Who Bears Climate Change Damages? Evidence from the Gig Economy

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Abstract

This paper provides the first causal evidence that gig economy platforms enable consumer adaptation to climate change while shifting climate-related damages to workers. Across diverse markets and climates (UK, Germany, France, and Mexico), I leverage detailed transaction data and labor force surveys and exploit exogenous variation in daily maximum temperatures. On hot days relative to moderate days, I find an 8-16% increase in food delivery expenditures and a similar decline in dine-in restaurant spending, driven primarily by higher-income consumers. On these days, food delivery workers work 1.7 hours more on average, exposing them to material health risks. Yet, I find that their hourly wages do not increase, despite the flexibility of wages in this setting. This response to heat is unique to platform-based work. I show that worker beliefs are the main mechanism: platform workers believe that declining tasks — particularly during periods of peak demand such as hot days — deprioritizes them for future work. My findings raise broader questions about algorithmic fairness and highlight environmental equity concerns from unequal access to climate adaptation.

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"Most of the time, you have headaches because of the heat. If you have a proper job, you can take a break in the heat. If I take a break, what will they eat?"

- Food delivery cyclist in Milan, as told to a *New York Times* reporter

1 Introduction

Adaptation will be increasingly important for managing the unavoidable harms of climate change resulting from historical greenhouse gas emissions. Gig economy platforms that mediate labor activities — such as Uber, DoorDash, Shipt, and TaskRabbit — may facilitate consumer and worker adaptation to climate change. For consumers, platforms might enable avoidance (e.g., Neidell 2009; Burke et al. 2022) of extreme temperatures by substituting outdoor trips with same-day delivery services. For workers, flexible hours could allow schedule adjustments (e.g., Graff Zivin and Neidell 2014; Rode et al. 2022; Hoffmann and Rud 2024) to lower-risk periods, while dynamic pay may compensate for working under adverse weather conditions. These adaptation actions may, however, lead to a redistribution of environmental damages across groups.[1] Despite a growing share of the global workforce participating in the gig economy (Garin et al. 2023; Datta et al. 2023), the extent of these adaptations and their effects on the distribution of climate damages remain unknown.

In this paper, I study how adaptation to extreme temperatures affects both the demand and supply of platform-based services, and in turn, how climate change adaptation affects economic and environmental inequality. I focus on the food delivery industry due to advantages in its classification in consumer data and labor surveys and the large share of the consumer budget dedicated to food.[2] I test two novel predictions from a simple framework: 1) time-sensitive increases in demand (from consumer adaptation) may drive up hours worked by gig economy workers during extreme temperatures and 2) wage increases may be limited if workers' beliefs about and responses to platform incentives during periods of high demand outweigh temperature's direct negative effects on labor supply.

I use exogenous variation in the timing of hot days to estimate the effects of extreme temperatures on food delivery demand and the hours and wages of platform delivery workers. I combine detailed credit card and email transaction data with local labor force surveys in multiple countries. I address an important research challenge by demonstrating the utility of public labor force survey data in examining the gig economy — a sector rapidly growing in economic significance but notoriously difficult to study due to its novelty and the employment status of its workers. I supplement my empirical analyses with a survey on gig economy worker beliefs.

I first recover the relationship between extreme temperatures and food delivery demand. I use

[1] For example, the COVID-19 pandemic demonstrated how platforms can shift health risks from consumers to workers, as consumers opted for delivery services to avoid exposure while workers faced increased health risks working in person. A similar reallocation of environmental damages may be increasingly relevant as climate change intensifies.

[2] Food makes up 11% of the US consumer's budget (roughly half of which is on food-away-from-home).

transaction data from credit card statements and email receipts across four diverse markets and climates (UK, Germany, France, and Mexico). I find 8-16% (standard error 2-3%) increases in food delivery spending on days with high maximum temperatures (>33°C or >91°F in Europe and >36°C or >97°F in Mexico),[3] relative to days with moderate temperatures, and a concurrent decrease in dine-in restaurant expenditures. This increase in food delivery spending is driven primarily by more orders on hot days, especially during lunch and mid-afternoon (when temperatures are at their intraday peak). Delivery fees, distances, and times, on the other hand, do not vary with temperatures. I show that access to this adaptation measure is not equal as higher-income consumers (of all ages) drive the surge in demand for delivery on days with extreme temperatures.

Having established the responsiveness of demand for platform-based food delivery services to extreme temperatures, I turn to study the labor supply of platform workers, most of whom deliver food on two-wheeled vehicles and are thus highly exposed to the elements.[4] For this part of the paper I focus on Mexico due to data availability, though I find similar results in the UK and the US. Detailed questions on job characteristics in Mexico's quarterly National Survey of Occupation and Employment (ENOE) allow me to identify delivery workers working on app-based platforms. I find that food delivery platform workers work 1.7 hours (standard error 0.7) more on average on days with high maximum temperatures (>36°C or >97°F), relative to moderate days (24-27°C or 75-81°F). These temperatures are harmful to human health. All-cause mortality responds strongly to all temperatures above 26°C (80 °F) (Barreca et al. 2016; Carleton et al. 2022), including for young working-age adults,[5] as do morbidity, mental health, and cognition (White 2017; Mullins and White 2019; Graff Zivin et al. 2020). Indeed, I show that in the same setting, non-platform food industry and agricultural workers work fewer hours than usual on days with extreme temperatures.

Next, I examine the hourly wages of app-based delivery workers to determine whether platforms compensate workers for their increased exposure to health risks. I calculate hourly wages using two different data sources, each offsetting the limitations of the other. I first analyze monthly income and weekly hours worked from the ENOE surveys and isolate exogenous shocks in temperatures in the week prior to the survey date (the reference week) by flexibly controlling for weather in the first three weeks of the month. I show that while food delivery workers increase their average daily hours by 13.3% (standard error 7.2%) for each additional day above 36°C, their hourly wages do not increase. These findings are corroborated by analysis of UberEats transaction data, which allows for estimation of implied hourly wages based on delivery fees and approximate driving times derived from pick-up and drop-off coordinates. Across these data sources, I consistently find that despite increased demand and risks from extreme heat, food delivery workers do not experience

[3] In both Europe and Mexico, I observe increases in food delivery spending even below these temperatures. I highlight results at these temperatures for brevity and consistency.

[4] In Latin America, for example, Rappi's fleet is fully two-wheeled. Similarly, 97% of UberEats trips in the region are done either by motorcycle, bicycle or walking. In New York City, 77% of food delivery trips are conducted by non-car modes of transportation (NYC Consumer and Worker Protection 2022).

[5] Wilson et al. (2024) show in Mexico that when accounting for humidity, heat-related mortality is concentrated among young people, including young working-age adults. My results are robust to using wet-bulb temperatures.

a compensating increase in their hourly wages. These findings are especially relevant given the flexibility of platform wages and their response to other shocks, such as local COVID-19 cases.

In the final part of my paper, I demonstrate the role of the gig economy and gig worker beliefs in the increase of labor supply even in the absence of wage increases during higher environmental risks. First, I show that food delivery platform workers work fewer hours on hot days in quarters when they are not working for platforms, indicating that these workers are not inherently indifferent to extreme temperatures. I also find that the increase in labor supply on hot days is not a characteristic of self-employment in general. Finally, I compare service jobs with similar characteristics but different employment structures and find that the combination of increased hours but lack of increase in wages is unique to platform-based work.[6]

But why do platform workers work more if their wages do not increase? After ruling out intertemporal substitution, I show evidence that supports worker beliefs about algorithmic management (Schor et al. 2020) as the main mechanism. As platform workers are independent contractors, they do not have set schedules, but their future opportunities may be determined by the platform algorithms that depend on present choices (e.g., workers may believe that being offline or turning down orders during high-demand periods will adversely affect future opportunities). In addition to suggestive empirical evidence from labor force survey data,[7] I conduct my own survey examining platform workers' beliefs. I present four key findings that support worker beliefs as the main mechanism for driving workers' increase in labor supply during extreme temperature days. First, the majority of platform workers believe that declining tasks influences the quantity and pay of future offers from platforms. Second, this belief is particularly strong regarding peak demand periods — such as hot days — compared to off-peak hours (62.7% vs. 37.3%, $p < 0.001$) and third, for workers who work more hours on platforms. Lastly, on average, gig economy workers report that they would be willing to sacrifice 23% of their daily earnings for their actions on the platform (e.g., hours worked or orders accepted) to not affect the future tasks that the platform offers them.

Together, these results document consumer adaptation alongside a voluntary and regressive shift of climate burdens through gig economy platforms. I show that higher-income consumers adapt to extreme temperatures through food delivery platforms and are less exposed to associated risks, while these risks are shifted to lower-income platform workers in turn. Platform workers work more hours in extreme temperatures, facing the substantial health risks from exposure to temperatures that deviate from optimal for human health, but without associated increases in their hourly wages. Back-of-the-envelope calculations suggest an increase in per-worker mortality risk of 0.08 per million on a day with mean temperatures of 30°C (86°F) relative to 20°C (68°F). I find that if delivery

[6] Although workers in some non-platform service jobs (e.g., private chauffeurs) do work more in extreme heat, their hourly wages also increase. In contrast, gig economy drivers work more without wage increases.

