The Impact of Heat Hazard on Gig Economy Workers: Evidence from An On-demand Food Delivery Platform

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Abstract

This study examines the impact of heatwave exposure on the operational performance and well-being of food delivery couriers, a significant segment of the gig economy workforce. Focusing on a major food delivery platform in China, we utilize a two-step Heckman estimation model to analyze data from the hottest months of July and August in 2015. Our findings reveal that while high temperatures lead to an increase in orders and consumer spending, they also contribute to a decline in operational efficiency which negatively affects courier income. We find that couriers working during heatwaves (when heat index indicates "danger" or "extreme danger" for outdoor activities) experience a 9.1% increase in orders per hour, a 6% increase in working time, but also a 21.8% increase in delivery delays. This results in a disproportionate increase in workload with only an 8.6% rise in hourly income. Furthermore, by integrating our findings with medical research on the impact of heat on human health, we demonstrate that the health costs associated with heat exposure for couriers are significantly higher than their income gains. This highlights the need for policies that address the well-being of gig workers in the face of escalating climate challenges.

Keywords: Climate Change, Global Warming, Corporate Social Responsibility, Responsible Operations, Operation Efficiency, Welling-being, Health, ESG

1 Introduction

Global warming has significant consequences, one of which is exposure to extreme heat (e.g., Deschênes and Greenstone, 2007; Burke and Emerick, 2016). This exposure can result in occupational hazards and injuries to people of all ages and professions, affecting both the healthy and the vulnerable (e.g., Stocker et al., 2013; Yu et al., 2019). For instance, during a heat wave in Tucson, Arizona, USA, in 2023, the National Weather Service (NWS) issued an excessive heat warning, with highs reaching up to 113°F in the Tucson metro area and surrounding deserts.[1] The extreme heat caused several fatalities. Similarly, in 2024, a heat wave in India resulted in temperatures reaching 122°F and at least 15 deaths.[2]

It is crucial to consider how excessive heat affects workers who spend long hours working outdoors. A 2022 letter from the American Federation of Labor and Congress of Industrial Organizations (AFL-CIO) highlighted that as global temperatures rise, workers face increased risks of occupational heat exposures. Occupational Safety and Health Administration (OSHA) has also noted that heat impacts cognitive ability, causing workers to make more mistakes and potentially not realize the problems caused by heat hazards. "*Workers suffering from heat may be listed as dying from natural causes, such as heart attacks, or they might go home, become ill, and die without their deaths being counted as work-related.*" In this study, we aim to evaluate the impact of heatwave exposure on workers' operational performance and its subsequent effects on their well-being, with a specific focus on two key dimensions: income and health.

As the surge of gig economy, a significant portion of the workforce laboring outdoors during hot weather consists of gig workers. For example, India has over 7.5 million gig workers who frequently face heat waves with temperatures reaching 113°F to 122°F in April and May.[3] Similar conditions exist in China, which has over 406 million users of online food delivery services. Most parts of China experience high temperatures during July and August, especially in the southern regions such as Shanghai and Hangzhou. Despite the large workforce of gig economy workers serving delivery platforms, there are few labor regulations to protect their interests because they are not officially recognized as employees with formal worker status. This situation demands attention from society,

[1] "Tucson heat records continue to be set, broken", accessed on Aug 19, 2024.
[2] "The heat will kill the economy. But it will kill us first", access on Aug 19, 2024.
[3] "For eight million Indians, life is a gig and a mostly terrible one at that", accessed on Aug 19, 2024.

academia, and businesses to explore labor issues arising from these innovative business models (e.g., sharing economy, network economy), new technologies (e.g., smart algorithms with delivery services), or humanitarian operations (Lee and Tang, 2018).

This paper aims to study the impact of heat hazards on gig economy workers. The trend of high temperatures has created more business opportunities for online shopping platforms (Lazo et al., 2011; Steinker et al., 2017). During hotter summers, many gig workers in countries like Spain, Turkey, India, and China ride bicycles, tricycles, and other forms of transportation without adequate protection from heatwaves. They hurry through the streets to deliver food or other products on time, sometimes facing potential income reduction for late deliveries. The health of these gig workers is severely impacted by heatwaves, often with little to no financial subsidies. In this study, we analyze data from one of the pioneering food delivery platforms in China, focusing on gig workers, commonly referred to as couriers. During hot summer days, these couriers spend an average 8.8 hours per day waiting on street corners and outside restaurants for food orders, often without sufficient protection from heat exposure.

We employ a two-step Heckman estimation model to evaluate the impact of heat hazards on couriers' performance. In the first equation, we estimate the factors influencing a gig courier's decision to work. The second equation examines the impact of high temperatures on couriers' operational performance. Our findings reveal that working under dangerously hot conditions leads to a 9.1% increase in the number of orders per hour compared to working in less risky temperatures during the summer. Consequently, the duration of couriers' working time increases by 6%. However, despite working longer time, these gig couriers experience 21.8% more delays which negatively impact their income. Correspondingly, couriers' hourly income increases by only 8.6%, which seems lower than the increase in their workload.

These findings are supported by the platform's performance and consumer behavior in response to the excessive heat. During heat waves, consumers place more orders, spend more per order and a larger number of new users utilize food delivery services. This surge in demand introduces variability into the system's order processing, as consumers are spread across different locations with varying requests. As a result, while higher temperatures drive an increase in orders and consumer spending, the system's efficiency diminishes under heat stress. This inefficiency results in more delays in deliveries, which in turn negatively impacts demand on the platform, diminishes

user satisfaction, and ultimately reduces couriers' income.

Finally, we integrated our research with medical studies on the impact of heat hazards on human morbidity (Agarwal et al., 2021; Li et al., 2023). The literature suggests that rising temperatures significantly increase the probability of various heat-related diseases, leading to severe health risks for workers who spend long hours working outdoors. We used the estimations from these studies and conducted a back-of-the-envelope analysis to quantify the health costs associated with heat exposure for couriers. Translating this into financial terms, while these gig workers' hourly earnings may increase by around 1 RMB during heatwaves, their health costs could rise dramatically (at least) by 501 RMB per courier over our data period (July and August, the two hottest months in China). This imbalance highlights the disproportionate sacrifices gig couriers make while working in extreme heat, enabling platforms to continue offering ultraconvenient services. Consumers benefit from staying protected indoors, yet the burden of health risks falls heavily on these workers, underscoring the need for policies that address their well-being in the face of escalating climate challenges.

Our paper makes three key contributions. First, it adds to the growing literature on gig economy workers, which has primarily focused on incentives and behavioral issues regarding participation (Allon et al., 2023). While most existing studies address how to regulate this new type of work, including discussions on minimum wage, very little research has examined the impact of environmental factors like heat hazards on the well-being of gig economy workers who are not officially recognized as employees and thus fall outside occupational health and safety protections. This lack of adequate protection is a significant issue, particularly in developing countries, severely affecting couriers' health and safety. Our findings highlight the need for policymakers to develop regulations and policies that address these critical concerns.

Second, although environmental, social, and governance (ESG) criteria have become widely accepted for assessing firms' sustainability and social impact, it is still uncommon for the management and operations fields to formally address ESG issues, particularly the "social" aspect (Dai and Tang, 2022). In our paper, we evaluate the impact of heat hazards on couriers' income and health costs, revealing that on-demand delivery operations are largely sustained by the disproportionate sacrifices of a vast number of gig workers. This heat-related perspective offers platforms a new approach to promote responsible operations, providing valuable managerial insights for developing metrics that effectively address "social" issues. Our study therefore aligns with several key goals

set by the United Nations, specifically focusing on *"Good Health and Well-being"* and *"Decent Work and Economic Growth"*.[4] By integrating these objectives, we offer a holistic framework for platforms to operate more sustainably while improving worker welfare in the face of environmental challenges.

Third, our paper contributes to the extensive literature on global warming and climate change, particularly by addressing a gap in how heat hazards impact new online business models, such as on-demand food delivery platforms. While there is significant research on how climate change affects production operations and consumer behavior in traditional brick-and-mortar industries (Cai et al., 2018; Badorf and Hoberg, 2020), little attention has been given to how environmental stressors affect online gig-based businesses. In addition, most literature on the negative impacts of global warming tends to focus on industry sectors where harm is directly observable, such as agriculture (Burke and Emerick, 2016). In contrast, the food delivery platform we examine benefits from higher temperatures, as they lead to increased consumer demand. However, this situation imposes hidden costs on couriers, who are essential to the platform's operations. Our study fills this gap by examining the effects of heatwaves from both the supply and demand sides. We provide detailed insights into the operational challenges couriers face, as well as the surge in demand for services during extreme temperatures. By exploring the economic and health implications for gig workers, we reveal how environmental factors pose unique challenges to these innovative business models. This dual approach offers a comprehensive understanding of how labor conditions and environmental stressors intersect in the evolving digital economy.

2 Background, Literature Review, and Hypotheses Development

2.1 The Food Delivery Platform

The food delivery platform business has rapidly expanded over the past decade, transforming the way people access meals and groceries. These platforms connect customers with local restaurants and delivery couriers through a user-friendly digital interface, facilitating the entire ordering and delivery process. By offering convenience and a wide selection of options, food delivery services

[4] "The 17 Goals, initiated by the Department of Economic and Social Affairs, United Nations", accessed on Sep 6, 2024.

have become an integral part of urban life, particularly in bustling cities. Platforms like Meituan and Ele.me in China, Zomato and Swiggy in India, and various other platforms globally have seen exponential growth, driven by the increasing consumer demand for convenience and the rise of online shopping trends.

However, this growing demand faces significant challenges, especially during heatwaves. The phenomenon known as the "high temperature economy" has led to a marked increase in online shopping and food delivery orders as consumers prefer to stay indoors to escape the extreme heat.[5] In China, which boasts over 406 million users of online food delivery services, the impact of heatwaves is particularly acute. Major urban areas such as Shanghai experienced extreme temperatures, with records reaching 105.6°F on July 21, 2017.[6] This surge in demand due to heatwaves has sometimes overwhelmed leading food delivery platforms like Meituan and Ele.me, causing service disruptions.[7] Unlike other on-demand platforms that typically involve interactions between two parties (consumer and provider), food delivery platforms require coordination among three parties—customers, restaurants, and couriers (Mao et al., 2022). This complexity makes the system more vulnerable to extreme weather conditions. Disruptions in service not only lead to delivery delays but also result in couriers spending more time exposed to the heat.

These couriers, who typically use bicycles, tricycles, or two-wheel motorcycles, are directly exposed to these harsh conditions during their long working hours, which often exceed eight hours daily.[8] Often stationed at street corners and outside restaurants for extended periods, these couriers have limited access to personal protective equipment and medical care under the extreme weather conditions. Similar situations are observed in other countries. For instance, in India, which has over 7.5 million gig workers serving in food delivery and other on-demand services, severe heatwaves with temperatures reaching 113°F to 122°F have had a substantial impact.[9]

The platform studied in this paper is one of the pioneering food delivery platforms in China (Mao et al., 2022). It operates in a manner typical of most food delivery platforms. We use data from 2015, when the platform was in its early stage. To ensure delivery capacity, the platform recruited couriers by offering contracts that featured a low monthly base salary, contingent on the completion

[5] "Scorching heat turns pleasant for food delivery, ride-hailing services", accessed on Sep 18, 2024.
[6] "Shanghai grilled by hottest day in 145 years", accessed on Aug 19, 2024.
[7] "Online food orders surge for delivery giants like meituan as China endures heatwave", assessed on Sep 22, 2024.
[8] "A typical day in the life of a Chinese delivery worker", accessed on Sept 22, 2024.
[9] "Heatwave fee for Asia's gig workers does little to cool climate stress", accessed on Sep 22, 2024.

of a minimum number of orders. Additionally, couriers received a delivery fee for each completed order. The delivery fee per order at that time was primarily determined by the distance between the customer and restaurant, with minimal adjustments for changes in demand and supply.[10] The assignment of delivery orders was determined by an algorithm mainly based on the distance between a courier and the specified restaurant, as well as the availability of couriers nearby. Couriers had the right to decide whether to work, but they had limited freedom in choosing which orders to accept. It was not uncommon for a single courier to take on multiple orders simultaneously, and moreover, each order was normally requested to be delivered to the customer's location within one hour (starting from the time when the customer placed this order). As a result, a courier's income was largely driven by the number of orders they completed. Couriers typically earned more during meal hours or when they were familiar with local routes.

