator, air conditioner, and car), loan status and loan amount, health insurance coverage, and payment structure. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.3 Including the Endline Survey Round

TABLE D7: Impact on Labor Supply (Including the Endline Survey Round)

	(1) Days per week	(2) Hours per day	(3) Deliveries per day	(4) Deliveries per hour
Heatwave	-0.817***	-1.234***	-9.158***	-0.563***
	(0.109)	(0.181)	(0.872)	(0.064)
Treat × Heatwave	0.534***	-0.481*	5.476***	0.840***
	(0.174)	(0.246)	(1.115)	(0.088)
PostHeat	-0.599***	-1.205***	-6.840***	-0.317***
	(0.089)	(0.157)	(0.824)	(0.060)
Treat × PostHeat	0.457***	0.213	4.922***	0.519***
	(0.120)	(0.190)	(0.955)	(0.076)
Individual FE	Yes	Yes	Yes	Yes
Control Mean	6.14	10.18	37.75	3.73
R^2	0.35	0.40	0.64	0.75
Observations	1,906	1,906	1,906	1,856

Notes: "Days per week" = Number of days worked in a week. "Hours per day" = Average number of hours worked per day in a week. "Deliveries per day" = Average number of pieces delivered per working day in a week. "Deliveries per hour" = A derived measure equal to deliveries per day divided by hours per day (i.e., the average number of pieces delivered per hour). "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. All regressions include individual fixed effects. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

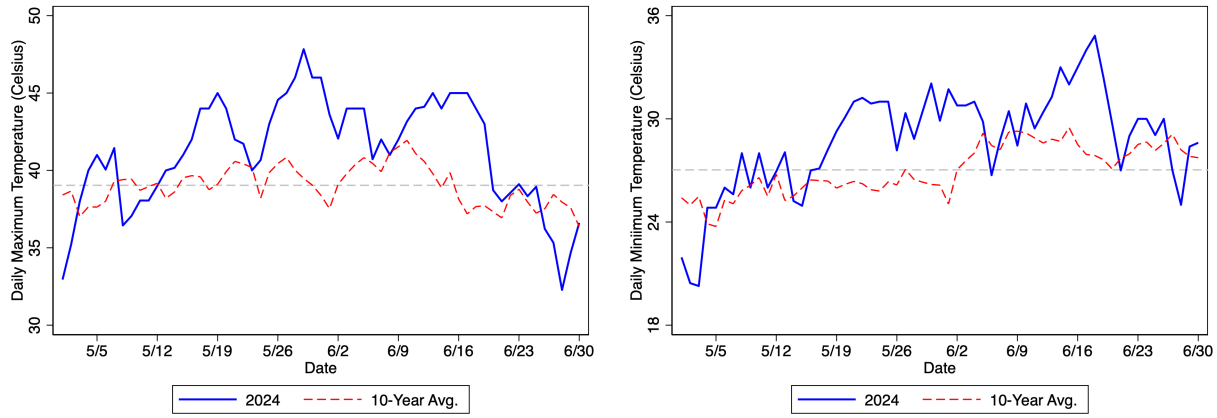
TABLE D8: Impact on Health Outcomes (Including the Endline Survey Round)

VARIABLES	(1) Headache	(2) Stomachache	(3) Vomiting	(4) Tiredness	(5) Any symptom
Heatwave	0.173***	0.014	0.011	0.360***	0.284***
	(0.036)	(0.021)	(0.017)	(0.035)	(0.036)
Treat × Heatwave	-0.131***	-0.007	0.001	-0.355***	-0.242***
	(0.048)	(0.033)	(0.028)	(0.062)	(0.061)
PostHeat	0.128***	0.043*	0.004	0.163***	0.176***
	(0.032)	(0.023)	(0.016)	(0.035)	(0.035)
Treat × PostHeat	-0.125***	-0.037	-0.024	-0.111**	-0.149***
	(0.039)	(0.032)	(0.021)	(0.049)	(0.046)
Individual FE	Yes	Yes	Yes	Yes	Yes
Control Mean	0.12	0.06	0.03	0.58	0.66
R^2	0.21	0.26	0.16	0.27	0.26
Observations	1,905	1,905	1,905	1,905	1,905

Notes: "Headache" = A binary indicator equal to one if an individual experienced a headache during the week, and zero otherwise. "Stomachache" = A binary indicator equal to one if an individual experienced a stomachache during the week, and zero otherwise. "Vomit" = A binary indicator equal to one if an individual experienced vomiting during the week, and zero otherwise. "Tiredness" = A binary indicator equal to one if an individual experienced tiredness during the week, and zero otherwise. "Any" = A binary indicator equal to one if an individual experienced any of the four symptoms during the week, and zero otherwise. "Heatwave" = A binary indicator equal to one if a week coincides with a heatwave event (i.e., the third and fourth weeks of the experiment), and zero otherwise. "Treat" = A binary indicator equal to one if an individual is assigned to the treatment group, and zero otherwise. "PostHeat" = A binary indicator equal to one if a week falls after the heatwave period (i.e., the fifth and sixth weeks of the experiment), and zero otherwise. "Control Mean" is the average value of the respective variable for gig delivery workers in the control group during the first and second weeks of the experiment. All regressions include individual fixed effects. Standard errors clustered at the individual levels are reported in parentheses. Significance levels are indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E Additional Figures