[7] Workers new to platforms, for whom the marginal impact of each order on their performance is larger, indeed work even more on hot days relative to moderate days than other workers. This is further supported by evidence from the Mexican ridesharing platform market: when it was dominated by a single company, workers increased their hours on hot days despite lower wages, but this pattern did not hold once a large competitor entered the market. This suggests that non-wage incentives play a role in worker behavior under more monopolistic conditions.

orders reduce consumers' time outdoors by less than 25 minutes on average, total consumer and worker welfare also decreases. By the end of this century, under the SSP 3-7.0 emissions scenario, Mexico is expected to experience mean daily temperatures above 30°C for 18% of days (Wilson et al. 2024). The *increase* in labor supply on hot days alone could result in approximately 10 additional work-related deaths per year for food delivery platform workers. This is a large increase relative to about 3,900 annual heat-related deaths in Mexico historically (Wilson et al. 2024).

I contribute to and connect several areas of the economics literature. First, my findings are closely related to the literature documenting the existence and extent of individual adaptation to environmental risks, including adaptation through avoidance. Adaptation and avoidance behavior has been documented in response to rainfall (e.g., Connolly 2008), extreme temperatures (e.g., Barreca et al. 2016; Deschênes and Greenstone 2011; Aroonruengsawat and Auffhammer 2011; Auffhammer 2022), and air pollution (e.g., Neidell 2009; Barwick et al. 2019; Burke et al. 2022; Chu et al. 2021).[8] My contributions show adaptation to environmental harms through app-based platforms, and to my knowledge, I am the first to document a shift in climate burdens that may result from adaptive avoidance. This shifting of risk is especially important for environmental equity concerns in a warming world. To this end, I also build on results from Burke et al. (2022) and Doremus et al. (2022), who show inequalities in access to adaptation, and further document that access to climate adaptation is not equal.

This paper is also related to the literature on labor adaptations to environmental risks. Studying the effects of extreme temperatures, Graff Zivin and Neidell (2014) and Garg et al. (2020) both document decreases in hours worked in response to heat in climate-exposed industries in the US and China, respectively. Rode et al. (2022) also recover an inverted U-shaped relationship using harmonized daily worker-level data from seven countries, where extreme hot and cold temperatures both lead to decreases in labor supply for climate-exposed workers. These adaptations extend to pollution exposure (e.g., Hanna and Oliva 2015; Hoffmann and Rud 2024). Several recent papers also examine adaptation to weather changes and climate uncertainty beyond its impact on daily labor supply (Colmer 2021; Kala 2019; Downey et al. 2023). A related strand of literature looks at the on-the-job consequences of environmental hazards and finds important negative effects on labor productivity (e.g., Adhvaryu et al. 2022) and occupational injuries (e.g., Dillender 2021).

I advance this literature in several significant ways. First, I demonstrate a novel fact: extreme temperatures can *increase* work hours for certain workers. This contrasts sharply with the existing literature, which shows a decrease in labor supply during extreme temperatures for climate-exposed work (e.g. Graff Zivin and Neidell 2014; Rode et al. 2022; Garg et al. 2020). My findings reveal that adaptation to climate change by consumers can lead app-based platform workers to work more hours precisely when conditions are most detrimental to human health. Relatedly, I study the effects of climate change for workers outside commonly examined sectors (such as agriculture

[8] The paper closest to my findings on the *demand* for food delivery is Chu et al. (2021), who use surveys and photographic evidence to document the increase in food delivery on days with high pollution in China. I expand this paper to extreme temperatures, several geographies, and consider the effects on platform workers.

and construction). As gig workers now constitute a growing share of the global workforce (Datta et al. 2023), it is crucial to extend existing work to these new types of labor arrangements. Lastly, I connect the literature on labor adaptations to the previously discussed work on avoidance behavior in response to climate change, and demonstrate a link between them.

Lastly, I contribute to the empirical literatures on gig-economy labor markets and the value of alternative work arrangements and flexibility. Existing work on two-sided platforms examine pricing-related questions and the allocation efficiency of platform algorithms (e.g., Wei and Lin 2017; Einav et al. 2018; Dubé and Misra 2023; Gaineddenova 2022). Other related work evaluates platform policies, including platform-initiated fare increases (Hall et al. 2023) and government-imposed price-floors (Nakamura and Siregar 2024). I extend this literature and consider climate adaptation as a driver of app-based platform demand.[9] My paper and especially my survey results exploring mechanisms are also related to the value that workers place on alternative work arrangements (Mas and Pallais 2017) and gig workers' preferences for flexibility (Chen et al. 2019; Chen et al. 2024; Angrist et al. 2021; Fisher 2024). My contribution is to show that gig worker beliefs about platform algorithms may constrain the actual flexibility of gig work, particularly during periods of high environmental risk.

My findings also inform policy. As avoidance behavior becomes more common in a warming world and the gig economy continues to expand, consumers with the means to adapt may increasingly shift various tasks, including last-mile delivery of packages, childcare,[10] and more, to app-based platform workers. This shift in consumer behavior underscores the need to design optimal platform algorithms that account for changing climatic conditions and for informed legislation that regulates platforms. If regulations that protect workers from the heat only apply to employees—and not independent contractors—they may reinforce inequality in exposure to climate harms. Additionally, my findings highlight the important role of algorithmic management in labor markets and raise policy-relevant questions about the monopsony power of gig platforms, the future of work, AI governance, and algorithmic fairness - particularly as algorithms mediate which workers face environmental risks and how they are compensated for these exposures. My work also has lessons for forms of climate adaptation that expose workers to environmental harms while protecting others, beyond platforms and last-mile delivery.

The rest of this paper proceeds as follows. In Section 2, I provide a brief background on food delivery platforms, while in Section 3 I present a simple theoretical framework that guides my analyses. Section 4 describes the data used for the analysis and Section 5 details the empirical strategy. Results are presented in Section 6, while Section 7 describes back-of-the-envelope welfare calculations. Finally, Section 8 discusses my findings and concludes.

[9] In addition to the gig economy literature, my paper is also related to the older literature on taxi drivers and income targeting (Camerer et al. 1997; Farber 2005; Farber 2008).

[10] Garg et al. (2020) find a decrease in time spent on childcare on hot days in China for women.

2 Background

The gig economy: The gig economy refers to the provision of on-demand work, often facilitated through digital platforms. These platforms connect consumers with workers' services in real-time via apps or websites. The gig economy encompasses a wide range of services, including ridesharing (e.g., Uber, Lyft), food and grocery delivery (e.g., DoorDash, Instacart), and labor services (e.g., TaskRabbit), and has been rapidly growing in economic significance. Its impact extends globally, with low and middle-income countries accounting for 40% of traffic on over 500 platforms (Datta et al. 2023). Up to 4-12% of the global workforce participates in various types of gig work (Garin et al. 2023; Datta et al. 2023), possibly far surpassing employment in healthcare or education (2-3% of the workforce each). The pandemic further accelerated the growth: Garin et al. (2023) use data on tax returns in the US and find a dramatic growth (approximately 150% net growth) in the number of workers with app-based platform gig work around the time of the COVID-19 pandemic.

The global food delivery market: The global online food delivery market has experienced remarkable growth, exceeding $150 billion in value and more than tripling since 2017, largely due to boosts from user-friendly gig economy apps and the COVID-19 pandemic (Ahuja et al. 2021). While food delivery is not a new phenomenon, the emergence of "aggregators" in the mid-2010s has drastically altered the industry.[11] These online platforms are third-party providers that connect consumers and restaurants through delivery services fulfilled by independent contractors, and charge fees to both parties. Lockdowns and social distancing measures during the COVID-19 pandemic further accelerated the adoption of food delivery services (Ahuja et al. 2021). A few companies—including UberEats, DoorDash, and JustEat, which operate across multiple countries, often through the acquisition of local platforms—dominate most food delivery markets. Throughout the paper, I refer to third-party food delivery companies as food delivery platforms, app-based platforms, and digital platforms interchangeably.

Platform workers: Platforms present a mix of opportunities and challenges for workers. Most delivery platforms compensate workers with a base pay for each trip—which varies based on factors such as time and distance—and potential offers (e.g., peak pay). Workers also often receive tips in addition to the base pay and promotions. The exact pay algorithms vary and are often opaque. Many platforms also offer "rewards" programs for workers who meet certain criteria, such as earning high customer ratings or maintaining fast deliveries. While workers can choose when they work, some report fear of being deprioritized for orders if they are not consistently working. For example, in an interview conducted by Tejada et al. (2021), a 21-year-old food delivery worker in Mexico mentions: *"If you don't invest time in some platform, that is, if you don't connect for more than four or five hours, it puts you aside and doesn't take you into account much when assigning orders."*

[11] The history of restaurant food delivery supposedly dates back to 1889, when King Umberto and Queen Margherita of Italy asked for a pizza be brought to them from the famous Pizzeria di Pietro e Basta Cosi. Food delivery (e.g., pizza or Chinese food in the US) has existed for decades, but delivery workers were employees of restaurants. Grubhub was founded in 2004 as an alternative to paper menus but later transitioned to facilitating third-party delivery. DoorDash and UberEats launched in 2012 and 2014, respectively.