Till today, these couriers have not been classified as employees and lack occupational health and safety protections under existing labor regulations. In China, despite government mandates, platforms such as food delivery services (e.g., Meituan and Eleme) do not provide basic social or medical insurance for couriers, which should be a fundamental right for employees working for a firm.[11] Moreover, despite their essential role in food delivery services, little attention has been given to how these on-demand delivery couriers manage extreme weather conditions (Moda et al., 2019). As climate change continues to increase the frequency and intensity of heatwaves and other extreme weather events, it is crucial to address the well-being challenges faced by food delivery couriers.

2.2 Literature Review

2.2.1 The impact of Climate Changes on Economic Activities

With the increasing global concern regarding climate change, there is a growing need to understand its impact on economic activities. Numerous studies have estimated the effects of extreme temperatures and climate change on agricultural output, highlighting the sensitivity of crop yields to changing climate conditions (e.g., Deschênes and Greenstone, 2007; Burke and Emerick, 2016;

[10] We regress the delivery fee for each order on the straight-line distance between the restaurant address and the consumer address using order-level data. The results shown in Appendix Table A1 confirm this fee schedule.

[11] "Chinese delivery giants Meituan, Ele.me pledge to not force drivers to register as independent businesss", accessed on Sep 1, 2024.

Chen et al., 2016). Additionally, research has shown significant impacts on the productivity of both indoor and outdoor workers in sectors such as traditional manufacturing and service industries (e.g., Graff Zivin and Neidell, 2012, 2014; Cai et al., 2018; LoPalo, 2023; Zhang et al., 2024).

Beyond these sectors, it is well-documented that weather conditions influence consumer demand and product sales across various categories and channels. Variables such as temperature and rainfall can directly affect store traffic, shaping consumer decisions on when, where, and what to purchase (e.g., Steele, 1951; Parsons, 2001; Divakar et al., 2005; Murray et al., 2010; Ramanathan and Muyldermans, 2010; Bahng and Kincade, 2012). For instance, Bertrand et al. (2015) found that sales of different apparel categories, including men's, women's, and children's clothing, respond differently to the same weather conditions. Similarly, Badorf and Hoberg (2020) examined the impact of daily weather on brick-and-mortar retail sales and found that weather generates complex effects on daily sales, varying by store location and sales themes. Even with the shift to online shopping, weather continues to affect consumer behavior. For example, Lazo et al. (2011) and Steinker et al. (2017) demonstrated that variables such as sunshine, temperature, and rain significantly impact online sales, and incorporating weather data into sales forecasts can reduce forecast errors, thus improving logistics and warehousing operations.

As the on-demand service platform economy grows, recent research has explored how weather conditions affect driver supplies on ridesharing platforms. Brodeur and Nield (2018) found that on rainy days, the number of Uber (Lyft) rides per hour increases by 22% (19%), while taxi rides per hour increase by 5%. Furthermore, Shokoohyar et al. (2020) examined the effects of weather on three key metrics—pickup waiting time, trip duration, and ride fare for Uber and Lyft rides in Philadelphia—finding that these metrics increase under extreme weather conditions on weekdays but decrease on weekends.

Despite extensive research in various sectors, to our knowledge, there is little study examining the impact of climate change on food delivery services, particularly the effects of heat hazards on the associated parties. While industries like agriculture face direct (negative) consequences, such as decreased crop output, gig economy sectors like food delivery benefit from higher temperatures due to increased consumer demand, complicating the evaluation of hidden negative effects. As detailed in Section 2.1, food delivery services are inherently more time-sensitive and involve a complex system of interactions among consumers, delivery couriers, and restaurants, making it challenging to

isolate the effect of climate change on each party. Moreover, compared with drivers in ridesharing service, couriers of food delivery who usually use motor bicycle as the traffic tool, are more vulnerable to extreme weather (e.g., heatwave), and the heat hazard can lead to physically and mentally discomfort for couriers, which further influences couriers' working decisions and performance.

Further, previous studies have often examined the impacts of weather on demand and supply separately, lacking comprehensive analyses that incorporate both aspects by linking each individual consumer with the corresponding supplier. This gap is primarily driven by the absence of complete data from both the demand and supply sides. Our research has a unique opportunity to combine demand (consumer consumption) and supply (delivery couriers) data from a meal delivery platform to thoroughly examine the impact of weather conditions on platform operations. By bridging this gap, we aim to provide a more holistic understanding of how extreme weather affects food delivery services and to inform better protective measures for this essential segment of the labor force.

2.2.2 Heat Hazard and Gig Economy Workers

The increase in average temperatures, leading to more frequent heatwaves, presents a fundamental threat to human health (Stocker et al., 2013). Excessive heat can lead to a multitude of health issues, including heat exhaustion, heat stroke, and the exacerbation of pre-existing cardiovascular and respiratory conditions.[12] Extensive public health and epidemiology literature has found that extremely hot conditions (thresholds typically ranging between 80°F and 90°F) are associated with higher mortality rates, with consistent results observed in both developed countries (e.g. Barreca, 2012; Deschenes, 2014; Karlsson and Ziebarth, 2018) and developing countries (e.g. Burgess et al., 2014; Geruso and Spears, 2018; Yu et al., 2019; Li et al., 2023). Additionally, high temperatures are linked to increased morbidity, which can impose significant costs on medical systems. These include expenses related to emergency department visits (White, 2017), hospital admissions (Karlsson and Ziebarth, 2018), and medical bills (Agarwal et al., 2021).

Health harms induced by high temperatures and heatwaves during work hours can be recognized as work injuries if the affected individuals are employees of a firm. This recognition can provide some compensation for their health-related costs. However, gig workers, who are not clearly defined as employees of the platforms they work for, lack sufficient protection from such potential harm

[12] "WHO Climate change report", accessed on Sept 22, 2024.

caused by high temperatures, despite the gig economy's growth.

The current literature on gig economy workers predominantly focuses on incentives and behavior issues affecting workers' participation. Research by Guda and Subramanian (2019) investigated surge pricing and forecast communication, which influence how gig workers manage their time and resources. Ai et al. (2023) explored the effect of team formation on workers' performance. Additionally, Xu et al. (2023) highlighted the implications of earnings, ratings, and penalties on gig workers' motivation and job satisfaction. The broader impacts of the gig economy have also been studied, with Burtch et al. (2018) examining the effects of Uber's entry into the U.S. market on entrepreneurial activity, and Gong et al. (2017) assessing how Uber's presence in China correlates with new vehicle ownership. Shin et al. (2023) discussed the interplay between ride-sharing services and restaurant quality. Norris and Xiong (2023) demonstrated that ride-sharing technology leads to significant and substantial growth in the consumption industries. Regarding governance, Yu et al. (2017) advocated for moderate regulation, while Hu and Zhou (2020) discussed the potential benefits and costs of implementing a minimum wage for gig workers.

2.2.3 Responsible Operations

Our study also relates to responsible operations research (Netessine et al., 2022). While the environmental impact of firm operations is well-covered in the literature, the "social" aspect of responsible operations research has received less attention from scholars and businesses (Dai and Tang, 2022).

Research on the "social" or human aspects often examines the impact of diversity and inclusion initiatives (e.g., race, gender, and disability) on firm operations and how to align firm incentives with achieving both efficiency and social responsibility (Deshpande and Swaminathan, 2020). For instance, Narayanan and Terris (2020) studied the impact of the number of disability categories and the evenness of disability category dispersion among workers in an apparel production line on the productivity of apparel manufacturing teams, and found that having moderate levels of disability categories on a team with higher levels of evenness in disability category dispersion is associated with better productivity. Plambeck and Ramdas (2020) provided a comprehensive overview of opportunities and innovative business models that empower women and alleviate poverty. Lee and Tang (2018) introduced a project named "Men on the Side of the Road" from South Africa in 2003, which successfully achieves socially responsible practices. The project provides education and skill

development, as well as necessary facilities (such as rest locations with water and toilets) for over 100,000 day laborers (mostly men) who stand by the roadside hoping to find odd jobs to survive. It also conducts background and reference checks for both labor suppliers and customers to ensure a safe working environment. This project has helped place over 6,500 workers for over 120,000 work days by 2008, and got into the finalist of BBC World Challenge Award in 2005.

To our knowledge, there is little literature concerning the impact of heat hazards on the well-being of gig economy workers, particularly those involved in the food delivery process. We aim to clearly visualize the harm caused by climate change and provide new policy guidance and governance implications for on-demand platforms. Our findings not only advance academic discourse but also offer practical insights for business leaders looking to balance operational efficiency with the well-being of gig workers, crucial for long-term sustainability in the gig economy.

2.3 Hypotheses Development

During heatwaves, people tend to reduce outdoor activities and minimize their exposure to the heat. As a result, services that help consumers achieve these goals become particularly popular. On-demand food delivery platforms effectively meet this need, with both new and existing users more likely to place orders when outdoor temperatures rise. Some customers may even pool their orders. Consequently, we often see a surge in online demand for food delivery services and an increase in food expenditure per order. This surge can boost potential earnings for couriers, who are often sensitive to income opportunities, motivating them to work during hot weather periods despite the natural inclination to stay indoors when temperatures soar.

Hypothesis 1: *Gig couriers are more inclined to work during heatwaves.*

The surge in online demand for food delivery services during hot weather presents significant challenges to the platform's daily operations. A distinct feature of food delivery services is the uneven distribution of workload, with couriers being busiest during meal times and relatively idle during non-meal periods. Balancing staffing levels with operating costs becomes particularly complex under uncertain weather conditions (Lu and Lu, 2017). Maintaining high service quality is essential for a food delivery platform, but this requires careful staffing decisions and proper training for new hires, who may vary in attitudes and aptitudes (Benson et al., 2020). Over-recruiting couriers not only increases training costs but also intensifies competition among gig workers, reduc-

ing their income and making the platform less appealing to high-performing couriers. Conversely, under-recruiting leads to excessive workloads and potential delays, which can harm the platform's reputation and future demand (Mao et al., 2019). Additionally, the time needed to recruit and train new couriers limits the platform's ability to respond swiftly to sudden spikes in demand.

The gig economy further complicates staffing planning, as gig workers, such as couriers, have the flexibility to choose their working hours and whether to work during hot weather (Huang et al., 2020; Allon et al., 2023). This added uncertainty creates operational challenges, often forcing the platform to rely on its existing workforce to manage surges in demand. As a result, couriers are tasked with handling more orders, leading to longer working time per courier.

Hypothesis 2: *Gig couriers receive and accept more orders during heatwaves.*

Hypothesis 3: *Gig couriers work longer time during heatwaves.*

The surge in online orders for food delivery during hot weather also increases process variability, as consumers have diverse preferences for restaurants and live in different locations (Benjaafar and Hu, 2020). These variations complicate route planning for individual couriers and extend the service time for each order, especially for those managing multiple orders simultaneously. The increased utilization of couriers, coupled with greater variability in both order arrivals and service times, leads to longer waiting time and more frequent delivery delays. These challenges are particularly pronounced during peak hours, such as lunchtime when temperatures are at their highest.