FIGURE E1: Historical Daily Maximum and Minimum Temperatures (°C) in Delhi

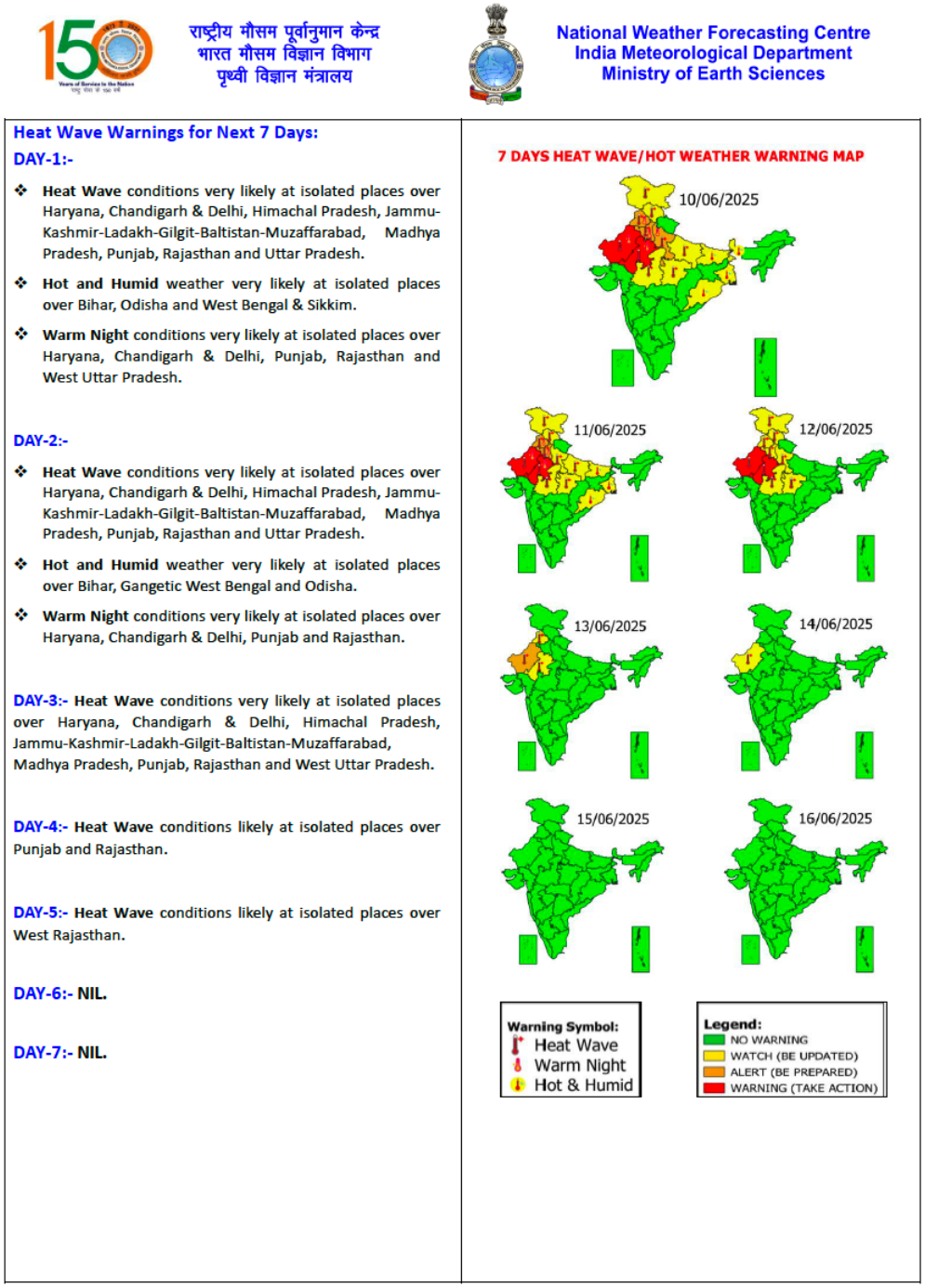


(a) 2024 vs. 10-Year Average, Maximum

(b) 2024 vs. 10-Year Average, Minimum

Notes: This figure compares daily maximum (Panel a) and minimum (Panel b) temperatures in Delhi during May and June of 2024 with the corresponding 10-year historical average. The solid blue line shows the observed daily maximum and minimum temperatures in 2024, respectively, while the red dashed line represents the 10-year average maximum and minimum temperature for each corresponding calendar date, calculated over the period 2014–2023. The horizontal gray dashed line indicates the average daily maximum temperature (39.0°C) between May 1 and June 30 during the same 10-year period in Panel a, and the average daily minimum temperature (27.0°C) in Panel b. Historical temperature data for Delhi is obtained from Visual Crossing and is accessible via this website.