Digital platform workers may face precarious working conditions despite gig work's flexibility. Accident rates are high, especially as many workers deliver on two-wheeled vehicles.[12] In New York City, for example, the injury rate for e-bike and moped delivery workers is more than double that of nursing assistants, who have the highest rate of occupational injury of major occupations in the US, while on-the-job fatality rates are almost three times as high for delivery workers as construction workers (NYC Consumer and Worker Protection 2022). Furthermore, classified as independent contractors, these workers typically lack access to benefits such as health insurance, unemployment protection, and paid leave. This classification has been a contentious issue globally, with ongoing legal battles concerning the reclassification of these workers as employees.[13] However, in most markets platform workers remain independent contractors without benefits like health or unemployment insurance, overtime, or minimum wages. Section A.2 provides more details about the food delivery markets relevant for this paper.

3 Theoretical Framework

In this section, I present a simple model of food delivery demand and labor supply and their relationship to temperatures. The framework is not meant to comprehensively model the food delivery market, but rather to highlight relevant dynamics. Although I use the nomenclature of the food delivery industry, this paper's main takeaways apply to any market where wages are a linear function of the quantity of the good or service provided and inversely proportional to hours worked.

I model the consumer demand for food delivery (number of orders) as

$$Q_d = q_d(p, f, t, T) \tag{1}$$

where p is the price of food, f is the delivery fee, t is the estimated delivery time, and T is the temperature. The demand for food delivery is inversely proportional to p, f, and t. Delivery fees may depend on a base fee per distance and a surge multiplier. Total delivery time is the sum of the estimated order preparation (which I assume stays constant), the driver-consumer matching time (θ), and the time it takes for the worker to deliver the order (τ). I model a potentially sublinear relationship between the number of orders (Q_d) and the hours of labor demanded, such that $H_d = Q_d^{\alpha} \times \tau$, where $\alpha \in (0, 1]$ determines potential efficiency gains from grouping orders.

[12] As of 2021, 46% of UberEats deliveries were conducted on two-wheels globally. Outside of the US, the use of two-wheeled vehicles is much higher. In Latin America, almost all deliveries are on two-wheels. In India, 18% of Zomato workers use bicycles, with most of the rest relying on motorcycles.

[13] In California, for example, voters approved a ballot measure in 2020 sponsored by various platforms to continue treating the over 1 million gig workers in the state as independent contractors, though since then, Proposition 22 has been at the center of a years-long legal process. Regulatory changes have introduced minimum hourly wages for delivery workers in France and New York City. In Colombia, some platforms like Rappi have introduced limited social security benefits to drivers, even as independent contractors.

The labor supply of workers (hours worked) is a function of observable factors for the worker,

$$H_s = h_s(\phi(Q_d), \gamma(f), E[I_{t+1}], T) \tag{2}$$

including some indication of current demand ($\phi(Q_d)$), the base pay per order, which depends on delivery fees ($\gamma(f)$, see below), and temperature (T). Additionally, given that workers are independent contractors without contracts fixing their future hours or earnings, their labor supply might depend on their expectations and beliefs about future opportunities on the platform, $E[I_{t+1}]$. For example, workers may be able to substitute hours across days (intertemporal substitution) or believe that their amount of time active on platforms, acceptance rate of orders, or consumer ratings affect their future earnings through the platform's algorithm.

Hourly "wages" are not ex-ante observable to workers on the platform. However, given the above demand and supply functions, if all orders are fulfilled ($H_d \leq H_s$), the realized (ex-post) average hourly wage of delivery workers is

$$w = \frac{A \times Q_d}{H_s} \tag{3}$$

where for each delivery trip worked in H_s total hours, workers receive a (possibly dynamic) amount A. For example, a simple formula for A may be $A(f, g) = s \cdot f + g$, where s is the share of the delivery fee (f) workers receive and g is the consumer tip. There is evidence that major food delivery platforms compensate couriers in a similar manner.[14] The exact formula here is less relevant, but what is important is that for each order, workers receive some function of fees and tips.[15]

Change in wages: In considering the effects of temperature on the food delivery market, a central question is whether workers are compensated for the additional risks of working in the heat. For simplicity, I first assume that delivery fees (f), tips (g), and total estimated delivery times (t) are not affected by temperatures, labor supply, or delivery demand. I later relax these assumptions.

Based on these assumptions and equations 1-3 and considering a deviation from optimal temperatures, the elasticity of realized hourly wages with respect to temperature ($\varepsilon_{w,T}$) is

$$\varepsilon_{w,T} = \underbrace{\varepsilon_{D,T}\,(1 - m \cdot \varepsilon_{S,D})}_{\text{demand effects}} - \underbrace{\varepsilon_{S,T}}_{\text{direct supply effect}} - \underbrace{\left(\varepsilon_{S,E} \cdot \varepsilon_{E,T}\right)}_{\text{indirect supply (future opportunities) effect}} \tag{4}$$

[14] For example, according to Tejada et al. (2021), UberEats pays workers a base rate of 25%-35% of the delivery fee in Mexico, based on the mode of transportation. In the US, the app mentions that "[Service fees] vary based on factors like basket size and help cover order-related costs. You pay \$0.10 of these fees directly to Uber for marketplace services [...], and the rest is given to your courier, who may pay a portion of these fees to Uber for various services." In the model, the "delivery fee" represents various delivery-related fees (e.g., delivery fee, service fee, other fee).

[15] I note that since delivery fees and gratuity are a small part of the total order ($f << p$ and $g << p$), demand for labor is likely to be inelastic to wages, unless wages meaningfully affect estimated delivery times (t). Delivery fees are about 10% of the delivery total in Mexico. See Appendix Table A2. Tips in the country are likely to be an even smaller share of the total order cost as consumers usually just round up.

where this elasticity may be decomposed into (direct and indirect) demand effects and supply effects. See Appendix Section A.1.1 for details. The first term represents direct and indirect demand effects, where $\varepsilon_{D,T}$ is the elasticity of demand with respect to temperatures, $\varepsilon_{S,D}$ is the elasticity of hours worked in response to demand, and m is an adjustment term based on $\phi(Q_d)$, the function of demand that workers see. The next term, $\varepsilon_{S,T}$, is the elasticity of labor supply with respect to temperatures. The final term represents indirect supply effects through future opportunities, where $\varepsilon_{S,E}$ is the elasticity of labor supply with respect to expectations of future opportunities, while $\varepsilon_{E,T}$ is the elasticity of expectations of future opportunities with respect to temperatures.

The sign of $\varepsilon_{w,T}$ depends on the signs and magnitudes of these elasticities. Given a deviation from optimal temperatures, if there is an increase in demand due to consumer adaptation ($\varepsilon_{D,T} > 0$), workers dislike working in the heat ($\varepsilon_{S,T} < 0$), and the other channels are negligible, wages are expected to increase. However, either a large positive elasticity of labor supply with respect to demand ($m \cdot \varepsilon_{S,D}$ term) or a large increase in labor supply through the future opportunities channel ($\varepsilon_{S,E} \cdot \varepsilon_{E,T}$ term) would put negative pressure on wages.

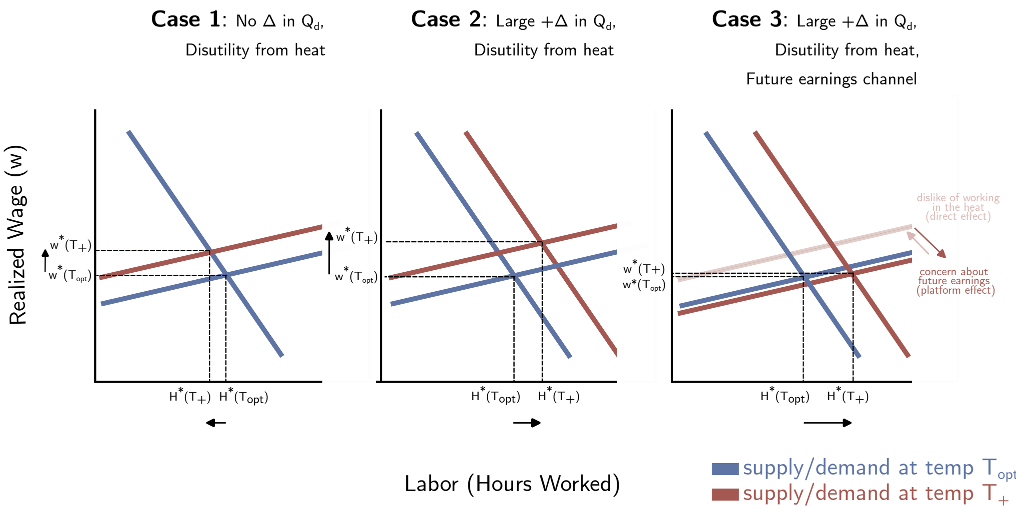
Assumptions: Of course, delivery fees, tips, and estimated delivery times might all vary with temperatures. For example, consumers may tip more generously, platforms may offer peak pay, and delivery efficiency may slow down on days with adverse weather conditions. I now relax these assumptions and consider how each might affect wages.