Hypothesis 4: *Gig couriers experience a higher rate of delivery delays during heatwaves.*

Couriers' hourly incomes are influenced by two primary channels. The first, more straightforward channel relates to the demand side. During hot weather, particularly on extremely hot days, consumers are more inclined to use food delivery services. They may either place orders independently or pool them with others. Consequently, both the number of orders and the food expenditure per order increase significantly, which positively impacts couriers' potential income.[13]

The second channel involves platform operations. If the platform is able to recruit more gig workers during hot weather, the increased supply of couriers may spread the food orders more thinly, potentially driving down couriers' hourly income due to increased competition among couriers. On the other hand, if the platform cannot recruit enough gig workers, it must increase the workload for

[13]Though the delivery fee earned by the courier is piece-wise independent of food price, the new customers from the pooling orders (orders of great food expenditure) can become the platform's long-term customer after the use of food service, thus bringing more orders and income for the platform as well as for the courier.

individual couriers. However, this increased utilization, along with the increased order variability, can lead to more frequent delivery delays. These inefficiencies can harm the platform's reputation, discourage consumer use, and ultimately reduce couriers' hourly income. To conclude, the impact of hot weather through this supply-side channel on couriers' hourly income would be negative. In Section 5.1, we illustrate which gig workforce scenarios are observed during our sample period. By doing so, we provide empirical support for the assumptions made about gig workforce dynamics under extreme weather conditions.

Given the uncertainty of weather conditions, the natural human response to hot weather, and the challenges in staffing planning, the impact of hot weather on couriers' income is complex, leading to the following two competing hypotheses:

Hypothesis 5a: *Gig couriers earn a higher hourly income during heatwaves.*

Hypothesis 5b: *Gig couriers earn an hourly income during heatwaves that is no higher than during regular weather.*

3 Data

3.1 Sample Description

We use two primary data sources in this study. The meal delivery data is obtained directly from an online food delivery platform, covering the two hottest months (July and August) in 2015 in two large cities in China: Shanghai and Hangzhou. This dataset records all customer orders, detailing the dynamics of each order with various timestamps, locations, and the parties involved in the meal delivery process. Specifically, the data includes timestamps for customer order placement, platform dispatch, cycle-rider receipt, meal pick-up, and order delivery. Additionally, we have information on the addresses of both restaurants and consumers, the total expenditure for each order, and the corresponding delivery fee earned by the food delivery couriers. For a more detailed explanation of platform operations and data information, see Mao et al. (2022).

The meteorological data is collected from the National Climate Data Center. This dataset provides hourly information on temperature, precipitation, relative humidity, wind speed, wind direction, and air pressure for each station in major cities. Shanghai has 11 stations, while Hangzhou has 8 stations. We use data from those stations within the coverage area of the meal delivery

services and reconstruct these meteorological variables based on the unit of analysis. Additionally, we supplement the main data with air quality variables, including hourly concentrations of PM2.5 and ozone for each city from the National Environmental Monitoring Center database.

The entire dataset includes 585,994 orders, 137,881 consumers, and 1,272 drivers. We reshape the data and construct three different samples to cater to the needs of various analyses: the courier sample, the consumer order sample, and the platform sample. Overall, we observe three key features from the dataset as shown in Figure 1: (1) the peak hours for meal delivery services are lunchtime between 11:00 am and 1:00 pm, and dinnertime between 5:00 pm and 7:00 pm; (2) there is significant variation in temperature, with a few extreme weather days during the sample period; and (3) the average number of couriers working each day remained relatively stable, despite the significant fluctuations in temperature. These features allow us to identify patterns and behaviors specific to gig couriers, particularly how they respond to varying environmental conditions. Table 1 provides the summary statistics for key variables used in this study.

3.2 Key Variables

3.2.1 Explanatory Variables: Heat Hazard

For the sake of the interests of this research, we use two heat-related variables, air temperature and heat index, to describe hot weather conditions. Air temperature is commonly used to describe the degree of heat in our daily life. In our sample, both cities experienced highly variable temperatures, with mean and maximum 28.6 and 39.1 degrees Celsius.

Nevertheless, what the temperature feels like to the body does not merely depend on air temperature. Relative humidity also plays a role, as it directly affects the evaporation of sweat. High moisture held in the air would slow down evaporation and make people feel warm. The NWS thus introduced a helpful heat index that converts air temperature and relative humidity into "feels like" temperature. We construct the heat index using the following formula, where T refers to air

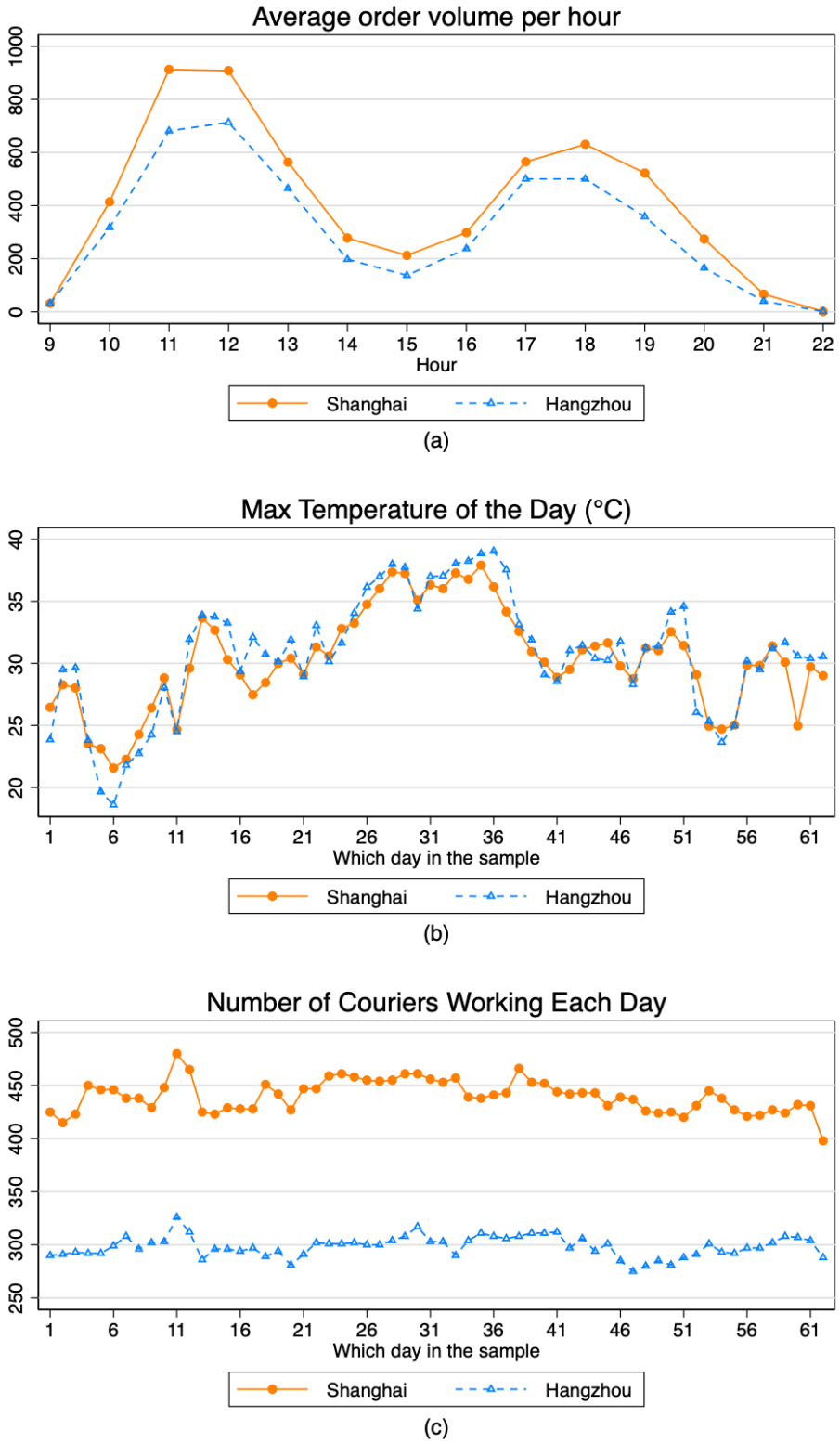


Figure 1. Pattern of Order Volume, Temperature, and Couriers

temperature measured by Fahrenheit and R relative humidity (measured by %).

$$\begin{aligned} Heat\ Index = &-42.379 + 2.04901523T + 10.14333127R - 0.22475541TR \\ &-6.83783 \times 10^{-3}T^2 - 5.481717 \times 10^{-2}R^2 + 1.22874 \times 10^{-3}T^2R \\ &+8.5282 \times 10^{-4}TR^2 - 1.99 \times 10^{-6}T^2R^2 \end{aligned}$$

The NWS utilizes a temperature and humidity matrix to classify the likelihood of heat-related disorders into various categories, including "danger" category and "extreme danger" category.[14] In our analysis, we adopt this classification to define a binary variable, *Heat Hazard*, which equals 1 if the heat index falls within the "danger" or "extreme danger" categories, and 0 otherwise. During this sample period, individuals experienced heat hazard conditions on 10.9% of the time (as shown in Panel B of Table 1). In this study, we use the *Heat Hazard* measure as the key explanatory variable to illustrate the impact of dangerous heat. Additionally, we employ an alternative continuous measures, air temperature, as a similar indicator for hot weather, as discussed in Section 4.2.

3.2.2 Courier Performance Measures and Income

We use four variables to measure courier performance and income: received orders, working time, delay, and hourly income.

The number of received orders is measured by the count of delivery orders an individual courier received and also executed in an hour. Here, we use the couriers' time of arrival at the restaurant as the reference point to calculate order volume for a courier within a given hour. This approach helps exclude canceled orders, ensuring that the analysis only reflects successful transactions and provides a more accurate representation of courier activity during that time frame.

Working time is defined as the total time a courier spends on service tasks within an hour, which may include completing multiple deliveries. This measure captures the cumulative time a courier is actively engaged in the delivery process during the specified time period.

We also calculate the proportion of delayed orders among all orders completed by a courier in a given hour. This metric provides insights into the operational efficiency of an courier under varying conditions, allowing us to assess the impact of factors such as heat hazards on delivery

[14] Please see this link for more information about the heat index: https://www.weather.gov/ama/heatindex.

performance.

Besides, we measure a courier's hourly income using the amount of money he earned during a specific hour. It is worth noting that delays may lead to consumer complaints or dissatisfaction, which could negatively affect customer retention on the platform. This, in turn, could have an indirect impact on couriers' future hourly income, as reduced customer satisfaction may result in fewer orders or lower tips for couriers over time (Mao et al., 2019).