FIGURE E2: Example: Daily Impact-Based Heatwave Warning Bulletin (June 10, 2025)



Notes: The figure displays a screenshot of the seven-day heatwave forecast from the Daily Impact-Based Heatwave Warning Bulletin issued by the National Weather Forecasting Centre, India Meteorological Department (IMD), Ministry of Earth Sciences, on June 10, 2025. It shows that the IMD predicted heatwave conditions in Delhi from June 10 to June 12, 2025. According to the IMD, "Hot and Humid" conditions are declared when the maximum temperature remains at least 3°C above normal, accompanied by above-normal relative humidity levels.

FIGURE E3: Example: Daily Weather Report and Forecast Bulletin (June 10, 2025)



DELHI FORECAST FOR NEXT SEVEN DAYS — **Time of Issue: 1810 Hrs. IST**

DATE	TEMPERATURE (°C)		DIRECTION/ WIND SPEED (KMPH)			HEAT WAVE/ HOT DAY/ WARM NIGHT FORECAST	WEATHER FORECAST
	MAX	MIN	0530-1130 (IST)	1130-1730 (IST)	1730-2330 (IST)		
10.06.2025	43.8	27.8	WSW/10-15	NW/15-20	NW/15-20	HEAT WAVE CONDITIONS AT A FEW PLACES	MAINLY CLEAR SKY. DUST RAISING WINDS (SPEED 20-30 KMPH) OCCASIONALLY GUSTING TO 40 KMPH.
11.06.2025	44-46	28-30	NW/15-20	W/15-20	W/15-20	HEAT WAVE CONDITIONS AT A FEW PLACES	MAINLY CLEAR SKY. DUST RAISING WINDS (SPEED 20-30 KMPH) OCCASIONALLY GUSTING TO 40 KMPH.
12.06.2025	42-44	26-28	NW/15-20	NW/15-20	E/05-10	HOT AND HUMID CONDITION	PARTLY CLOUDY SKY. VERY LIGHT TO LIGHT RAIN/ THUNDERSTORM/ LIGHTNING ACCOMPANIED WITH GUSTY WINDS 40-50 KMPH TEMPORARILY REACHING 60 KMPH DURING THUNDERSTORM WITH DUST RAISING WINDS TOWARDS EVENING/NIGHT.
13.06.2025	39-41	27-29	E/10-15	N/05-10	SE/10-15	NO HEAT WAVE CONDITION	PARTLY CLOUDY SKY. VERY LIGHT TO LIGHT RAIN/ THUNDERSTORM/ LIGHTNING ACCOMPANIED WITH GUSTY WINDS 40-50 KMPH TEMPORARILY REACHING 60 KMPH DURING THUNDERSTORM.
14.06.2025	37-39	27-29	SE/15-20	SE/05-10	SE/15-20	NO HEAT WAVE CONDITION	PARTLY CLOUDY SKY. VERY LIGHT RAIN/ THUNDERSTORM/ LIGHTNING ACCOMPANIED WITH GUSTY WINDS 30-40 KMPH TEMPORARILY REACHING 50 KMPH DURING THUNDERSTORM.
15.06.2025	37-39	27-29	SE/10-15	SE/05-10	SE/05-10	NO HEAT WAVE CONDITION	PARTLY CLOUDY SKY. VERY LIGHT TO LIGHT RAIN/ THUNDERSTORM/ LIGHTNING ACCOMPANIED WITH GUSTY WINDS 40-50 KMPH TEMPORARILY REACHING 60 KMPH DURING THUNDERSTORM.
16.06.2025	37-39	27-29	SE/10-15	W/05-10	SE/10-15	NO HEAT WAVE CONDITION	PARTLY CLOUDY SKY.