1. *Fees and gratuity affected by temperature ($A = A(f(T), g(T))$):* If delivery fees (f) and consumer tips (g) vary with temperatures, the change in wages will also depend on direct fee and gratuity effects. For example, if fees and tips increase, wages will increase as well, through the amount (A) workers receive for each order. Furthermore, since fees enter the demand and supply functions, they will also indirectly affect wages through these channels. For example, an increase in fees with temperatures may lead to a decrease in demand (increasing wages) and an increase in labor supply (decreasing wages). See Section A.1.2 for more details.

2. *Wait and delivery times affected by temperature ($t = \theta(T) + \tau(T)$):* Changes in the estimated total delivery time that consumers see (t) affect demand. Therefore, changes in consumer-driver matching times (θ) or the time it takes for workers to delivery orders (τ) due to a deviation from optimal temperatures may amplify or counteract changes in demand. For example, a decrease in matching times due to higher demand on hot days may further increase demand (increasing wages). On the other hand an increase in delivery times due to changes in worker efficiency may decrease demand (decreasing wages). See Section A.1.3 for more details.

Equilibrium: I consider the shifts in the supply and demand curves in response to temperatures. Figure 1 illustrates three cases within the supply-demand framework. Equilibria are shown for optimal temperatures T_{opt} (blue curves) and at a warmer temperature $T_+ > T_{opt}$ (red curves).

Figure 1: Effects of a Temperature Increase on Labor Demand and Supply in Illustrative Cases



Case 1 shows the case of climate-exposed jobs without time-sensitive changes in demand in response to daily temperature (e.g., agriculture or construction). The labor supply curve shifts left due to temperature's direct effects. Equilibrium hours worked decrease and wages increase. These predicted effects are consistent with prior work showing decreases in hours worked by outdoor laborers in response to extreme temperatures (e.g., Graff Zivin and Neidell 2014; Rode et al. 2022).

__Observation 1:__ **Time-sensitive demand increases may drive up hours worked during extreme temperatures.** Case 2 and 3 illustrate that unlike traditional climate-exposed jobs, workers in industries with time-sensitive demand (e.g., food delivery, ride-hailing, same-day errands) may see increased hours worked during extreme temperatures due to heightened demand. If there is a large increase in demand and the labor demand curve shifts to the right due to the increase in temperatures, hours worked in equilibrium will increase.[16]

__Observation 2:__ **For workers whose beliefs about future earnings may affect present labor supply, wage increases may be limited.** In Case 3, the positive indirect labor supply effect cancels out the negative direct effects of temperature on labor supply. Consequently, equilibrium hours worked increase on hot days, but without meaningful wage growth. This increase in labor supply is connected to expectations about future opportunities. Workers may substitute hours intertemporally to avoid future work during extreme weather or allow for rest following days with high temperatures. Or, they may believe that declining work during high-demand periods could result in algorithmic deprioritization, jeopardizing future opportunities. These mechanisms are particularly salient for independent contractor platform workers who lack set schedules and whose earning prospects are determined by the "algorithmic management" of digital platforms (Schor et al. 2020). For instance, the executive director of a delivery worker collective noted that high temperatures in New York City lead to *"heavier workloads for delivery workers who, as independent*

[16]Of course, if the labor supply curve simultaneously shifts far enough to the left, this may not be the case.

contractors, have no means to turn down jobs without fear of losing future work" (Howard 2024).

In this paper, I empirically examine the overall effects of temperature increases on the key factors outlined: delivery demand, hours worked, and wages. I also test the effects of temperature on other variables such as fees, tips, and delivery times. I evaluate which case described above most closely aligns with the observed dynamics of platform-based food delivery work.

4 Data and Summary Statistics

I use four main types of data: weather, consumer transaction, public labor force survey, and worker belief survey data. Table 1 summarizes the main variables. I describe each of the main data sources in detail below.

Table 1: Main Data Sources and Variables

Variable	Description	Geography
Weather Data		
Daily Maximum Temperature	Population-weighted avg. daily maximum temperature	All
Transaction Data		
Daily Food Delivery Spend	Total credit card spending on food delivery services	UK, Germany, France
Daily Rappi/UberEats Spend	Total spending on Rappi and UberEats platforms	Mexico
Labor Force Survey Data		
Daily Hours Worked	The number of hours worked each day	Mexico
Weekly Hours Worked	Total hours worked in survey reference week	Mexico, UK, US
Income	Reported last period income (standardized to monthly)	Mexico
Hourly Wage	Income divided by 4× hours worked in past week	Mexico
Platform Worker Survey Data		
Various	Various survey responses	Mexico, US

4.1 Weather Data

I construct daily maximum, mean, and minimum temperatures, total daily rainfall, and average wind speed measures from various station-level and reanalysis sources. For my main temperature variables, I use the Hadley Integrated Surface Database (HadISD) product, which is a dataset of sub-daily in-situ observations for a number of meteorological variables. I keep weather stations with consistent reporting in the relevant time periods, fill in missing observations to construct a balanced panel of station records, and then use inverse-distance weighted interpolation to produce data at a 0.1° grid. See Section A.3.1 for more details on the processing of the station-level temperature data. For the US, I use PRISM temperature and precipitation data (Daly et al. 2008). For robustness checks, I download daily maximum temperatures from reanalysis and gridded products (ERA5-Land and Daymet V4), also at the 0.1° grid resolution. Finally, I also use reanalysis data (ERA5-Land, CHIRPS, Daymet, and PERSIANN-CDR) for precipitation and other weather controls. See Section

A.3.2 for more details on the reanalysis data. These steps produce a daily gridded data product for each country which includes various measures such as daily maximum, minimum, and mean temperatures, along with total precipitation and average wind speeds.

I follow the literature in aggregating the daily gridded climate data to administrative boundaries. To preserve the potential non-linearities in the relationships I estimate, I first compute various transformations (e.g., cubic or cubic spline) of temperature and precipitation for each grid cell. To average values across space, I then take population-weighted averages of each grid cell part of the administrative region.[17] I use time-invariant population weights calculated from the 2020 Gridded Population of the World dataset.[18] My final weather data is at the day-by-unit level, where units vary depending on the analysis (municipalities, or second-level administrative regions, in Mexico, postal codes in Europe, and core-based statistical areas (CBSAs) in the United States).[19] Section A.3.3 shows summary figures.

4.2 Consumer Transaction Data

I use various consumer transaction datasets as well as proxies for consumer transactions.

Fable credit card data: I analyze transaction-level credit card data provided by Fable Data. Fable Data provides anonymized consumer transaction data across several European countries, from which I use data from the UK, Germany, and France for 2016-2023.[20] The data in the Fable Signal product is akin to transaction rows shown on a credit card statement, with persistent anonymized customer identifiers. Postal codes and basic demographic information (gender, age group, and income bracket) are available for a large subset of users. I construct a panel of consistent credit card users in each country. I keep credit card users with at least one transaction per month between the first and last time they appear in the data and without changes in their associated postal code. See Section A.3.4 for more details on the construction of the credit card user panel.

For each user in my final sample, I then categorize all transactions charged in the currency of their home country. The Fable credit card data includes information on the merchant for each transaction and whether the transaction took place online or offline. I manually categorize all 564 food-related merchants (as indicated by Fable) into delivery platforms, restaurants, grocery delivery services, and brick-and-mortar grocery stores. See Section A.3.4 for more details on spending categories. I

[17] This spatial averaging is necessary as I do not know the exact grid cell location of each individual consumer or worker within an administrative unit. My spatial averaging method, following Rode et al. (2022), assigns the temperature exposure of the average person in the unit to every consumer or worker within that unit.

[18] Available on Google Earth Engine. Note that for analysis at smaller geographical divisions such as postal codes, I do not use population-weighted values. As postal codes in Europe are small, and contain, on average, only one grid cell, I simply assign each postal code to the grid cell it overlaps.

[19] For weekly analyses or those involving larger spatial units, I follow the above logic in preserving non-linearities and using population-weighing for spatial averaging.

[20] I focus on these markets as they are the largest economies out of the countries for which Fable has longer-term coverage. In addition to these three countries, Fable also provides longer-term data for Austria and, more recently, for Spain and Italy.

aggregate the credit card transaction data to the daily level and for each user construct total daily spending (across all categories) and daily spending on food-related categories.[21] Figure A3 shows the growth of food delivery spending in European markets and compares the annualized average food delivery spending derived from credit card purchases to market statistics. Appendix Table A2 shows additional summary statistics. The credit card data from the UK appears to be the most representative of the average UK food delivery consumer (given that the French and German users in the Fable Data skew older, likely biasing food delivery spending to be lower).

Measurable AI transaction data: Measurable AI extracts information on delivery orders from confirmation emails sent by delivery companies to consumers who opt-in to sharing access to their emails in return for cash rewards. The dataset comprises detailed, anonymized data on food delivery transactions, including the total payment amount (cost of food and delivery fees), the geographical coordinates (latitude and longitude) of both the order and restaurant locations (for select orders), and the date and time of the orders. I use 2019-2023 data on delivery transactions from Rappi and UberEats. I construct a panel of users who order at least twice. See Section A.3.5 for further details on Measurable AI panel and transaction processing steps. Figure A3 and Appendix Table A2 show trends and summary statistics. As the Measurable AI transaction data is exclusively from Rappi and UberEats consumers, it should not be viewed as representative of the average Mexican consumer, but rather of a moderate to frequent food delivery customer.[22]

Google Trends data: In all geographies, I use daily Google Trends search data at the state or country level in robustness checks, as a proxy for food delivery spending. Search volumes are based on a sample of Google web searches and represent relative interest on a normalized 0-100 scale.