Table 1. Summary Statistics

Variable	Definition	N	Mean	SD	Min	Max
Panel A: Courier Sample (at courier-hour level)						
Work	If a courier works during a specific hour = 1; otherwise = 0.	628,244	0.557	0.497	0	1
Number of orders	The number of orders a courier receives and accepts during a specific hour.	349,985	1.740	0.867	1	9
Work minutes	The number of minutes a courier works during a specific hour.	349,285	41.715	15.076	0.017	60
Delay ratio	The proportion of delayed orders among all orders received by a courier during a specific hour.	348,025	0.262	0.393	0	1
Income	The income earned by a courier during a specific hour.	349,984	10.910	5.481	5	52
Panel B: Platform Sample (at city-hour level)						
Order volume	The total number of delivery orders in a city during a specific hour.	1,619	377.104	262.746	1	1,100
Throughput time	The duration between placing an order and receiving the ordered meal.	1,619	33.590	7.003	20.917	80.800
Variability	$CV_a^2 + CV_p^2$	1,586	5.143	3.082	0.587	16.717
Delay ratio	The proportion of delayed orders among all orders in a city during a specific hour.	1,619	0.237	0.183	0	1
Heat Hazard	Heat index falls within danger or extreme danger categories = 1; otherwise = 0.	1,619	0.109	0.311	0	1
Temperature	The temperature in a city at a specific hour.	1,619	28.584	4.251	17.543	39.050
Panel C: Consumer Order Sample (at order level)						
Food expenditure	The food expenditure of this delivery order.	585,994	57.931	44.608	1	267
New customer	Whether this customer is a new customer, new=1, otherwise=0.	585,994	0.416	0.493	0	1
Food expenditure next 7 days	The food expenditure of this customer in the 7 days following this order.	538,166	127.898	228.732	0	4,587.200
Number of orders next 7 days	The total number of orders placed by this customer in the 7 days following this order.	538,166	2.624	5.292	0	127

As shown in Panel A of Table 1, the average orders a courier received in an hour is 1.7 with maximum 9 orders. The average working time is 41.7 minutes per hour and the probability of delay is 26.2%. However, during the hot summer, couriers' average hourly income is only 10.9

RMB, which is approximately 1.5 USD per hour.

3.2.3 Platform Performance Measures

We use four variables to measure the system performance of the meal delivery platform: order volume, throughput time, variability, and delays. Panel B of Table 1 reports the summary statistics for these variables. Order volume refers to the total number of orders placed by customers per hour in a city. We use the couriers' time of arrival at the restaurant as the reference point and calculate the total number of orders in each hour for each city. Hence, the order volume is measured at the city-hourly level. On average, there are 377 orders per hour per city in our sample. During the peak hours, the order volume reaches the maximum of 1,100.

Throughput time refers to the duration between consumer placing an order and consumer receiving the ordered meal. Using these time stamps, we calculate the average throughput time for orders placed in the same hour and in the same city. The average throughput time of this platform is 33.6 minutes per order.

We calculate variability as the sum of squares, $CV_a^2 + CV_p^2$, where CV_a is the coefficient of variation of interarrival time (representing the ratio of the standard deviation to the mean of the time intervals between orders placed by consumers in a specific city during a particular hour) capturing the variability from the demand side, and CV_p is the coefficient of variation of processing times (representing the ratio of the standard deviation to the mean of the service times for consumers in a specific city during a particular hour) capturing the variability from the supply side.

We also measure the service quality using the probability of delay. Here, delay ratio refers to the proportion of delayed orders among all orders within a specific hour in a city. The raw data suggests that 23.7% of the orders are delayed in delivery.

3.2.4 Measures on Consumer Responses

By examining the details of customer orders, we describe customer responses using two sets of variables. The first set captures customers' immediate responses with the respect to heatwave. The first variable is food expenditure per order, which is recorded in the meal delivery dataset and reflects the cost of the food. The second variable identifies whether the customer is new or existing, with new customers defined as those placing an order on the platform for the first time (coded as

1 for new customers and 0 for existing ones). On average, customers spend 57.9 RMB per order, with new users accounting for 41.6% of the total order volume (see Panel C of Table 1).

The second set of variables measures customers' future responses based on the current order's delivery service. The first is the total food expenditure in the 7 days following a given order, with an average of 127.9 RMB. The second is the total number of orders placed by a customer in the 7 days following a specific order, with an average of 2.6 orders.

3.2.5 Control Variables

In the regressions, we concern that other environmental factors may also affect consumer decisions and platform/courier performance and hence control for weather conditions such as precipitation, wind speed, wind direction, and air pressure, as well as air quality variables such as hourly concentrations of PM2.5 and ozone. In the courier regressions, we also control for some time-varying courier characteristics such as daily earnings till now.

3.3 Model-free Evidence

Figure 2 provides model-free evidence of the relationship between air temperature and courier performance. The X-axis represents the temperature, while the Y-axis in the eight panels represents the number of orders, working time, the probability of delays, and hourly income. The four panels in the left column show the situation in Shanghai, while the four panels in the right column show the situation in Hangzhou. Overall, the relationships between temperature and performance metrics are consistent across both cities. This suggests that the impact of heat on gig workers' performance is not city-specific but rather a broader trend that can be generalized across different urban environments with similar climate conditions.

We begin by using binned scatter plots to demonstrate the correlation between temperature (measured by Celsius) and couriers' operational performance. Figure 2a and Figure 2b show an upward slope between temperature and the number of orders executed by couriers, indicating that couriers receive more consumer orders in hot weather compared to cooler conditions. Figure 2c and Figure 2d demonstrate the positive correlation between temperature and couriers' working time, showing that couriers tend to work longer in extremely hot weather. Figure 2e and Figure 2f depict the relationship between temperature and the proportion of delayed orders. The raw

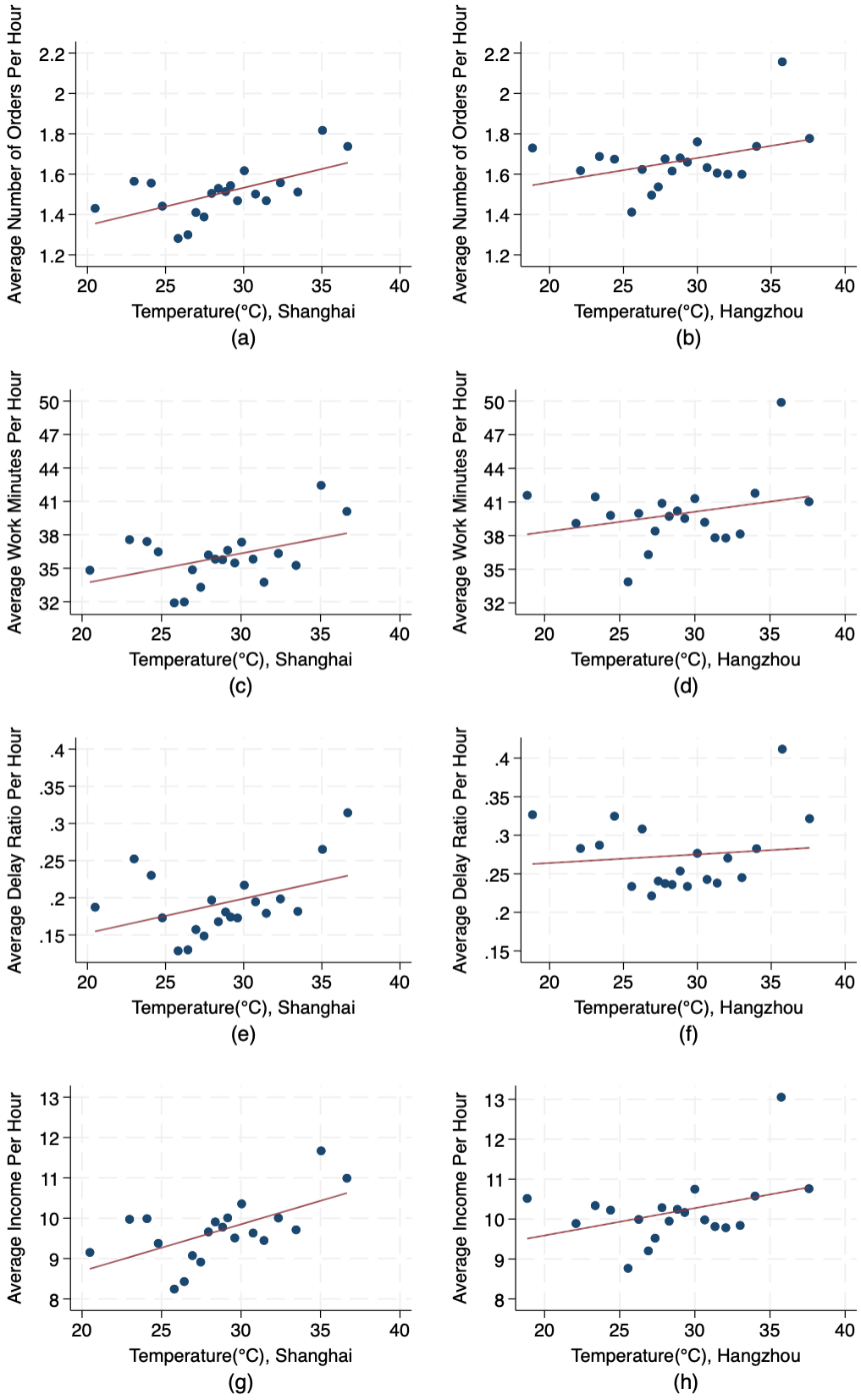


Figure 2. Relationship between Air Temperature and Courier Performance

data indicates that couriers are more likely to experience delays in hot weather, largely due to the increased workload. Interestingly, this pattern is most evident in Shanghai. A possible explanation for the weaker correlation in Hangzhou could be that lower temperatures in this city are often accompanied by rainfall, which consistently leads to delivery delays. When we exclude observations with temperatures below 25°C, we still observe a positive correlation between higher temperatures and the likelihood of delays.

Finally, we investigate the correlation between temperature and couriers' hourly income. Figure 2g and Figure 2h illustrate the positive relationship between air temperature and couriers' hourly income. This income is affected by delivery fees, the number of orders completed, and possible penalties for complaints due to delays. Although high temperatures generally increase couriers' hourly income, this gain can be offset by potential losses resulting from delays. For example, previous delays may reduce a consumer's willingness to use the food delivery service, thereby negatively impacting future income (Mao et al., 2019).

4 Empirical Analysis: Heat Hazard Impact on Courier Performance

In this section, we first introduce our baseline estimation model and then analyze the impact of heat hazard on couriers' performance using courier-hour level data. Additionally, we present the results of the heterogeneity analysis.

4.1 Estimation

We are interested in studying the impact of high temperatures on couriers' performance. Similar to most of the literature that treats temperature as exogenous (e.g., Deschênes and Greenstone, 2007; Brodeur and Nield, 2018), endogeneity issues such as reverse causality and omitted variables are less concerning in our study. It is unlikely that couriers significantly impact temperature levels, and there are few variables that would simultaneously affect both temperature and courier behavior. However, high temperatures may influence their work decisions. If a courier does not work during a specific hour, we cannot observe their performance, leading to a sample selection issue. To address this sample selection bias, we use the Heckman two-step model (Heckman, 1979). First,

we estimate the decision to work across all couriers using a probit regression. Then, we estimate the performance of couriers who chose to work during a given hour using an ordinary least squares (OLS) regression.

We model the two steps of courier decisions, $Work_{ict}$ and $Performance_{ict}$, of courier i working in city c at time t as follows:

$$Performance_{ict} = \begin{cases} Performance^*_{ict}, \text{ if } Work_{ict} = 1 \\ \text{unobserved, otherwise} \end{cases} \tag{1}$$

$$Work_{ict} = \begin{cases} 1, \text{ if } Work^*_{ict} > 0 \\ 0, \text{ otherwise} \end{cases} \tag{2}$$

$$Work^*_{ict} = \alpha_0 + \alpha_1 HeatHazard_{ct} + \boldsymbol{\alpha X_{ict}} + v_{ict} \tag{3}$$

$$Performance^*_{ict} = \beta_0 + \beta_1 HeatHazard_{ct} + \boldsymbol{\beta Z_{ict}} + u_{ict} \tag{4}$$

$$\begin{bmatrix} \sigma_v^2 \\ \sigma_u^2 \end{bmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho\sigma_u \\ \rho\sigma_u & \sigma_u^2 \end{bmatrix} \right) \tag{5}$$

The two steps that we estimate are given by:

$$P(Work_{ict} = 1 | \boldsymbol{X_{ict}}) = \Phi(\alpha_0 + \alpha_1 HeatHazard_{ct} + \boldsymbol{\alpha X_{ict}}) \tag{6}$$

$$f(Performance_{ict}) = \beta_0 + \beta_1 HeatHazard_{ct} + \boldsymbol{\beta Z_{ict}} + \theta\lambda_{ict} + u_{ict} \tag{7}$$

where $\Phi(\cdot)$ is the normal cumulative distribution function (c.d.f.) and λ_{ict} is the inverse Mills ratio (IMR) calculated from the predicted probability in Equation (6). Thus, we essentially estimate a probit model for the work decision in Equation (6) and compute the IMR for each observation. We then fit an OLS model of the (transformed) performance conditional on all covariates and the IMR (Equation (7)), while controlling for the couriers who worked. The estimated coefficient θ will potentially confirm the existence of a sample selection bias.