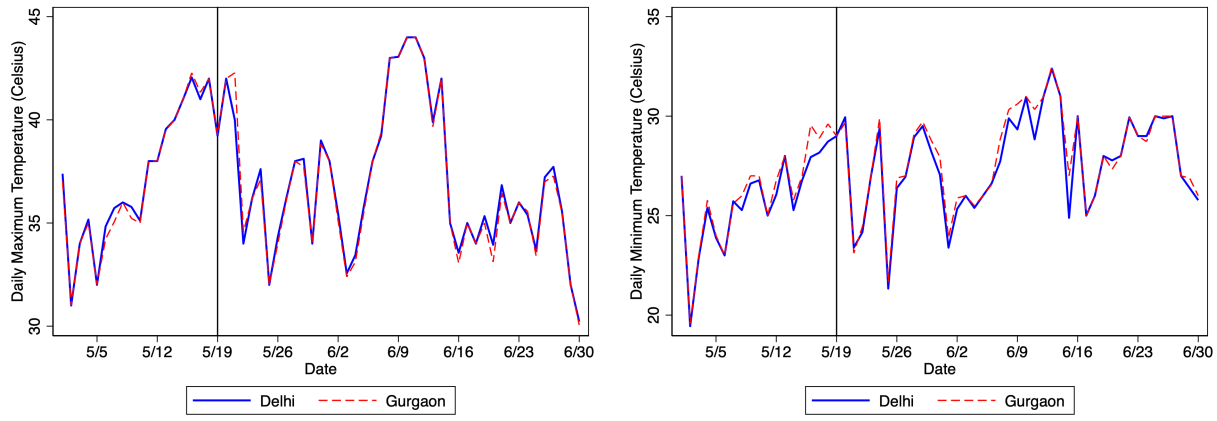
Note: The forecast accuracy decreases with the increase in lead period.
For location specific weather forecast kindly refer the link: https://city.imd.gov.in/citywx/localwx.php
For monthly climatology and extremes of Safdarjung and Palam kindly refer the link:

https://mausam.imd.gov.in/newdelhi/mcdata/safdarjung2.pdf
https://mausam.imd.gov.in/newdelhi/mcdata/palam2.pdf

TEMPERATURE NORMALS OF SAFDARJUNG		
DATE	MAX	MIN
10 JUNE-14 JUNE	39.9	28.0
15 JUNE-19 JUNE	38.8	27.5
20 JUNE-24 JUNE	38.6	28.0
25 JUNE-29 JUNE	37.2	27.9

Notes: This figure displays a screenshot of the seven-day heatwave forecast from the Daily Weather Report and Forecast Bulletin issued by the Regional Meteorological Centre (RMC), New Delhi, India Meteorological Department (IMD), Ministry of Earth Sciences, on June 10, 2025. The forecast indicates that the RMC predicted heatwave conditions in Delhi on June 10 and June 11, 2025. Although there is a discrepancy regarding the prediction for June 12, 2025 between the regional and national bulletins, both sources predicted heatwave conditions in the bulletins published on June 11, 2025. According to the IMD, "Hot and Humid" conditions are declared when the maximum temperature remains at least 3 °C above normal, accompanied by above-normal relative humidity levels.

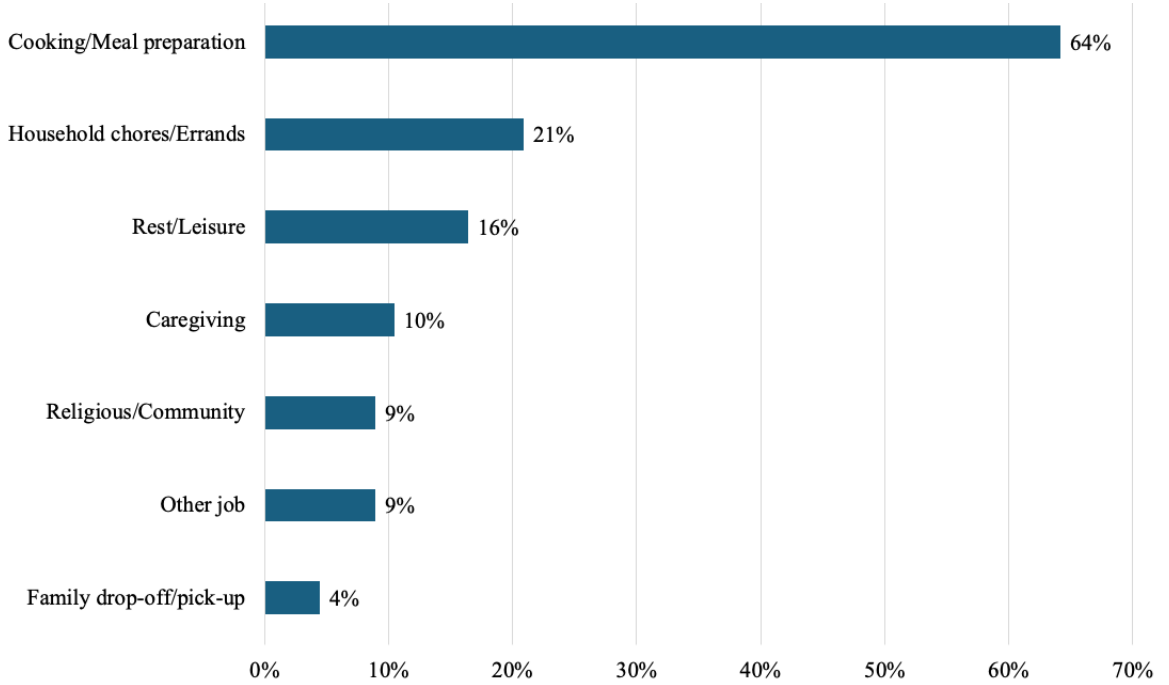
FIGURE E4: Daily Maximum and Minimum Temperatures (°C) in Delhi and Gurgaon, 2025