I match the credit card and email transaction data to weather data using the day of the transaction and the postal code or municipality associated with each user or transaction.

4.3 Labor Force Survey Data

I use quarterly labor force survey data from Mexico for my main analysis of platform workers, due to the detailed job characteristic categorizations. I also replicate my analysis using small samples from the UK Labor Force Survey and the US Current Population Survey (CPS).

Mexico: I rely on the National Survey of Occupation and Employment (ENOE) labor force survey collected quarterly by the National Institute of Statistics and Geography (INEGI). The survey employs a rolling panel of participants who are interviewed up to five consecutive quarters. The survey is conducted through face-to-face and telephone interviews, and includes approximately 120,000 responses per quarter. During each interview, participants provide information on their

[21] Since the transaction data reflect totals charged to credit cards, they do include customer tips.

[22] The average annual food delivery spending of the consumers in the data is up to 17 times higher than for all Mexicans, on average, based on approximate revenues of \$1.45 billion from platform-to-consumer apps in 2023 from Statista and a population of 127.5 million. Given that in 2019 about a tenth of the total population ordered food delivery according to Trecone, the data is more representative of a moderate to frequent food delivery consumer.

days and hours worked during the previous (reference) week, as well as details about their job, including industry and typical tasks.

Using questions in the survey about job characteristics, I identify participants who are likely to be delivery workers employed by third-party delivery platforms. The main survey questions I use are those on the main job descriptions and the industry of each participant's job. For my main sample of food delivery platform workers, based on Carreón Rodríguez et al. (2021), I include survey respondents described as "delivery workers of merchandise" or "motorcycle drivers" in food-related industries, who do not have a boss at work.[23] My main sample includes data from 2015-2023 on 2,532 days worked by 414 unique food delivery workers. The number of food delivery workers using this classification criterion increased rapidly around the launch of food delivery platforms in Mexico (2015-2016), as well as the COVID-19 pandemic (Figure A4), which I take as evidence of identifying platform workers correctly. Appendix Section A.3.7 shows additional summary statistics.

I use various other screening criteria for robustness checks, weighing the trade-off between sample size and confidence in accurately identifying platform delivery workers. My main results are robust to using all "delivery workers of merchandise" in the food industry (larger sample) as well as a smaller sample of self-employed food delivery workers without health insurance (smaller sample that is most likely to be platform workers).

UK: The UK Labour Force Survey (LFS) is another quarterly survey that includes questions on days and hours worked in the previous (reference) week. I define food delivery platform workers as "delivery drivers and couriers" and "delivery operatives" in "restaurant and mobile food service activities".[24] As these categorizations are only available post-2021, the sample of food delivery workers from the UK Labour Force Survey is small. Furthermore, the geographical information in the survey is limited to 19 regions within the UK and hours worked are available only on a weekly level. My final data consists of weekly hours worked by 223 workers from 2021-2023 labor force surveys. Nevertheless, I conduct tests of external validity using the survey.

US: I use the US Current Population Survey (CPS), which is the US government's monthly survey of unemployment and labor force participation and includes questions on topics such as employment, earnings, and demographics. The surveys include questions on the actual number of hours worked in the respondent's main job in the reference week. I define food delivery platform workers as self-employed "couriers and messengers."[25] The CPS provides the CBSA of each respondent. I download 2016-2023 data from NBER. My final sample includes weekly hours worked for 841 distinct delivery workers. I use the data for additional tests of external validity of my main findings.

[23] More specifically, in the ENOE labor force survey, I keep workers whose job description corresponds to either 4214, 8244, 9321, 9721, 9722, or 9723 (question `p3`) and whose industry classification is one of 3110, 3120, 4611, 7221, 7222 (question `p4a`). This is similar to how Carreón Rodríguez et al. (2021) classify delivery workers, although my sample is slightly less restrictive. In robustness checks, I use the same classification and find similar results.

[24] These correspond to 8214 (delivery drivers and couriers) and 9253 (delivery operatives) in the SOC2020 classification (`SOC20M` variable) and 561 (restaurant and mobile food service activities) in the industry groups (`INDG07L` variable).

[25] These criteria correspond to `peio1ocd/ptio1ocd` = 5510 or `peio1icd/ptio1icd` = 6380 and `peio1cow` = 7.

Table 2: Delivery Worker Characteristics - Comparison to Specialized Surveys

	Mexico		UK		US	
	(1)	(2)	(3)	(4)	(5)	(6)
	ENOE LFS	Survey	UK LFS	Survey	CPS	Survey
Male (%)	96.4	93	87.0	94	78.3	75
Foreign Born (%)	-	-	37.2	72	56.7	>39†
Age						
Mean	37.0	-	35.8	-	35.6	-
18-34 (%)	50.9	-	52.9‡	42‡	56.7	57
34-54 (%)	35.5	-	47.1‡	58‡	33.3	38
54+ (%)	12.1	-	-	-	8.3	4
Hours Worked						
Mean (per Week)	44.4	46.3	28.3	-	25.5	21.2
Median (per Week)	48.0	48.0	25	28	30	-
Income						
Median HH ($k)	-	-	-	-	40-50	-
Mean Weekly ($)	103.7	103	316.7	-	-	-
Median Weekly ($)	79.5	84	283.5	-	-	-
Mean Hourly ($)	2.8	2.6	11.6	-	-	14.2
Median Hourly ($)	2.0	2.0	11.3	11.3	14.4$^{\wr}$	-
Relative Income						
Income Perc.	52^{nd}	-	$\sim 20^{th}$	-	$\sim 30^{th}$	-
Count	330	986	223	510	60	7,956
Geography	Mexico	CDMX	UK	UK	NYC	NYC
Time Period	2016-2023	2021	2021-2023	2023	2016-2023	2021 4Q

Notes: Table shows the comparison of various characteristics of food delivery workers from labor force surveys in odd columns and food delivery worker specific surveys in the even columns. Food delivery surveys are from NYC Consumer and Worker Protection (2022); Wood et al. (2023); Tejada et al. (2021), respectively. †: shows the percentage of respondents who "speak English less than very well"; ‡: for the UK, the age categories are below 35 and at least 35; $^{\wr}$: estimated based on median household income and median hours worked. UK and US income percentiles approximated based on weekly and annual income.

To confirm that the individuals identified according to the preceding criteria accurately represent food delivery workers, I compare their demographic characteristics with data from studies that specifically survey food delivery workers (Tejada et al. 2021; Wood et al. 2023; NYC Consumer and Worker Protection 2022). Table 2 shows these comparisons for food delivery workers in Mexico, the UK, and the New York City metropolitan area. Reassuringly, the demographics of the samples are very similar. Food delivery workers are overwhelmingly male (75-96%) and young (average age of 36-37). Food delivery workers in Mexico are even more likely to be male and work more hours per week than their counterparts in the UK and US.

Finally, I match labor force survey data to weather data using the day and location (municipality) of respondents. For the UK LFS data and the US CPS, I match using weeks and regions or CBSAs.[26]

4.4 Platform Worker Survey Data

I conduct an online survey of gig economy platform workers through Prolific. I run the survey in Mexico and the US. I recruit from all active Prolific users and implement in-survey screening questions to select those with past or present gig economy platform (ridesharing and food or grocery delivery) experience. I survey 2,000 Prolific participants in total. My final sample includes 440 respondents with either ridesharing or food/grocery delivery experience (174 in Mexico and 266 in the US). I ask these workers various questions about their experience on platforms. Appendix Section A.3.8 contains further details on the survey. Table A5 shows summary statistics about the survey sample. For about 23% of the respondents in the final sample, gig work is their primary source of income. The median worker works 20 hours a week, both in Mexico and the US. Of the final sample, 29.9% (25.2%) of respondents in Mexico (US) have food delivery experience, while the majority (62.6-69.5%) have rideshare experience. Around half of the workers (48.9-53.8%) have worked on multiple platforms simultaneously, but most do not switch between different types of gig work (e.g., ridesharing to food delivery). Compared to the sample in the labor force survey (Table 2), the average Prolific gig worker is more likely to be female and younger and work only part-time for platforms. An important question is, therefore, how representative or comparable the survey sample is to all platform workers. To address these concerns, in Section 6.3, I compare survey responses between various subgroups of respondents and argue that these characteristics do not influence their beliefs about platform algorithms and practices.

4.5 Other Data

Pollution Data: For additional analyses, I use particulate matter ($PM_{2.5}$) concentration data from the Copernicus Atmosphere Monitoring Service (CAMS), which is based on satellite data. I calculate (population-weighted) daily averages for geographies in Google Earth Engine.