In the first step of our analysis, we incorporate heat hazard, air quality, atmospheric pressure, wind speed, rainfall, wind direction, hourly rate, daily income earned so far, and daily working

hours so far as instruments. Building on Allon et al. (2023), we consider daily income earned so far and daily working hours so far as additional variables for the working decision, as they might not significantly impact couriers' performance in the following hour.

The results shown in Appendix Table A2 reveal some intriguing patterns. For instance, we find that couriers often choose to work even in unfavorable heat conditions (supporting hypothesis 1), potentially compromising their health, driven by the prospect of increased income from a surge in orders. Interestingly, income earned since 9 o'clock in the morning has a negative effect on the decision to continue working. This aligns with the target income theory (Sweeney, 1982), which suggests that couriers have daily earnings goals. Once their cumulative income approaches or meets their target, they may reconsider whether to keep working, particularly during extremely hot periods. Further, they are inclined to work throughout the day once they decide to start in the morning. These two findings are consistent with Allon et al. (2023), in which the working decision of ride-hailing drivers is negatively impacted by the income earned so far but positively affected by accumulated working hours so far. However, different from Allon et al. (2023) that a higher hourly income increases the probability of working, we observe that hourly rate does not affect couriers' decision to work, which possibly because the hourly rate is fixed across hours in this platform. All of these results are consistent when we change the heat hazard measure to air temperature.

4.2 Main Results

We are interested in understanding how hot weather affects couriers' well-being. In this section, we examine the impact of heat hazard on couriers' operational performance and their corresponding income. Specifically, we analyze operational performance from three perspectives: the number of orders received, working time, and the probability of delivery delays. Using courier-hour level data, we estimated the Heckman two-step model. In Equation (7), we control for various variables, including PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level, as well as a set of fixed effects (month, day of the week, hour, and courier) and account for the IMR, which is obtained from the first-step estimation.

We present the results in Table 2. The columns in Panel A use *Heat Hazard* as the explanatory variable to assess the impact of extreme heat on couriers' operational performance and income, highlighting how couriers without adequate protection respond to dangerous hot weather. In Panel

B, we replace *Heat Hazard* with air temperature to confirms the robustness of our main findings, ensuring they are not influenced by the transformation of temperature measures.

Table 2. Impact on Couriers' Operational Performance and Income

Variable	(1) Number of orders	(2) Work minutes	(3) Delay ratio	(4) Income
Panel A				
Heat Hazard	0.158***	2.501***	0.057***	0.934***
	(0.020)	(0.328)	(0.010)	(0.118)
IMR	-0.398***	-18.317***	-0.156***	-2.301***
	(0.072)	(1.566)	(0.046)	(0.461)
R-squared	0.302	0.429	0.189	0.270
Panel B				
Temperature	0.018***	0.291***	0.007***	0.110***
	(0.002)	(0.041)	(0.001)	(0.014)
IMR	-0.405***	-18.653***	-0.162***	-2.332***
	(0.070)	(1.519)	(0.045)	(0.453)
R-squared	0.301	0.429	0.190	0.269
Observations	349,985	349,284	348,025	349,984
Control Variables	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
Courier FE	YES	YES	YES	YES
Mean of dept. var.	1.740	41.71	0.262	10.91

Notes. For regressions in Panel A, control variables include PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level. For regressions in Panel B, in addition to the variables already controlled for in Panel A, relative humidity is also included. Standard errors in parentheses are calculated by clustering at city-hour level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

The results shown in Table 2 deliver two important messages. First, all the coefficients of IMR are significant, indicating the presence of sample bias and supporting the appropriateness of using the Heckman two-step model instead of the basic OLS model. Second, the results demonstrate that heat hazard significantly impacts various aspects of a courier's performance and income during the summer.

Extremely hot weather leads to an increase in the number of orders couriers received. As shown in Column (1) of Panel A on the number of orders a courier receives and accepts in an hour, the coefficient of *Heat Hazard* is 0.158, which is positive and significant at the one percent level. This suggests that couriers tend to accept 9.1% more orders on hours with dangerous heat compared to hours when the temperature poses less risk to the health of couriers with limited protection from heat hazards. Similarly, as shown in Panel B, the coefficient of temperature is positive and

significant (0.018), suggesting that a one standard deviation increase in temperature leads to a 4.4% increase in the number of orders received per hour on average. This increase in received orders is largely driven by the rise in consumer online demand for offline delivery due to hot weather.

This higher demand naturally extends couriers' working time. As shown in Column (2) of Panel A, the coefficient of *Heat Hazard* is 2.501 at the one percent significance level, indicating a 6% increase in couriers' total working time per hour during extremely hot weather. In Panel B, the temperature coefficient for working time is 0.291, also positive and significant at the one percent level. For a one standard deviation increase in temperature, a courier's working time increases by 3% per hour on average. The increase in orders significantly boosts courier utilization, which in turn increases consumer waiting times.

We also examined whether hot weather affects the probability of delivery delays by couriers. As shown in Column (3) of Panel A, the proportion of delayed orders increased by 21.8% (=0.057/0.262) when the hot weather conditions are classified as "danger" or "extreme danger". The results in Panel B confirm this pattern, showing that a one standard deviation increase in temperature raises the chance of delivery delays by 11.4% on average.

Finally, we investigated whether couriers receive higher compensation for working during extremely hot hours. As previously mentioned, couriers' income is influenced by delivery fees, the number of completed orders, and other factors. The results in Column (4) of Panel A show a positive and significant coefficient of 0.934, indicating an 8.6% increase in hourly income during dangerous hot weather compared to regular time periods. Although the heat hazard leads to a 9.1% increase in the number of orders received and accepted shown in Column (1), the rise in hourly income is slightly lower than the increase in workload. We suspect that the higher incidence of delays may negatively impact couriers' income, offsetting some of the gains from the increased order volume. In Section 5.2.2, we present evidence to support this conjecture. Additionally, the results in Panel B reassure a positive and significant correlation between temperature and income.

In summary, couriers' operational performance and income are significantly affected by heat hazard. During extremely hot hours, they receive more orders, have less idle time, and experience more delays, which supports hypothesis 2, hypothesis 3, and hypothesis 4 separately. Despite these challenges, their earnings are higher during hours classified as "danger" or "extreme danger" compared to hours with temperatures that pose less risk to their health, supporting hypothesis 5a.

4.3 Robustness Checks

Our results remain robust when we use alternative methods (i.e., OLS) and alternative measures (i.e., heat index). We report the results of these robustness checks in Appendix Table A3 and Table A4. Moreover, a small number of couriers join or leave the platform each day. To account for the potential impact of fluctuations in the number of couriers on our results, we control for the number of couriers working in a given city during each specific hour in the second-step estimation. The results, presented in Table A5, remain consistent with those in Table 2.

4.4 Heterogeneity Analyses

We perform two sets of heterogeneous analyses by applying the same Heckman two-step model in this subsection. Specifically, we analyze the heterogeneous effects (1) from peak versus non-peak hours, and (2) from experienced versus inexperienced couriers.

4.4.1 Peak versus Non-peak Hour

Panel A of Table 3 presents the result of the analysis on heterogeneous effects during peak versus non-peak hours. Peak hours are defined as meal times in China, specifically from 11:00 to 13:00 and 17:00 to 19:00 each day. We create a binary variable (referred to as "peak hour" in Panel A of Table 3) that takes the value of 1 for observations during these peak hours, and 0 for other time slots. We include the interaction term between this binary variable and *Heat Hazard* in Equation (7). Since we control for hour fixed effects, the peak hour variable itself is absorbed by these time fixed effects.

The results in Panel A of Table 3 indicate that, compared to non-peak hours, hot weather conditions during peak hours lead to couriers accepting more orders, working longer time, having a higher likelihood of delays, and earning more money. It is easy to understand that couriers are more likely to be fully occupied when the food orders surge in a short time (i.e., peak hours), and it can lead to more delays due to the congestion of food orders exceeds the limit of couriers' capacity. These results remain robust when the heat hazard is replaced with air temperature. See the relevant results in Panel A of Table A6.

Table 3. Heterogeneity Analyses

Variable	(1) Number of orders	(2) Work minutes	(3) Delay ratio	(4) Income
Panel A				
Heat Hazard × Peak Hour	0.146***	1.632***	0.043***	0.881***
	(0.028)	(0.494)	(0.015)	(0.163)
Heat Hazard	0.063***	1.441***	0.029***	0.361***
	(0.017)	(0.355)	(0.010)	(0.105)
IMR	-0.481***	-19.238***	-0.180***	-2.798***
	(0.073)	(1.568)	(0.047)	(0.463)
Observations	349,985	349,284	348,025	349,984
R-squared	0.302	0.429	0.190	0.270
Mean of dept. var.	1.740	41.71	0.262	10.91
Panel B				
Heat Hazard × Experience	0.697***	2.668	0.010	3.933***
	(0.127)	(2.061)	(0.060)	(0.808)
Heat Hazard	-0.021	2.085***	0.073***	-0.084
	(0.026)	(0.497)	(0.015)	(0.164)
Experience	0.236***	1.116	-0.023	1.278***
	(0.052)	(1.021)	(0.032)	(0.311)
IMR	-0.368***	-15.836***	-0.034	-2.616***
	(0.110)	(2.820)	(0.085)	(0.750)
Observations	45,555	45,337	45,128	45,555
R-squared	0.251	0.422	0.211	0.231
Mean of dept. var.	1.606	42.47	0.353	10.03
Control Variables	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
Courier FE	YES	YES	YES	YES

Notes. Control variables include PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level. Standard errors in parentheses are calculated by clustering at city-hour level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

4.4.2 Experienced versus Inexperienced Couriers

Panel B of Table 3 presents the result of the analysis on heterogeneous effects arising from courier experience. Because we cannot observe when a courier joined the platform, we construct the experience variable by considering couriers who appeared within the first seven days of our data as those who likely joined before our sample period. We exclude these couriers from our analysis and focus only on those who first appeared after the initial seven days of our sample. For these couriers, we calculate the number of orders they had completed by a specific hour on a specific day to reflect their experience.[15] We include the interaction term between this experience variable and *Heat Hazard* in Equation (7).

[15] We standardize the experience variable to a range between 0 and 1, and include it in regression Equation (7).

The results in Panel B of Table 3 indicate that, compared to less experienced couriers, those with more experience are able to complete more number of orders and earn more amount of money in the same time and with a similar probability of delay under hot weather conditions. These results remain robust when the heat hazard is replaced with air temperature. See the relevant results in Panel B of Table A6. These findings support the conventional wisdom that experience enhances efficiency and helps workers perform better in challenging conditions (Lin et al., 2023).