(a) Daily Maximum Temperature (b) Daily Minimum Temperature

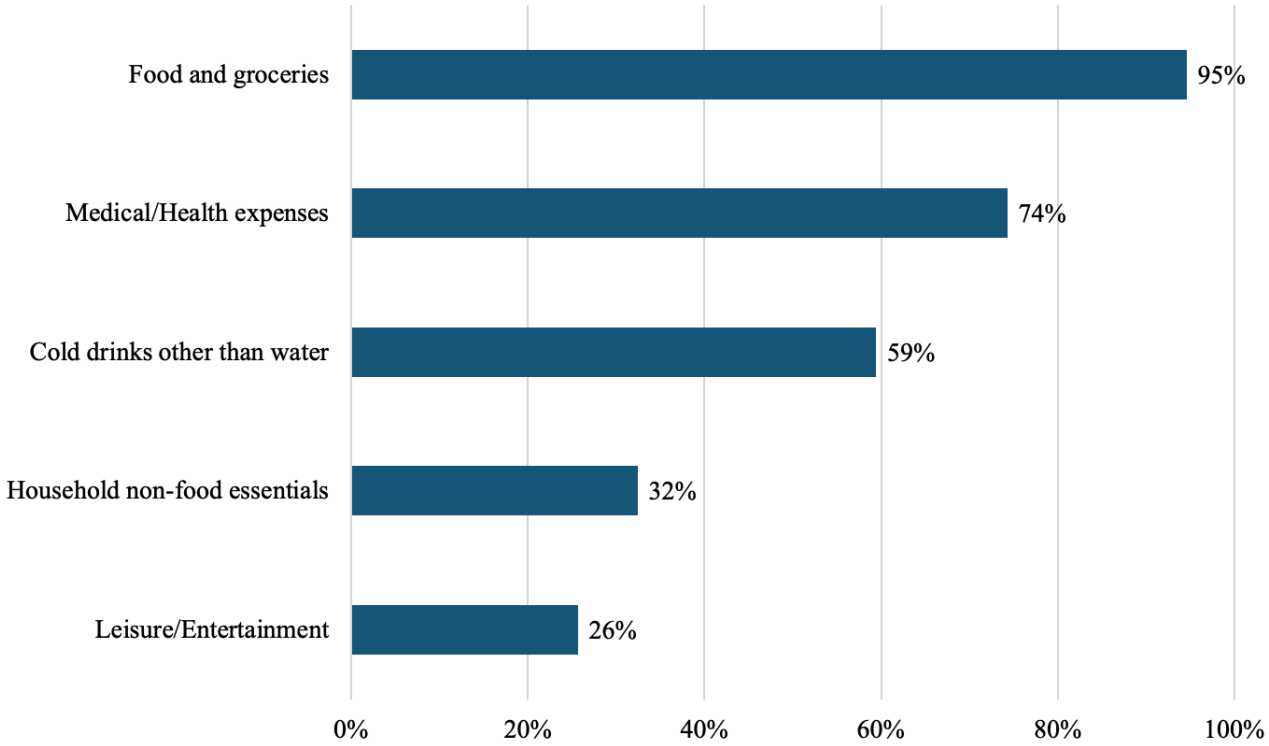
Notes: Historical temperature data for Delhi are obtained from Visual Crossing and are accessible via this website. Figure E4a presents daily *maximum* temperatures, while Figure E4b displays daily *minimum* temperatures in Delhi and Gurgaon over the period from May 1 to June 30, 2025. In both figures, the blue line corresponds to Delhi, the red dashed line corresponds to Gurgaon, and the vertical black line denotes the start date of the randomized controlled trial.

FIGURE E5: Activities Typically Performed in Early Morning or Evening



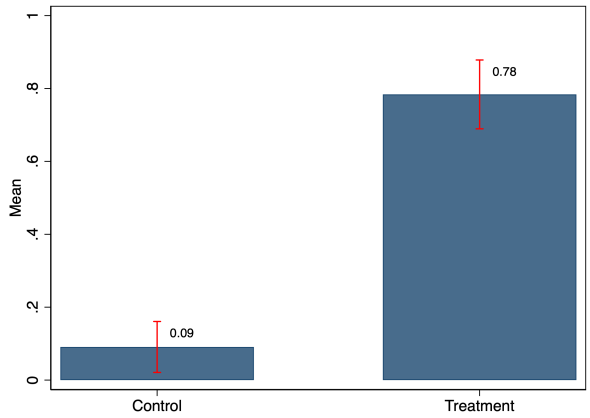
Notes: In this question of the follow-up survey, respondents were asked what they typically do in the early morning or evening if they have ever shifted their work schedule during the summer. They were allowed to select multiple activities. For the subgroup substituting to cooler hours, the figure depicts the share reporting each activity they typically performed during those hours before the treatment. "Religious/Community" = Participating in religious or community activities. "Family drop-off/pick-up" = Dropping off or picking up family members (e.g., school, work, errands).