COVID-19 Data: I use daily COVID-19 case counts and deaths across various geographies. For France and Germany, I download data from the European Centre for Disease Prevention and Control (ECDC). For the UK, I use data from Our World In Data's COVID-19 tracker. For Mexico, I download daily confirmed cases and deaths by municipality, state, and national levels from the Government of Mexico's COVID-19 dashboard.

[26]I aggregate climate data to the week-by-region level in a similar manner to aggregating gridded data to administrative boundaries. To preserve potential non-linearities, I calculate the number days in each temperature bin at the postal code level for each week, then take population-weighted averages across regions.

5 Empirical Strategy

I use exogenous variation in realized daily maximum temperature to recover the causal effect on food delivery spending and hours worked and hourly wages of delivery workers. I estimate versions of the following regression when examining the effects of temperatures on food delivery spending:

$$y_{ict} = f(\mathbf{T}_{ct}) + g(\mathbf{P}_{ct}) + h(\mathbf{W}_{ct}) + \omega_i + \psi_y + \delta_w + \phi_d + \epsilon_{ict} \tag{5}$$

In these regressions, y_{ict} is the outcome of interest for individual i, in locality c, at time t. My main explanatory variables are various functions of maximum temperature ($f(\mathbf{T}_{ct})$) in locality c and time t. I also control for daily precipitation ($g(\mathbf{P}_{ct})$), and other weather variables such as wind speeds ($h(\mathbf{W}_{ct})$). I use binned[27] and restricted spline functions of temperatures[28] and third degree polynomials for precipitation and winds. I include fixed effects to isolate plausibly exogenous variation in daily temperatures within locality or individual and account for long-term trends and seasonality. When regressing credit card spending and email transaction spending on temperatures, my main specification includes individual (ω_i), year (ψ_y), week-of-year (δ_w) and day-of-week (ϕ_d) fixed effects. I cluster standard errors at postal area (Europe) or municipality (Mexico) and month level for binned regressions and bootstrap (across individuals) for cubic spline regressions.

I modify the regression to match the specifics of the context in Mexico when using data from labor force surveys to study hours worked and wages:

$$y_{ict} = f(\mathbf{T}_{ct}) + g(\mathbf{P}_{ct}) + h(\mathbf{W}_{ct}) + \mathbf{X}_i\lambda_i + \alpha_c + \psi_{ys} + \delta_{ws} + \phi_d + \epsilon_{ict} \tag{6}$$

In these regressions, the main explanatory variables remain the same. However, I use locality (α_c), year-by-state (ψ_{ys}), week-of-year-by-state (δ_{ws}), and day-of-week (ϕ_d) fixed effects in my preferred specification. This is because the climates and cultures of Mexico's states vary considerably and, for example, the seasonality of labor may be very different across regions. In labor supply regressions, I also add individual-level characteristics such as gender, age (age squared), and education (education squared), and worker industry and job descriptions ($\mathbf{X}_i$). I also include holiday and pay-day fixed effects. I show robustness to numerous other combinations of spatiotemporal fixed effects, individual fixed effects, and controls (including those equivalent to equation 5).

To ease comparisons and back-of-the-envelope calculations connecting the demand and labor supply side of the food delivery market in Mexico, I use weights in my preferred specification when estimating the effects of temperatures on food delivery demand. These weights are equivalent to the share of delivery workers in each municipality in the ENOE labor force survey data. I show unweighted regressions in the Appendix.

[27] The baseline bin is 12-24°C in Europe and 24-27°C in Mexico and I use 3°C bins. The baseline bin is wide in Europe to capture moderate days across seasons and to help interpret results, as delivery is not very responsive to temperatures in this range. Therefore, results are very similar with smaller baseline bins (e.g., 15-18°C or 21-24°C).

[28] I use a restricted cubic spline with three knots, at temperatures 25.5°C, 33°C, and 37°C in Mexico and 18°C, 27°C, and 33°C in Europe.

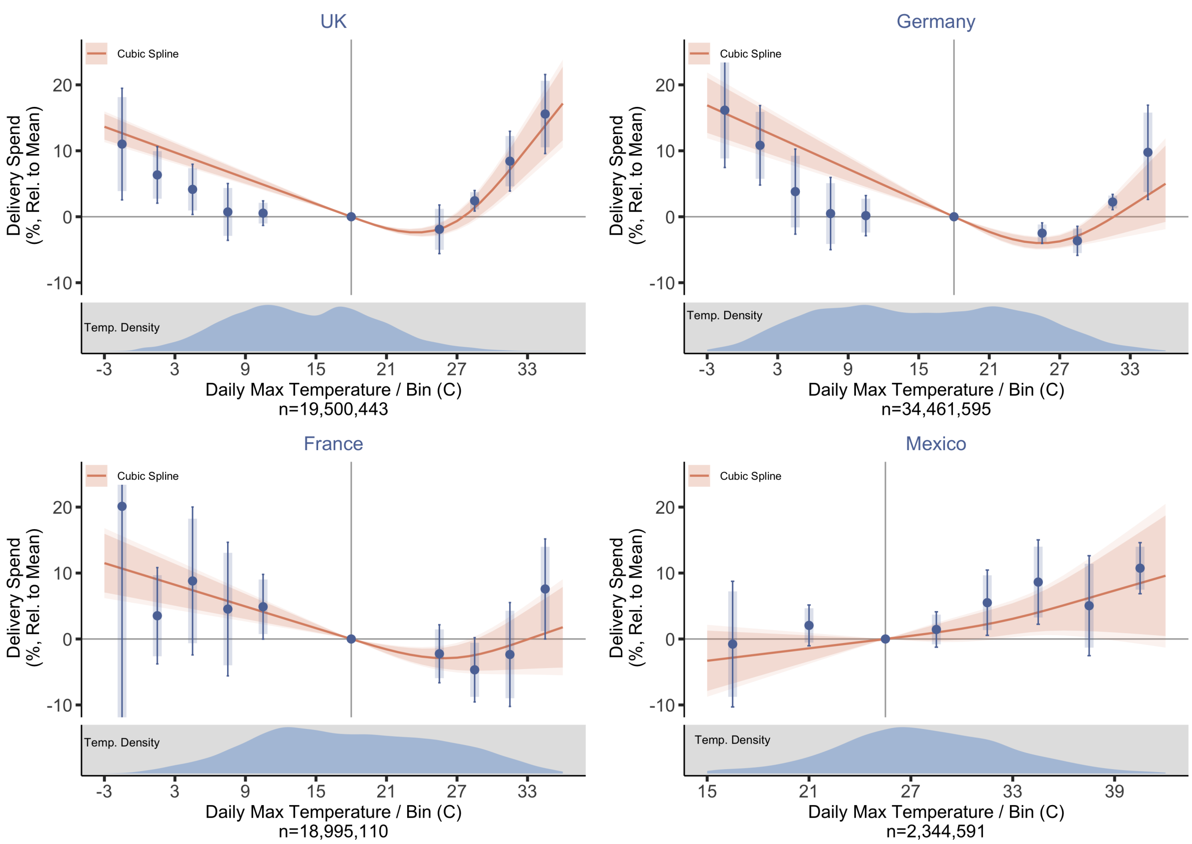
6 Results

I present results on the effects of extreme temperatures on the demand for food delivery (Section 6.1) and labor supply and wages of delivery workers (Section 6.2). In Section 6.3, I study the role of platforms and algorithmic management.

6.1 Delivery Demand

I first examine the response of food delivery spending to daily maximum temperatures across four countries (the UK, Germany, France, and Mexico). Figure 2 shows the results. Despite differences in food delivery markets and variation in climate, I recover a U-shape curve for all countries: food delivery spending increases on days with extreme temperatures relative to mild days.

Figure 2: Food Delivery Spending Results



Notes: Figure shows the relationship between daily maximum temperature and food delivery spending (estimated according to equation 5) in the UK, Germany, France (using Fable transaction data), and Mexico (using Measurable AI transaction data). The dependent variable is delivery spend, divided by the average spend per day for each country. Figure shows estimates both for binned (blue) and cubic spline (red) temperatures; relative to the baseline bin or temperature. Graphs below coefficient plots show the distribution of daily maximum temperatures in each sample. Standard errors clustered by postal-area/municipality & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline). Table version of binned results shown in Tables A6 and A7.

Main Results: To ease the interpretation and comparison of results across countries, I normalize the coefficients on the absolute increase in food delivery spending (shown in Tables A6 and A7) by dividing by the average daily delivery spending in each country. Compared to days with mild temperatures, on days with high maximum daily temperatures (>33°C or >91°F) food delivery spending increases 15.6% in the UK, 9.8% in Germany, and 7.6% in France (Figure 2). There are similar increases on very cold days (maximum temperatures <0°C or <32°F): 11.0% in the UK, 16.2% in Germany, and 20.1% in France (although the last is an imprecise estimate). In Mexico, I focus on hotter days given the warmer climate. On days with high maximum temperatures (>33°C or >91°F), Rappi and UberEats spending is 9.3% higher than on days with moderate temperatures, while on days with extreme maximum temperatures (>39°C or >102°C), food delivery spending is 12.5% higher.