5 Mechanism Discussion and Extension

In this section, we explore how the entire food delivery platform operates and how consumers' eating behaviors change under these extreme weather conditions. By understanding these dynamics, we can gain insights into the operational decisions/performance, workload, and earnings that couriers experience during periods of intense heat.

5.1 Platform Operations during Heat Hazards

In this subsection, we analyze the impact of heat hazard on platform performance. Namely, we are interested in understanding how extreme heat affects consumer demand and courier delivery efficiency from the platform ecosystem perspective. The regression model of the primary interests is as follows:

$$Performance_{ct} = \beta_0 + \beta_1 HeatHazard_{ct} + \boldsymbol{\beta W_{ct}} + \theta_c + \mu_t + \varepsilon_{ct} \tag{8}$$

where $Performance_{ct}$ refers to the platform performance measures including order volume, throughput time, process variability, and delays at time t in city c. $HeatHazard_{ct}$ denotes the extreme heat in city c at hour t. $\boldsymbol{W_{ct}}$ accounts for other environmental conditions such as PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level. We include city fixed effects (θ_c) and a set of time fixed effects (μ_t) in our regression model. Specifically, μ_t includes fixed effects for hour, day of the week, and month to absorb all the unobserved factors that vary uniformly across these periods. ε_{ct} is the random error term and standard errors are clustered at the city-day level to control for any potential serial correlation within a single city-day unit. The unit of observation is at the city-hour level.

Table 4. Platform Performance

Variable	(1) Order volume	(2) Throughput time	(3) Variability	(4) Delay ratio
Panel A				
Heat Hazard	69.024***	2.494***	0.641***	0.050***
	(9.697)	(0.532)	(0.122)	(0.013)
R-squared	0.934	0.680	0.894	0.676
Panel B				
Temperature	7.222***	0.226***	0.073***	0.006***
	(1.309)	(0.083)	(0.015)	(0.002)
R-squared	0.933	0.677	0.894	0.677
Observations	1,619	1,619	1,586	1,619
Control Variables	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Mean of dept. var.	377.1	33.59	5.143	0.237

Notes. For regressions in Panel A, control variables include PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level. For regressions in Panel B, in addition to the variables already controlled for in Panel A, relative humidity is also included. Standard errors in parentheses are calculated by clustering at city-day level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

We analyze the effects of hot weather on several key performance measures, including order volume, throughput time, process variability, and delay ratio. The results shown in Table 4 indicate that hot weather correlates with more consumer orders, longer throughput time, greater process variability, and more delays. Specifically, during periods when the heat index falls within the "danger" or "extreme danger" category, the hourly order volume per city increases by 18.3% compared to hours below the heat safety cutoff. Additionally, throughput time per order increases by 7.4%, process variability sharply increases by 12.5%, and the ratio of delayed orders rises by 21.1% on average.

These results remain robust when replacing the heat index with air temperature, further supporting the idea that extreme heat negatively affects operational efficiency. Notably, our findings align with the assumption that heatwaves do not attract a significant influx of new gig workers. During our sample period, Shanghai and Hangzhou saw an average of just 4.1 and 3.3 new couriers joining each day, respectively. This means that new couriers accounted for only 0.57% and 0.61% of the total workforce in these cities, underscoring the limited entry of new gig labor during periods of extreme heat. Correspondingly, the average number of couriers resigning each day accounted for

0.50% and 0.65% of the total workforce in Shanghai and Hangzhou, respectively. Overall, the total number of gig workers remained relatively stable despite substantial fluctuations in temperature. As a result, platforms must rely on their existing workforce, increasing the workload and utilization of individual couriers to meet the surge in demand.

In summary, during periods of heat hazard, order volume significantly increases, benefiting the platform with higher revenue compared to hours with normal weather. However, this surge in orders also raises the utilization of individual couriers and increases process variability. As a result, couriers may experience burnout and face more frequent delays in deliveries. The platform-level results further support our main findings that extreme heat leads to longer working hours for couriers under hazardous conditions and results in more delays.

5.2 Consumer Responses to Heatwaves

5.2.1 Do Heatwaves Increase Consumers' Use of Food Delivery Services?

In this subsection, we use order-level data and analyze the impact of hot weather on consumer responses. Specifically, we aim to understand whether extreme heat impacts consumer spending and attracts new consumers to use the food delivery services. The regression model of the primary interests is as follows:

$$Response_{jirct} = \beta_0 + \beta_1 HeatHazard_{ct} + \boldsymbol{\beta W_{jirct}} + \epsilon_{jirct} \tag{9}$$

where $Response_{jirct}$ refers to the consumer response measures including food expenditure and new customer acquisition. This food delivery order was placed by consumer j at time t from restaurant r in city c, and delivered by courier i. $HeatHazard_{ct}$ denotes a binary variable representing heat index in city c at hour t. It equals 1 if the heat index falls into the "danger" or "extreme danger" category, and 0 otherwise. $\boldsymbol{W_{jirct}}$ accounts for other environmental conditions such as PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level. $\boldsymbol{W_{jirct}}$ also includes the straight-line distance between the customer and restaurant locations. Since we use order-level data, we include courier fixed effects, restaurant fixed effects, and a set of time fixed effects (fixed effects for hour, day of the week, and month) in our regression model. ϵ_{jirct} is the random error term and standard errors are clustered at the city-hour level to

control for any potential serial correlation within a single city-hour unit.

Table 5. Consumer Responses

Variable	(1) Food expenditure	(2) New customer	(3) Food expenditure	(4) New customer
Heat Hazard	1.212***	0.069***		
	(0.257)	(0.012)		
Temperature			0.161***	0.033***
			(0.032)	(0.001)
Observations	585,994	585,994	585,994	585,994
R-squared	0.349	0.119	0.349	0.144
Month FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
Courier FE	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES
Mean of dept. var.	57.93	0.416	57.93	0.416

Notes. In Columns (1) and (2), control variables include PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level, as well as the straight-line distance between the customer and restaurant for each order. In Columns (3) and (4), in addition to the variables already controlled for in the first two columns, relative humidity is also included. Standard errors in parentheses are calculated by clustering at city-hour level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 5 presents the OLS estimation results using order level data to estimate Equation (9). The results in Column (1) suggest that consumers tend to spend 2.1% more per order on food during periods of dangerously hot weather. This increase in expenditure per order indicates that consumers, including some who may not typically use the platform, are likely pooling orders together during these extremely hot periods. Additionally, as shown in Column (2) the probability of a consumer being a new user increases by 16.6% due to the heatwaves. The results remain robust when we replace the heat hazard measure with air temperature in Columns (3) and (4).

In summary, we analyze consumer order-level data to assess the impact of heat hazards on consumer behavior in using food delivery services. The analysis shows that more consumers join the platform and spend more on orders during periods of extreme heat. This evidence, along with the aforementioned increase in the platform's order volume, supports our main findings that couriers receive more orders and earn higher income during these heatwave periods, making them more likely to work during extreme heat conditions.

5.2.2 Do Delays in Extreme Heat Significantly Discourage Consumers?

In this subsection, we examine the potential impact of delays on consumer behavior during heatwave periods. Specifically, we assess how these delays affect food expenditure and the number of orders in the subsequent seven days. The specification of interest is outlined as follows.

$$Y_{jirct} = \beta_0 + \beta_1 HeatHazard_{ct} + \beta_2 Delay_{jirct} + \beta_3 HeatHazard_{ct} \times Delay_{jirct} + \boldsymbol{\beta W_{jirct}} + \epsilon_{jirct} \quad (10)$$

We define a variable, $Delay_{jirct}$, which equals 1 if a delay occurred at the order level and 0 otherwise. We then aggregate the expenditure and number of orders for each specific consumer over the following 7 days, using these as the dependent variables, Y_{jirct}. The interaction term between $HeatHazard_{ct}$ and $Delay_{jirct}$ captures the impact of delays during periods of extreme heat. All other variables remain consistent with those in Equation (9).

The results presented in Table 6 highlight the heterogeneous effects of heat hazards based on whether consumers experience delays. Consistent with Mao et al. (2019), delays discourage consumers from using food delivery services under normal weather conditions, with the coefficients indicating a 1.9% reduction in food spending and a 4.4% decrease in the number of orders in the subsequent seven days. This reduction due to delays, in turn, negatively impacts couriers' hourly income.

Moreover, our analysis reveals additional insights. First, hot weather seems to motivate consumers to continue using food delivery services in the following days. As shown in Columns (1) and (2), the coefficients for *Heat Hazard* are positive for 7-day food expenditure and the number of orders. More importantly, we find that delays occurring during periods of extreme heat may have a more severe impact on consumers' willingness to use food delivery services than delays during normal weather. Specifically, for consumers who experience delays during heat hazard periods, both food expenditure per order and the number of orders decrease significantly—by 5.5% and 4.8%, respectively—compared to those who experienced delays under normal weather over the following seven days. The results remain robust when we replace *Heat Hazard* with air temperature in Columns (3) and (4).

In summary, extremely hot weather encourages consumers to continue using food delivery services. However, the platform must avoid overburdening couriers and reduce delays during these hot

Table 6. Future Demand and Current Order's Delivery Outcome

Variable	(1) Food expenditure next 7 days	(2) Number of orders next 7 days	(3) Food expenditure next 7 days	(4) Number of orders next 7 days
Heat Hazard × Delay	-7.059***	-0.125***		
	(2.103)	(0.047)		
Heat Hazard	5.682***	0.117***		
	(1.640)	(0.036)		
Temperature × Delay			-0.433***	-0.009***
			(0.147)	(0.003)
Temperature			1.130***	0.026***
			(0.123)	(0.003)
Delay	-2.382***	-0.116***	9.053**	0.130
	(0.802)	(0.018)	(4.248)	(0.091)
Observations	538,156	538,156	538,156	538,156
R-squared	0.087	0.102	0.087	0.102
Month FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
Courier FE	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES
Mean of dept. var.	127.9	2.624	127.9	2.624

Notes. In Columns (1) and (2), control variables include PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level. In Columns (3) and (4), in addition to the variables already controlled for in the first two columns, relative humidity is also included. Standard errors in parentheses are calculated by clustering at city-hour level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

periods, as such delays have a more pronounced negative effect on consumers' willingness to use the services. As a result, when examining the courier's income (as well as platform's profitability), we shall always expect to see these seemingly conflicting two effects on consumer purchase behavior due to hot weather.

6 Back-of-the-Envelope Estimation of Health Costs

Exposure to heat hazards can lead to numerous potential losses, with health being a significant one. In this study, we highlight this potential health loss for couriers, which is often overlooked by couriers themselves, platforms, and policymakers.

As discussed in Section 2.2.2, a substantial body of literature has demonstrated the link between high temperatures and an increase in both mortality and morbidity rates. In particular, we find two crucial papers–Agarwal et al. (2021) and Li et al. (2023)–using Chinese data to estimate the impact of temperature on medical expenditure and health issues. These studies provide valuable insights

into how rising temperatures exacerbate health risks and increase healthcare costs, especially for individuals who work outdoors for extended periods, such as gig workers.

Agarwal et al. (2021) utilize a random sample of inpatient visit claims from the Urban Resident Basic Medical Insurance (URBMI) and Urban Employee Basic Medical Insurance (UEBMI) programs, covering 47 cities across 28 provinces in China. The dataset spans three years (2008-2010) and includes detailed information such as hospitalization admission dates, patients' ages and genders, diagnoses for each visit, and billing details.[16] Specifically, they define an extremely hot day as one with a daily average temperature higher than 27°C. It is found that compare with the outcome in the baseline temperature group (9°C-12°C), the hospitalization admissions increase by 7.3% and medical expenditure increases by 8.7% on extremely hot days. Hot weather is strongly related with diseases categories like infectious/parasitic, nervous system, digestive, endocrine, nutritional, and metabolic diseases and immunity disorders. Furthermore, Agarwal et al. (2021) conduct a cost analysis showing that the impact of temperature on medical bills related to inpatient services. We list some medical expenditures for both insurers and patients in Appendix Table A7.