FIGURE E6: Top Five Reported Uses of the June 2025 Cash Transfer

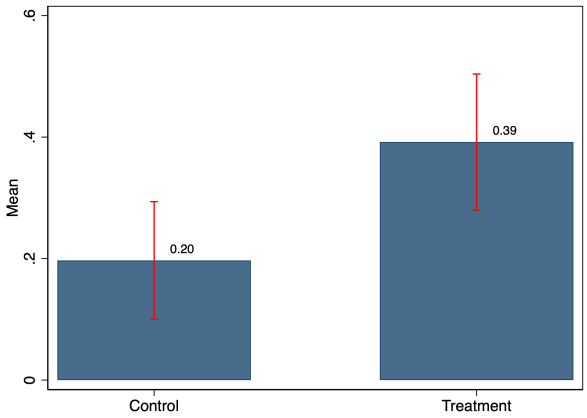


Notes: In this follow-up survey question, we asked treated workers only about the top three uses of the cash transfer they received in June 2025. Respondents were allowed to select up to three categories from the following options: transportation (for themselves and their family members), children's education expenses, childcare, food and groceries, household non-food essentials, clothes/shoes, medical and health expenses, bills or housing costs, debt repayment, savings for future use, and leisure or entertainment. The figure displays the five most commonly reported uses of the cash transfer.

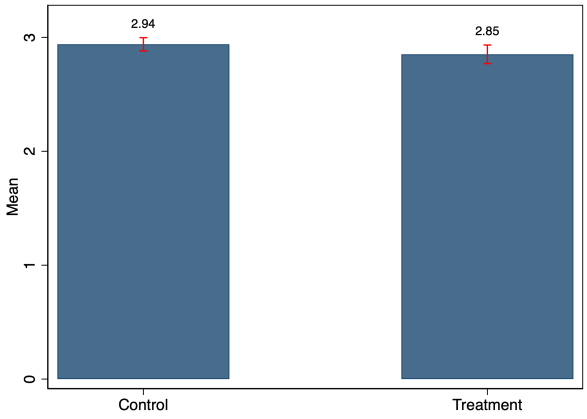
FIGURE E7: Insurance Understanding, Trust in Government, and Heatwave Expectations by Treatment



(a) Insurance Understanding



(b) Trust in Government



(c) Expected Summer Heatwaves

Notes: Panel (a) shows the share of respondents who reported understanding how the heatwave insurance product works. Panel (b) shows the share of respondents who reported trusting the government to provide such an insurance product. Panel (c) shows respondents' expectations about the number of heatwave episodes in the coming summer, coded as 0 for no heatwave, 1 for 1-2 heatwaves, 2 for 3-4 heatwaves, and 3 for 4 or more heatwaves. Bars report group means, and red capped lines indicate 95% confidence intervals. The treatment-control difference is statistically significant in panel (a) ($p < 0.001$) and panel (b) ($p = 0.012$), but not in panel (c).

F Additional Tables

TABLE F1: Summary Statistics: Full vs. Resurveyed

Variable	(1) Full (276) Mean/SD	(2) Resurveyed (140) Mean/SD	Difference (1)-(2) Bootstrapped p-value
Delhi	0.438	0.429	0.010
	(0.497)	(0.497)	[0.854]
Age	27.540	27.421	0.118
	(5.849)	(6.372)	[0.868]
Male	0.993	1.000	-0.007
	(0.085)	(0.000)	[0.489]
Married	0.620	0.643	-0.023
	(0.486)	(0.481)	[0.668]
Education Level			
High school and below	0.025	0.021	0.004
	(0.158)	(0.145)	[0.797]
Undergraduate	0.815	0.821	-0.006
	(0.389)	(0.384)	[0.894]
Graduate and above	0.159	0.157	0.002
	(0.367)	(0.365)	[0.951]
Household Members			
No. of non-child dependents	2.630	2.629	0.002
	(1.271)	(1.283)	[0.989]
No. of dependents: Children	0.899	0.921	-0.023
	(1.022)	(1.025)	[0.837]
Home Ownership			
Own house	0.163	0.157	0.006
	(0.370)	(0.365)	[0.900]
Rented house	0.833	0.836	-0.002
	(0.373)	(0.372)	[0.958]
Household Assets			
Has a bike	0.953	0.964	-0.011
	(0.212)	(0.186)	[0.632]
Has a cooler	0.308	0.250	0.058
	(0.462)	(0.435)	[0.525]
Has a fridge	0.149	0.136	0.013
	(0.356)	(0.344)	[0.735]
Has an A/C	0.011	0.014	-0.003
	(0.104)	(0.119)	[0.789]
Has a car	0.007	0.007	0.000
	(0.085)	(0.085)	[0.944]