These results are robust to various spatiotemporal and weather controls—including different fixed effects, time trends, reanalysis temperature and precipitation data, and other controls[29]—as well as alternative clustering of standard errors (Figure A5) and using the log of delivery spending instead of levels (Figure A7).[30] I also find broadly similar patterns using Google Trends searches for popular food delivery platforms instead of transaction data (Figure A8).

Delivery Demand Details: Is this increase in food delivery expenditures driven by more orders, or by larger ones? Figure A9 shows that the increase in spending is primarily due to large increases in the odds of food delivery orders on hot days, or the extensive margin (e.g., 10.3% increase in the odds ratio of food delivery purchases in UK; 8.5% in Mexico). This is notable, as a growth in order count requires more deliveries, while larger orders may not. The limited increases in expenditures per order in the UK (where the total spend includes tips) suggest that larger tips on hot days are not common. I do not find evidence of meaningful intertemporal substitution (Figure A10).

Using detailed transaction data from Rappi and UberEats email receipts in Mexico, I can further investigate the rise in food delivery on days with extreme temperatures. Using the hour of each order, I show that the increase in food delivery demand peaks at the same time as daily maximum temperatures do. Orders during lunchtime—when daily temperatures tend to peak—increase by 18.1% on extremely hot days relative to moderate days. Mid-afternoon and dinner delivery expenditures are also higher on hot days (16.3% and 16.1% increase, respectively). Consistent with adaptation during peak temperatures, however, breakfast and late-night orders do not respond to extreme temperatures (Figure 3).

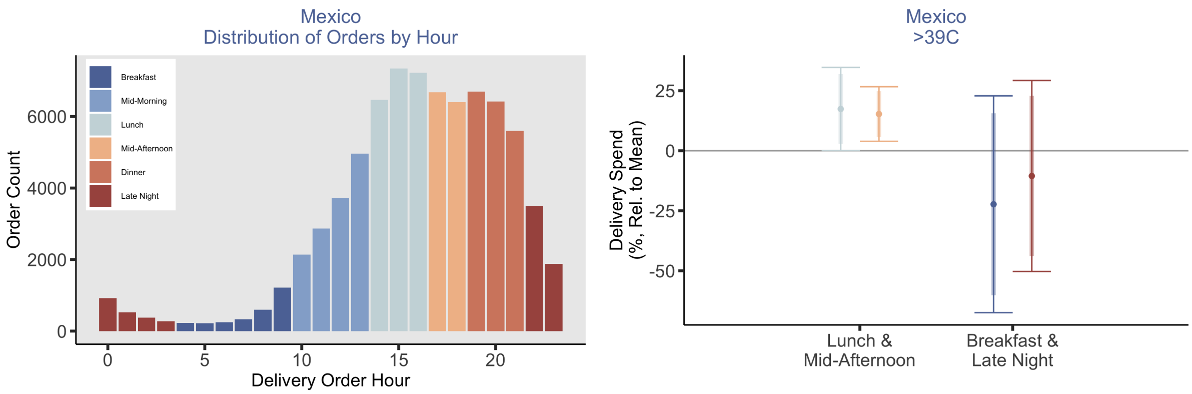
I also show that delivery fees, distances, and times (the latter two available for a small subset of orders) do not change with temperatures (Table A8). See Appendix Section A.4.3 for further analyses and details. The limited changes observed in spending per order—coupled with no changes in delivery fees and delivery times—suggest that tips, fees, and delivery speed do not

[29] Including using ERA-5 temperature data as well as dropping the peak of the COVID-19 pandemic (2020) and controlling for local COVID-19 case counts.

[30] Additionally, for Mexico, unweighted regression results are shown in Figure A6.

significantly impact wages. Relating this to the theoretical framework outlined in Section 3, I infer that $\varepsilon_{f,T}, \varepsilon_{g,T}, \varepsilon_{t,T}$ are all close to zero. Consequently, these channels are unlikely to meaningfully affect demand, labor supply, or wages at high temperatures.

Figure 3: Mexico Time-of-Day Results



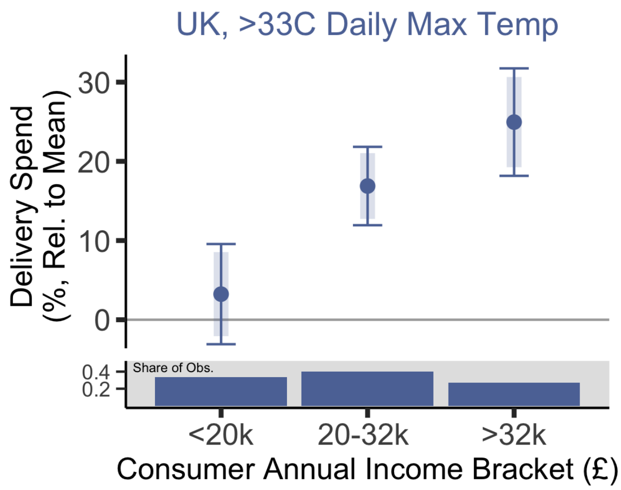
Notes: Left panel of Figure shows the distribution of Rappi and UberEats delivery orders by time of day. Right panel then shows the relationship between daily maximum temperature and delivery spend, estimated according to equation 5, separately for each part of the day, for days with maximum temperatures above 39°C (Figure A11 shows results for the entire temperature distribution). The dependent variable is food delivery spending, divided by average spend for each period. All estimates are relative to the baseline bin (24-27°C). Standard errors clustered by postal-area & month. Thin (thick) line shows 95% (90%) CI.

Heterogeneity by Income: I investigate whether consumer access to adaptation through platforms is equal for different income groups. I first focus on the UK, where my data is most representative of the average consumer and where I have credit card user income bands. I separately estimate the relationship between extreme temperatures and food delivery expenditures for low (<£20,000), medium (£20,000-32,000), and high-income (>£32,000) consumers (these groups, based on approximate terciles, are provided by the data provider). Figure 4 plots the relative change in food delivery spending for each group on days above 33°C relative to moderate days. The increase in delivery spending on hot days is driven by higher-income consumers. Lower-income consumers do not spend more on food delivery on hot days, indicating a disparity in the capacity for climate adaptation.

Appendix Section A.4.4 explores heterogeneity on other dimensions of user characteristics, including electricity spending, age, and gender. UK users likely to own an air-conditioner use food delivery orders to adapt to the heat more than those who do not have air-conditions. Importantly, older consumers, who may be more vulnerable to the heat, are not the sole or main drivers of increased food delivery expenditures (Figure A13).

Other Temperature Demand Results: I take advantage of the detailed credit card data in Europe to study other categories of expenditures. I do this both to further understand adaptation through platforms and to run falsification tests. I recover the opposite relationship between dine-in restaurant spending and extreme temperatures: I estimate *decreases* in restaurant spending similar in magnitude to the *increases* in food delivery spending on days with extreme temperatures (Figure A14). This is further evidence of avoidance behavior and adaptation through platforms. On very hot days, I also find large increases in other online food spending (e.g., grocery delivery), but no meaningful changes in other major categories of expenditures (Figures A15 and A16). See additional results in Appendix Section A.4.5 for more details.

Figure 4: Heterogeneity by Income



Notes: Figure shows the relationship between daily maximum temperature and food delivery spending for UK (using Fable transaction data), by annual income bracket, estimated according to equation 5. The dependent variable is delivery spend, divided by average spend per day for each group. Graphs below coefficient plots show the share of observations in each group. Standard errors clustered by postal-area/municipality & month (binned) or bootstrapped. Thin (thick) line shows 95% (90%) CI.

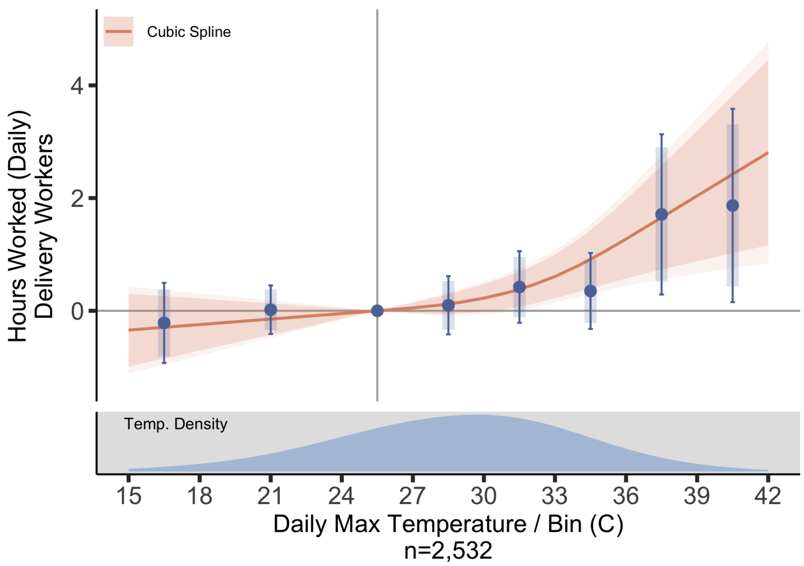
Other Shocks: While the paper's main focus is climate change and heat, I also examine the effects of other shocks—including rain, air pollution, COVID-19 cases, and pay days—on food delivery demand. Across most countries, I find that food delivery expenditures are higher on days with precipitation and high particulate matter ($PM_{2.5}$) concentrations. Higher case rates are also associated with increased food delivery spending during the COVID-19 pandemic. In Mexico, food delivery spending is also higher on bi-weekly paydays on which most workers' wages are paid (*la quincena*). Appendix Section A.4.6 details these analyses.