Different from Agarwal et al. (2021), Li et al. (2023) focus on the impact of extreme temperature on the out-of-pocket medical expenditure. They use the data from China Family Panel Study (CFPS) Survey which covers 162 counties or districts (counties thereafter) across 25 mainland provinces that represent 95% of the total population in China for the years 2014, 2016, and 2018. By constructing 10 temperature bins ranging from lowering -12°C to above 32°C at 6°C increments, it is found that compared with the baseline (10°C-16°C), an additional day with temperatures in the 27°C–32°C range results in a 2.34% increase in out-of-pocket medical expenses, while a day of extreme heat, defined as a daily mean temperature exceeding 32°C, causes out-of-pocket medical expenses to rise by 2.80%. Similarly, they also find the impact of extreme heat (exceeding 32°C) are stronger for males (2.9% increase) and outdoor workers (3.44% increase). Their estimation shows that individuals have to pay at least 181.9 RMB for each extremely hot day (exceeding 32°C).

These two studies, Agarwal et al. (2021) and Li et al. (2023), depict the general picture of the impact of extreme temperature on medical expenditure in China. By utilizing their estimation results, we can roughly calculate the average (incremental) medical costs for each courier due to

[16]These billing details encompass total charges, reimbursed amounts by insurance, copayments made by the insured, and expenses not covered by the insurance schemes, which are self-funded by the insured.

extremely hot temperature during the sample period in our data. Specifically,

$$\text{(Increased) Medical Expenditure per Courier} = \text{Number of Hot Days} \times \text{Payment} \times \gamma$$

where *Number of Hot Days* is the number of days that daily average temperature exceeding 27°C, a benchmark used in Agarwal et al. (2021), or the number of days that the daily average temperature exceeding 32°C as documented by Li et al. (2023). There are 33 days for Shanghai and 32 days for Hangzhou (exceeding 27°C) during our sample period, and 7 days (exceeding 32°C) for two cities. *Payment* represents increased total bills (shown in Table A7) divided by the number of population, or the out-of-pocket expenditure shown in Li et al. (2023) that is 181.89 RMB for each extremely hot day (exceeding 32°C).

Specifically, γ is a scalar parameter reflecting the normalized exposure time to heat. Couriers, as outdoor workers, are exposed to high temperatures for extended periods (making γ larger), and have limited access to insurance. We estimate health costs under three different scenarios: (1) $\gamma = 1$, serving as the benchmark value commonly used in the literature, (2) $\gamma = 8.8$, which represents the average outdoor working hours of couriers exposed to heat, compared with normal workers who usually spend eight hours indoors; and (3) $\gamma = 8.8 \times (100 + 6)\% = 9.3$, indicating the extended working hours for couriers due to the surge in demand and increased variability on the platform caused by the heatwave. The increase of 6% is measured by Column (2) of Panel A in Table 2 reflecting the extended working time for each extremely hot day.

The results of the back-of-the-envelope estimation are shown in Table 7 with details can be found in Appendix. Specifically, the increase in total medical bill is based on Agarwal et al. (2021), and we provide the incremental expenses that would be incurred by both insurers and couriers themselves. While, self-fund expense is based on Li et al. (2023), which provides a more comprehensive estimation for the out-of-pocket payment made by couriers, since they may not be able to fully access to insurance. Moreover, as most of couriers are male, we list the expenditure for male, and also list the medical cost for diseases specifically related with heat hazard as documented in Agarwal et al. (2021).

These estimates highlight the significant medical costs couriers face from heat exposure. In the best-case scenario, where couriers have access to insurance, the total medical cost increase due to

heatwaves would amount to 250,580.9 RMB for 500 actively working couriers during the sample period, or approximately 501.2 RMB per courier. Notably, the health cost for male couriers is estimated to be 712.4 RMB per person, which is greater than the average cost.

However, for uninsured couriers, even with just seven days exceeding 32°C during the sample period in China, the out-of-pocket medical expenses could reach 11,876.4 RMB per courier or 16,876.4 RMB per male courier based on the estimates in Li et al. (2023). These figures underscore the substantial financial burden that heat exposure imposes on gig workers, particularly those without access to health insurance.

Table 7. Estimated Medical Expenditure Based on Our Data

	Benchmark ($\gamma = 1$)		Courier's Hours Exposed to Heat ($\gamma = 8.8$)		Courier's Increased Working Time ($\gamma = 8.8 \times 106\% = 9.328$)	
	Increased Total Bill (per 500 couriers)	Self-paid Expense (per courier)	Increased Total Bill (per 500 couriers)	Self-paid Expense (per courier)	Increased Total Bill (per 500 couriers)	Self-paid Expense (per courier)
Average	¥26,863.3	¥1,273.2	¥236,397	¥11,204.2	¥250,580.9	¥11,876.4
Male	¥38,185.3	¥1,809.2	¥336,030.6	¥15,921.2	¥356,192.5	¥16,876.4
Diseases	¥100,427.6	¥4,759.2	¥883,763.2	¥41,881.3	¥936,789.0	¥44,394.0

Notes. The "Increased Total Bill" columns are based on estimates from Agarwal et al. (2021), and the number of hot days is that of days exceeding 27°C, which is used in Agarwal et al. (2021). There are 33 days for Shanghai and 32 days for Hangzhou during our sample period. We use 32 days. The "Self-paid Expense" columns are derived from estimations in Li et al. (2023), and the number of hot days is that of days exceeding 32°C (as documented by Li et al. (2023)), which is 7 days in our data sample.

If we consider the impact of morbidity and medical expenses for couriers within the U.S. healthcare system, health costs can be substantial. For instance, White (2017) examined the link between temperature and hospital usage in California from 2005 to 2014, discovering that a day with temperatures over 80°F (approximately 27°C) is associated with a 3.5% immediate rise in emergency department (ED) visits, with a cumulative increase of 5.1% over 30 days. This results in hospital service costs amounting to 7,994 USD per 100,000 population. Applying these estimates to the couriers in our dataset, if they were exposed to similar conditions in the U.S., the estimated health cost would be 1,279 USD for 500 couriers under the benchmark scenario ($\gamma = 1$), 11,256 USD accounting for average heat exposure ($\gamma = 8.8$), and 11,931 USD for the extended working hours due to extreme heat ($\gamma = 9.3$) over our sample period, which includes 32 days of temperatures exceeding 27°C.

The figures we calculated above are based on estimations from past literature, our analysis, and temperature data from our sample period. While they provide valuable insights into the health costs faced by couriers due to heat exposure, these estimates are context-specific, and may vary across

different platforms or evolve over time within the same platform. Nevertheless, these estimates offer a valuable initial attempt to address an often-overlooked aspect of courier well-being—health costs. As online shopping and platform-based economies grow, attention has largely shifted towards efficiency and profitability, often neglecting the health-related costs that gig workers incur due to extreme weather conditions.

7 Conclusion

Heatwaves, intensified by global warming, substantially affect the operational performance and well-being of gig economy workers, especially food delivery couriers. Our study reveals that extreme heat conditions lead to an increase in delivery orders and extended working hours but also result in more delays and significant health risks for couriers. We use the "danger" or "extreme danger" categories of the heat index as indicators of extreme weather, labeled as *Heat Hazard* in our regression analysis. The heat index provides a more direct reflection of the risk of heatstroke or related harm compared to air temperature, as recognized by many organizations in China, the United States, and the United Kingdom.[17]

Our findings indicate that during extreme hot weather, couriers experience a 9.1% increase in accepted food orders per hour, and their working time extends by 6% per hour. Although this surge in orders results in a modest rise in courier income (an 8.6% increase in hourly income, amounting to less than 1 RMB), it also results in more delays (up by 21.8%) and greater exposure to heat hazards. Calculations based on medical studies and our data show that the additional medical expenses incurred per courier are at least 11,204.2 RMB over the two hottest months (July and August) in China of year 2015. Given the ongoing trend of global warming and the limited insurance protection available to gig workers (who are not officially classified as employees), current health costs are likely to be even higher.

Figure 3 illustrates the tension between income from work and health-related losses concerning couriers' well-being. Specifically, our findings indicate that extremely hot temperatures can significantly influence couriers' income through consumer ordering behavior, platform systems, and couriers' own utilization, each of which can positively or negatively impact income, and the results

[17] "All hot and bothered about Hong Kong's new heat warning system for workers? Here is what you need to know", assessed on Sep 7, 2024.

have been shown in Section 4 and Section 5. More importantly, health losses can be substantial if heat hazards lead to increased medical expenditures and/or higher rates of disease or mental discomfort, which is characterized by Section 6.

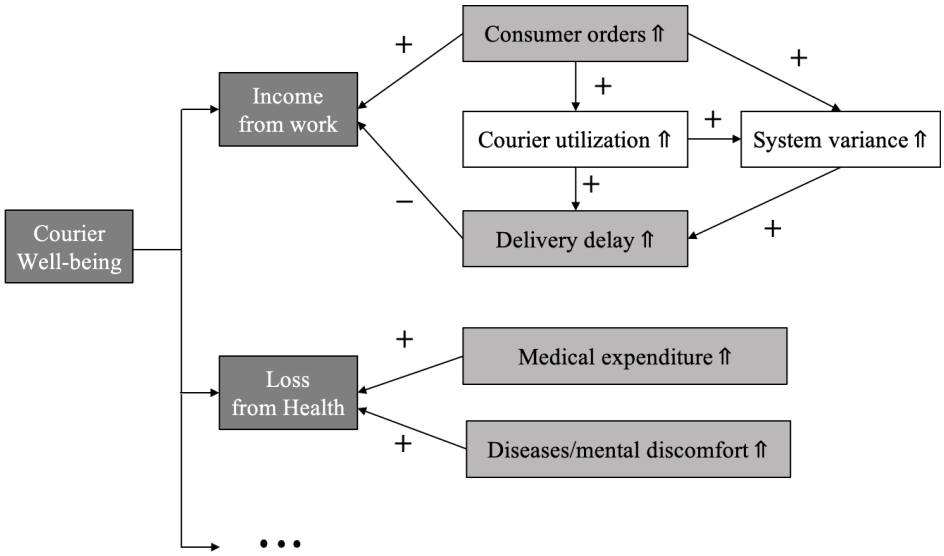


Figure 3. Mechanisms that Affect Courier Welfare with Extreme Heat

Our research highlights the disproportionate sacrifices that these workers make, often with insufficient protections, and calls on platforms to adopt more responsible practices and policies. Some major food delivery platforms in Asia, Europe, and the United States have recognized the risks of extreme heat and implemented measures to mitigate heat stress for couriers. For example, Grabapp has introduced a heatwave surcharge in Vietnam,[18] Meituan operates mobile catering vans in Shanghai and other cities in the Yangtze River Delta region, providing iced drinks, sunscreen outfits, and raincoats for couriers,[19] and Grubhub has partnered with e-bike rental platform JOCO to establish two indoor rest areas for delivery workers in New York City, offering access to occupational accident insurance and the RapidSOS app (which aids in sending location data during 911 calls).[20]

Despite these efforts, many platforms remain silent on the issue, as they classify food delivery couriers (mostly app-based) as independent contractors rather than employees, usually only offering advice like staying hydrated, using sunscreen, and taking cold showers.[21] This is a critical

[18] "Heatwave bonus for Asia's food delivery drivers does little to keep them safe", assessed on Sep 7, 2024.
[19] "Platforms, online retailers unite to help delivery staff beat the summer heat", assessed on Sep 7, 2024.
[20] "NYC's food delivery workers are sweltering in the heat — and demanding more protection", assessed on Sep 7, 2024.
[21] "Hot, bothered and precariously employed: Life as an app courier in extreme heat", assessed on Sep 7, 2024.

concern, as the "social" dimension, a key pillar of ESG criteria, has been overlooked in management and operations fields. Ignoring the risks and welfare of gig workers could result in high turnover rates, absenteeism, or decreased engagement. A survey conducted by Harvard Kennedy School and UCSF in 2020 found that over half (55%) of gig workers planned to find new jobs within three months, compared to 36% of service-sector workers.[22] Addressing these issues by providing proper protections, incentives, or subsidies during extreme heat can improve worker retention, reduce health-related losses, and ensure a steady supply of labor, especially in peak demand periods.