Table F1 continued from previous page

Variable	(1) Full (276) Mean/SD	(2) Resurveyed (140) Mean/SD	Difference (1)-(2) Bootstrapped p-value
Financial Situation			
Has a loan	0.399	0.350	0.049
	(0.490)	(0.479)	[0.526]
Amount of loan (₹)	2280.688	1960.214	320.474
	(3444.098)	(3190.536)	[0.539]
Has a health insurance	0.159	0.157	0.002
	(0.367)	(0.365)	[0.947]
Payment Structure			
Commission only	0.804	0.800	0.004
	(0.397)	(0.401)	[0.914]
Base salary + Commission	0.167	0.164	0.002
	(0.373)	(0.372)	[0.957]
Fix salary	0.029	0.036	-0.007
	(0.168)	(0.186)	[0.727]
Labor Supply			
Work days per week	6.351	6.364	-0.013
	(0.515)	(0.498)	[0.840]
Work hours per day	10.315	10.336	-0.020
	(1.454)	(1.328)	[0.880]
Deliveries per day	42.319	42.464	-0.145
	(9.862)	(9.440)	[0.884]

Notes: This table reports descriptive statistics and balance tests for baseline characteristics of re-interviewed workers we were able to successfully survey to the full sample. Column (1) presents means and standard errors (in parentheses) for workers in the full sample, and column (2) presents the corresponding statistics for the 140 re-interviewed participants. Column (3) reports the difference in means between the two groups, with bootstrapped p-values based on 999 replications shown in square brackets. Baseline characteristics include demographic variables, educational attainment, household composition, housing ownership, asset ownership, financial conditions, and payment structure. Adult dependents include parents, siblings, grandparents, and other adult dependents. We find no statistically significant differences between the two groups for any baseline variable at the 10% level.

TABLE F2: Sample Comparison: Summary Statistics

	(1) NCAER Survey (April/May 2022)	(2) IDinsight (Feb-May 2024)	(3) Our Experiment (April/May 2025)
Observations	924	1,044	276
Male	99.0%	99%	99.3%
Average household size	4.8	4.68	4.5
Married	50.2%	53%	61.6%
Own house	44.9%		16.3%
Age			
Average age	29.1	29.2	27.6
18∼24	28.9%		33.3%
25∼30	36.5%		42.8%
31∼35	17.7%		14.9%
36∼40	9.6%		6.5%
>40	7.3%		2.5%
Education			
Secondary education and above	93.5%	100%	100%
Work			
Average hours worked in a day	10.8 (long-shift) 5.2 (short-shift)		10.3
Average days worked in a week	6.4 (long-shift) 6.0 (short-shift)		6.4
Average hours worked in a week	69.1	65.51	65.9

Notes: Column 1 presents summary statistics for 924 delivery workers from a food-delivery platform, based on a survey conducted by the National Council of Applied Economic Research (NCAER) in April-May 2022 (National Council of Applied Economic Research, 2023). The NCAER categorizes workers into two groups: long-shift workers, who work 11-hour shifts, and short-shift workers. Column 2 presents summary statistics for the full-time active-driver subsample in the IDinsight study, based on survey data collected in February-May 2024 (Brailovskaya et al., 2025). Column 3 presents summary statistics for our 276 gig workers surveyed in April/May 2025.

G A Simple Equilibrium Calibration Under Universal Scale-Up

Our experimental estimates are identified under the market conditions prevailing during the study period. A broader rollout, however, may generate equilibrium feedback by changing compensation during the hottest hours, not just total labor supply. This is especially relevant in our setting because the treatment affects workers' schedule adjustment: the transfer facilitates avoiding work during the hottest afternoon hours and shifting activity toward cooler times of day.

To illustrate how equilibrium feedback may attenuate this timing response under *universal* rollout, we consider a simple calibration of the afternoon market. Let L_a denote afternoon labor supply and P_a the return to afternoon work (e.g., the surge-adjusted delivery price). Suppose that, absent equilibrium feedback, universal heatwave-indexed cash transfers would reduce afternoon labor supply by a fraction $\delta \in (0,1)$. That is, $\frac{\Delta L_a^{(0)}}{L_a} = -\delta$ where the superscript 0 denotes the no-feedback case. δ captures the *direct* behavioral response of workers to the transfer under fixed market conditions.

Let

$$\eta_a \equiv -\frac{\Delta Q_a^d}{Q_a^d}\frac{P_a}{\Delta P_a} > 0$$

denote the absolute elasticity of afternoon demand, and let

$$\varepsilon_a \equiv \frac{\Delta L_a^s}{L_a^s}\frac{P_a}{\Delta P_a} > 0$$

denote the elasticity of afternoon labor supply with respect to afternoon returns. A reduction in afternoon labor supply raises afternoon returns, and higher returns draw some, but not all, workers back into afternoon work. The equilibrium price response can be written as

$$\frac{\Delta P_a}{P_a} = -\frac{1}{\eta_a}\frac{\Delta L_a}{L_a},$$

where, in equilibrium, $\frac{\Delta Q_A^d}{Q_A^d} = \frac{\Delta L_A}{L_A}$. The induced labor-supply rebound is