In addition, platform and firm managers should anticipate challenges posed by heatwaves, such as delivery delays and increased variability in order processing. By understanding these patterns, they can develop better staffing strategies, optimize route planning, and enhance platform performance during extreme weather events.

Moreover, the study highlights the urgent need for policymakers to address shortcomings in labor protections for gig workers, especially concerning environmental hazards. For instance, public agencies should engage delivery workers in urban planning and disaster preparedness discussions when designing city infrastructure. Some progress has already been made in China—Shanghai, for instance, has established over 10,000 service stations in community neighborhoods, commercial districts, and shopping malls to support delivery workers during heatwaves. Labor regulations should be re-evaluated and updated to protect gig workers, who remain vulnerable without formal worker status despite facing significant occupational hazards. While non-profit organizations like Los Deliveristas Unidos—a New York City-based group advocating for delivery workers' rights—are helping gig workers pursue their rights and welfare, there is an urgent need for policymakers to establish comprehensive labor protections for these individuals. Our research therefore connects environmental risks and labor economics, providing a new framework for evaluating gig work in the context of climate change.

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A1 Supplemental Tables

Table A1. Determinants of Delivery Fees

Variable	(1) Delivery fee	(2) Delivery fee	(3) Delivery fee	(4) Delivery fee	(5) Delivery fee
Straight-line distance	1.706***	1.704***	1.705***	1.705***	1.689***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Food expenditure			-0.000***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)
Temperature			0.002***	0.001***	0.001***
			(0.000)	(0.000)	(0.000)
Rainfall			0.002***	0.001	0.001
			(0.001)	(0.001)	(0.001)
Observations	598,147	598,147	598,147	598,147	598,147
R-squared	0.714	0.714	0.714	0.714	0.722
City FE	NO	YES	YES	YES	YES
Hour FE	NO	YES	YES	YES	YES
Day of Week FE	NO	NO	NO	YES	YES
Month FE	NO	NO	NO	YES	YES
Courier FE	NO	NO	NO	NO	YES
Mean of dept. var.	6.267	6.267	6.267	6.267	6.267

Notes. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table A2. First Step Estimation

Variable	(1) Work	(2) Work
Heat Hazard	0.117***	
	(0.015)	
Temperature		0.013***
		(0.002)
Hourly rate	0.005	0.013
	(0.015)	(0.015)
Daily income so far	-0.042*	-0.044*
	(0.023)	(0.023)
Daily working hours so far	1.681***	1.682***
	(0.047)	(0.047)
Observations	628,244	628,244
Control Variables	YES	YES
Month FE	YES	YES
Day of Week FE	YES	YES
Hour FE	YES	YES
City FE	YES	YES
Mean of dept. var.	0.557	0.557

Notes. In Column (1), control variables include PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level. In Column (2), in addition to the variables already controlled for in Column (1), relative humidity is also included. Standard errors in parentheses are calculated by clustering at city-day level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table A3. OLS Estimation

Variable	(1) Number of orders	(2) Work minutes	(3) Delay ratio	(4) Income
Panel A				
Heat Hazard	0.164***	2.776***	0.059***	0.968***
	(0.020)	(0.327)	(0.010)	(0.117)
R-squared	0.302	0.428	0.189	0.270
Panel B				
Temperature	0.019***	0.322***	0.007***	0.114***
	(0.002)	(0.041)	(0.001)	(0.014)
Observations	349,985	349,284	348,025	349,984
R-squared	0.301	0.428	0.190	0.269
Control Variables	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
Courier FE	YES	YES	YES	YES
Mean of dept. var.	1.740	41.71	0.262	10.91

Notes. For regressions in Panel A, control variables include PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level. For regressions in Panel B, in addition to the variables already controlled for in Panel A, relative humidity is also included. Standard errors in parentheses are calculated by clustering at city-hour level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table A4. Heat Index Instead of Heat Hazard

Variable	(1) Number of orders	(2) Work minutes	(3) Delay ratio	(4) Income
Heat Index	0.003***	0.030***	0.001	0.016***
	(0.001)	(0.011)	(0.000)	(0.004)
IMR	-0.451***	-18.665***	-0.157***	-2.621***
	(0.071)	(1.557)	(0.046)	(0.456)
Observations	349,985	349,284	348,025	349,984
R-squared	0.300	0.427	0.188	0.268
Control Variables	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
Courier FE	YES	YES	YES	YES
Mean of dept. var.	1.740	41.71	0.262	10.91

Notes. Control variables include PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level. Standard errors in parentheses are calculated by clustering at city-hour level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table A5. Controlling for the Number of Working Couriers

Variable	(1) Number of orders	(2) Work minutes	(3) Delay ratio	(4) Income
Panel A				
Heat Hazard	0.117***	1.414***	0.041***	0.668***
	(0.019)	(0.302)	(0.010)	(0.112)
IMR	-0.253***	-14.495***	-0.099**	-1.365***
	(0.071)	(1.504)	(0.044)	(0.453)
Number of Working Couriers	0.002***	0.054***	0.001***	0.013***
	(0.000)	(0.004)	(0.000)	(0.001)
R-squared	0.305	0.435	0.191	0.273
Panel B				
Temperature	0.013***	0.156***	0.005***	0.076***
	(0.002)	(0.039)	(0.001)	(0.014)
IMR	-0.261***	-14.875***	-0.106**	-1.400***
	(0.070)	(1.487)	(0.043)	(0.451)
Number of Working Couriers	0.002***	0.055***	0.001***	0.013***
	(0.000)	(0.004)	(0.000)	(0.001)
R-squared	0.304	0.435	0.192	0.272
Observations	349,985	349,284	348,025	349,984
Control Variables	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
Courier FE	YES	YES	YES	YES
Mean of dept. var.	1.740	41.71	0.262	10.91

Notes. For regressions in Panel A, control variables include PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level. For regressions in Panel B, in addition to the variables already controlled for in Panel A, relative humidity is also included. Standard errors in parentheses are calculated by clustering at city-hour level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table A6. Results of Replacing Heat Hazard with Temperature in Table 3

Variable	(1) Number of orders	(2) Work minutes	(3) Delay ratio	(4) Income
Panel A				
Temperature × Peak Hour	0.008***	0.116**	0.002*	0.051***
	(0.003)	(0.046)	(0.001)	(0.015)
Temperature	0.013***	0.217***	0.006***	0.077***
	(0.002)	(0.044)	(0.001)	(0.014)
IMR	-0.407***	-18.675***	-0.162***	-2.343***
	(0.070)	(1.512)	(0.045)	(0.449)
Observations	349,985	349,284	348,025	349,984
R-squared	0.302	0.429	0.190	0.270
Mean of dept. var.	1.740	41.71	0.262	10.91
Panel B				
Temperature × Experience	0.010	-0.447***	-0.015***	0.052
	(0.009)	(0.155)	(0.005)	(0.056)
Temperature	0.019***	0.720***	0.016***	0.102***
	(0.004)	(0.083)	(0.003)	(0.026)
Experience	0.029	15.491***	0.389***	0.088
	(0.263)	(4.315)	(0.148)	(1.565)
IMR	-0.405***	-16.984***	-0.071	-2.879***
	(0.110)	(2.794)	(0.084)	(0.755)
Observations	45,555	45,337	45,128	45,555
R-squared	0.250	0.424	0.212	0.231
Mean of dept. var.	1.606	42.47	0.353	10.03
Control Variables	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
Courier FE	YES	YES	YES	YES

Notes. Control variables include relative humidity, PM2.5, ozone concentration, atmospheric pressure, wind speed, rainfall, and wind direction at the city-hour level. Standard errors in parentheses are calculated by clustering at city-hour level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table A7. Impact of Extremely Hot Temperature on Medical Bills Related to Inpatient Services

	Total bill (per 100k population)	Covered by insurers (per 100k population)	Covered by patients (per 100k population)
Whole sample	¥167,895.5	¥153,399.3	¥14,496.3
Males	¥120,561.6	¥118,853.9	¥1,707.7
Diseases	¥32,084.81	¥26,209.56	¥5,875.25

Notes. We only list the increase of medical expenditure (¥/RMB) for an additional extremely hot day (exceeding 27°C) for the whole sample, the subsample of male patients and the subsample of diseases related with hot weather (i.e., Endocrine, nutritional, and metabolic diseases and immunity disorders) in Agarwal et al. (2021).

A2 Back-of-the-Envelope Estimation

In Table 7, we use the estimates from Agarwal et al. (2021) to calculate the "Increased Total Bill" columns, and the number of hot days is that of days exceeding 27°C, which is 32 days in our data. We use the estimates from Li et al. (2023) to calculate the "Self-paid Expense" columns, and the number of hot days is that of days exceeding 32°C, which is 7 days in our data sample.

Specifically, Appendix Table A7 presents the increase of medical expenditure (¥/RMB) for an additional extremely hot day (exceeding 27°C) for the whole sample, the subsample of Male, and the subsample of diseases related with hot weather (i.e., Endocrine, nutritional, and metabolic diseases and immunity disorders) in Agarwal et al. (2021). According to the Table 1 in Agarwal et al. (2021), which provides summary statistics of hospital visits, 50.516% of the whole sample consists of male patients, and 5.112% of the whole sample has the diseases of endocrine, nutritional, and metabolic diseases and immunity disorders. This implies that the medical expenditure for the male subsample (120,561.6 RMB) and the diseases sample (32,084.81 RMB), as listed in Appendix Table A7, corresponds to approximately 50,516 male patients and 5,111 patients, respectively. Therefore, for benchmark ($\gamma = 1$), the average medical expenditure for a male patient (or a diseases patient) on a hot day is 2.4 RMB (or 6.3 RMB), which is higher than the overall average of 1.7 RMB per patient. For a group of 500 actively working male couriers, the total increase in medical costs due to heatwaves during the sample period would amount to approximately 38,185.3 RMB ($\approx 2.4 \times 32 \times 500$). The corresponding numbers for the "Diseases" row are similarly calculated. With numbers obtained for the benchmark case, the increased total bills for the cases of courier's exposed to heat ($\gamma = 8.8$) and courier's increases working time ($\gamma = 9.328$) can be easily calculated.

Note that Li et al. (2023) does not have the specific amount of expenses for the subsample of male, and it does not have a sumbsample of the same diseases specified by Agarwal et al. (2021). We then use the scale calculated from Agarwal et al. (2021) to estimate the self-fund expense for male and disease. Specifically, in Agarwal et al. (2021), the increased total bill of male is around 1.421 times the average level, while that of diseases is around 3.738 times. So we calculate, for example, the benchmark case for the self-fund expense made by male as $¥1,273.2 \times 1.421 = ¥1,809.2$. For the self-fund expenses of diseases documented by Agarwal et al. (2021), we simply calculate as $¥1,273.2 \times 3.738 = ¥4,759.2$, which should be the lower bound of the expense.