$$\varepsilon_a \frac{\Delta P_a}{P_a}.$$

Thus, the total change in afternoon labor supply (direct + indirect) is

$$\frac{\Delta L_a}{L_a} = -\delta + \varepsilon_a \frac{\Delta P_a}{P_a} = -\delta - \frac{\varepsilon_a}{\eta_a} \frac{\Delta L_a}{L_a},$$
$$\rightarrow \frac{\Delta L_a}{L_a} = -\delta \frac{\eta_a}{\eta_a + \varepsilon_a},$$

and therefore the equilibrium change in afternoon returns is

$$\frac{\Delta P_a}{P_a} = \frac{\delta}{\eta_a + \varepsilon_a}.$$

Because we do not directly estimate η_a or ε_a in our data, we present this exercise as a calibration. We proxy for δ using the estimated treatment effects on schedule adjustment, while recognizing that schedule adjustment is binary and therefore captures the incidence, rather than the magnitude, of shifting labor away from the afternoon. Accordingly, we set $\delta = 0.138$ for the overall sample in Panel A of Table G1, $\delta = 0.250$ for commission-only workers in Panel B, and $\delta = 0.292$ for workers in inflexible-demand sectors in Panel C, based on the corresponding treatment effects in Table 5, Table C3, and Table C6. We vary η_a from 0.3 to 1.0 to cover relatively inelastic to unit-elastic demand cases, and ε_a from 0.1 to 0.3 to reflect modest labor-supply responsiveness.[29] Across the scenarios shown, the direct timing response is attenuated but not fully offset. For example, when $\delta = 0.138$, $\eta_a = 0.3$, and $\varepsilon_a = 0.2$, the equilibrium change in afternoon labor supply is 8.3%, so about 40% of the initial effect is dampened by equilibrium feedback. More generally, attenuation is greater when afternoon demand is less elastic or when workers are more responsive to high afternoon pay.

This calibration should be interpreted as a stylized equilibrium bound. It shows that the treatment's adaptation effect may attenuate under broad rollout: if many workers simultaneously avoid the hottest hours, endogenous increases in afternoon returns may draw some of them back into work during those periods.

[29] Brailovskaya et al. (2025) show that only about 21% of food delivery workers in India report being able to respond to platform incentives and take advantage of surge pricing.

TABLE G1: Universal Scale-up Calibration

(1) $-\delta$	(2) η_a	(3) ε_a	(4) $-\Delta L_a / L_a$	(5) Dampening share
Panel A. Overall				
0.138	0.3	0.1	0.103	25.0%
0.138	0.3	0.2	0.083	40.0%
0.138	0.3	0.3	0.069	50.0%
0.138	0.6	0.1	0.118	14.3%
0.138	0.6	0.2	0.103	25.0%
0.138	0.6	0.3	0.092	33.3%
0.138	1.0	0.1	0.125	9.1%
0.138	1.0	0.2	0.115	16.7%
0.138	1.0	0.3	0.106	23.1%
Panel B. Commission-only				
0.250	0.3	0.1	0.188	25.0%
0.250	0.3	0.2	0.150	40.0%
0.250	0.3	0.3	0.125	50.0%
0.250	0.6	0.1	0.214	14.3%
0.250	0.6	0.2	0.188	25.0%
0.250	0.6	0.3	0.167	33.3%
0.250	1.0	0.1	0.227	9.1%
0.250	1.0	0.2	0.208	16.7%
0.250	1.0	0.3	0.192	23.1%
Panel C. Inflexible-demand sector				
0.292	0.3	0.1	0.219	25.0%
0.292	0.3	0.2	0.175	40.0%
0.292	0.3	0.3	0.146	50.0%
0.292	0.6	0.1	0.250	14.3%
0.292	0.6	0.2	0.219	25.0%
0.292	0.6	0.3	0.195	33.3%
0.292	1.0	0.1	0.265	9.1%
0.292	1.0	0.2	0.243	16.7%
0.292	1.0	0.3	0.225	23.1%

Notes: Column (1) reports the assumed direct reduction in afternoon labor supply in the absence of equilibrium feedback. Column (4) reports the total change in afternoon labor supply, $-\frac{\Delta L_a}{L_a} = \delta \frac{\eta_a}{\eta_a + \varepsilon_a}$. Column (5) reports the share of the direct effect dampened by equilibrium feedback, $\frac{\varepsilon_a}{\eta_a + \varepsilon_a}$. Panel A sets $\delta = 0.138$, corresponding to the overall treatment effect on schedule adjustment in Table 5. Panel B sets $\delta = 0.250$, corresponding to the implied treatment effect for commission-only workers in Table C3. Panel C sets $\delta = 0.292$, corresponding to the implied treatment effect for workers in inflexible-demand sectors in Table C6. These values should be interpreted cautiously because schedule adjustment is a binary measure.