6.2 Delivery Worker Labor Supply and Wages

What are the effects of increased food delivery demand during extreme temperatures on platform workers? The rise in demand, coupled with a lack of evidence of more efficient trips, suggests that on average platform workers work more on hot days. I test these predictions using data from labor force surveys. I focus on Mexico, due to the availability of data on food delivery platform workers in Mexico's National Survey of Occupation and Employment (ENOE), though I find directionally similar results using samples in the UK and US. I show an increase in the labor supply of food delivery platform workers on hot days relative to mild days, without increases in hourly wages.

Main Results: I first present results on the labor supply of food delivery platform workers. I find an increase in labor supply of 1.7-1.9 hours per food delivery worker on days with high maximum temperatures (>36°C or >97°F) relative to days with moderate temperatures (24-27°C or 75-81°F, Figure 5 and Table A10). This large increase in labor supply is roughly consistent with back-of-the-envelope calculations based on transaction data (2-2.8 hours of extra work per worker).[31] The increase in hours worked on hot days is in contrast to the *decrease* in labor supply for (non-delivery) food-industry workers and climate-exposed agricultural workers (Figure A20).

Figure 5: Changes in Daily Hours Worked by Food Delivery Workers in Mexico



Notes: Figure shows the relationship between daily maximum temperature and hours worked by food delivery platform workers in Mexico, estimated according to equation 6. Figure shows estimates for both binned temperatures (blue) and cubic spline temperatures (red); relative to the baseline bin or temperature. Graphs below coefficient plots show the distribution of daily maximum temperatures in the sample. Standard errors clustered by municipality & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline). Table A10 also shows results.

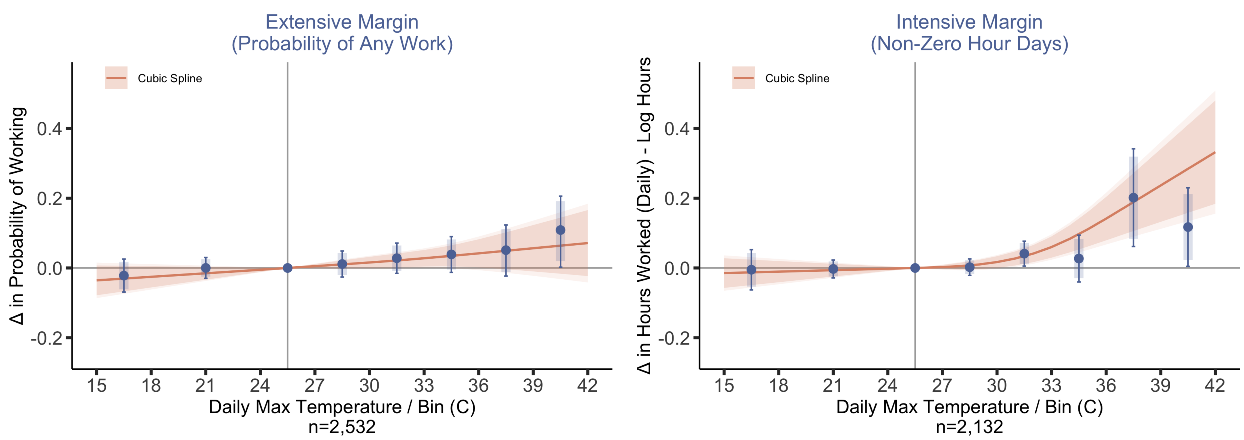
These results are robust to various spatiotemporal and weather controls – including different fixed effects, time trends, reanalysis temperature and precipitation data, and other controls – and alternative clustering of standard errors (Figure A21 and Columns (2)-(5) of Table A10), using the log of hours worked instead of levels (Figure A22), and using alternative samples of workers (Figure A23). The results are also robust to using different bins and similar when using wet-bulb temperatures (Figure A24). Lastly, I find directionally similar increases in the labor supply of small

[31] Based on the coordinates of delivery order pickups and drop-offs in Mexico, the average delivery order takes 22 minutes to deliver. The 9.3-12.5% increase in delivery demand (Figure 2) therefore corresponds to roughly 2-2.8 minutes of additional work per consumer. Since there are about 60 delivery consumers per delivery worker in Mexico (Tejada et al. 2021), the increase in demand translates to approximately 2-2.8 hours of additional work per delivery worker on hot days, relative to moderate days. These calculations assume that delivery times do not change on hot days. I find imprecise decreases of 3.2-4.2 minutes in this metric on hot days. Taking this into account does not meaningfully change the calculations and results in 1.7-2.4 hours more work per worker.

samples of delivery workers from the UK Labor Force Survey and the US CPS (Figure A25).

Labor Supply Details: Are workers more likely to work *at all* on hot days, or do they work longer hours? While there is an imprecise 5.1-10.9% increase in the probability of working on hot days relative to moderate days (left panel of Figure 6), the increase in hours is driven primarily by the intensive margin. I observe a 9.9-17.5% increase in hours worked on hot days (>36°C) compared to moderate days, considering only those days when food delivery workers are actively working (middle panel of Figure 6). The median food delivery worker works 6 days a week, and 33% of workers in the sample work every day of the survey reference week.

Figure 6: Delivery Worker Labor Supply - Extensive vs. Intensive Margin



Notes: Figure shows the relationship between daily maximum temperature and hours worked by food delivery platform workers in Mexico. Left panel shows the extensive margin, where the outcome is an indicator for any hours worked on a day (estimated using aconditional logit regressions), while the right panel shows the intensive margin, restricted to days with non-zero work (estimated according to equation 6). Figure shows estimates for both binned temperatures (blue) and cubic spline temperatures (red); relative to the baseline bin or temperature. Standard errors clustered by municipality & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline).

The increase in hours worked on hot days is not replacing lost hours from other, non-food delivery jobs. In Mexico, only 7-9% of food delivery workers report having another job at the time of the survey, which aligns with the median worker's 48-hour workweek. While workers with secondary jobs tend to work slightly more on hot days, this difference is not statistically significant (left panel of Figure A27).[32] For food delivery workers whose primary job is not food delivery, hot days do not lead to reduced hours in their main employment (right panel of Figure A27). A small subset of these workers with climate-exposed jobs in industries such as agriculture and construction do work a great deal less on hot days relative to mild days, but the share of these workers is very small (only 3% of the workers whose secondary job is food delivery).

[32] Job descriptions for secondary jobs are limited. Importantly, I do not know whether workers who report a secondary job have a boss or are self-employed in that job nor the hours worked in the secondary job during the reference week. This limits the possible analyses I can do. The 7% figure is for the food delivery workers in the main sample who report a secondary job. The 9% figure is pooling a less restrictive categorization of workers whose main job is delivery work and whose secondary job is delivery work and then counting those with any type of secondary job.

Heterogeneity by Worker Characteristics: The overall labor supply results reveal underlying heterogeneity, particularly when considering household size and income. Food delivery workers in Mexico generally fall within the middle of the income distribution for employed workers (Table 2) but there is substantial variation, and according to Tejada et al. (2021) 55% of delivery workers surveyed in Mexico City are below the poverty line when considering only their food delivery incomes. To analyze this further, I calculate the total income per person in each worker's household, excluding their own earnings. Figure A28 illustrates that the increase in hours worked on hot days (>36°C) compared to moderate days is most pronounced for workers with lower household income per capita. See Appendix Section A.5.3 for more details.

Hourly Wages: Do the hourly wages of delivery workers increase in response to the increased demand and disamenity of working in extreme temperatures? To answer this question, I examine whether workers get paid more per hour of work on hot days. I calculate hourly wages using two different data sources, each offsetting the limitations of the other. First, I use data on monthly income and weekly hours worked from ENOE to study worker wages. I isolate exogenous shocks in temperatures in the week prior to the survey date (the reference week) by controlling for temperatures and other weather variables in the first three weeks of the relevant month. This allows me compare income and hours worked for the same time period (the reference week) and infer changes in hourly wages.

However, I find no statistically significant change in the hourly wages of delivery workers in response to high temperatures. In the following analyses, I focus on the impact of an additional day with maximum temperatures above 36°C (97°F) in the reference week.[33] I find that while workers work 13.3% more with each additional day above 36°C (Table 3, Column (2)), the point estimate for implied hourly wages is negative ($p = 0.633$) (Table 3, Column (3)). Due to the imprecision of the estimate, as wages are only available at the monthly level, I repeat the analysis with a larger alternative sample of food delivery workers.[34] I find a more precise decrease of 6.6% ($p < 0.001$) in the hourly wages of these workers (Column (4) of Table 3) (and an increase of 4.5%, $p = 0.013$, in hours worked). Figure A29 shows results for the entire temperature distribution for the samples.

Finally, the detailed UberEats transaction data offers another alternative approach to studying food delivery worker wages. According to Tejada et al. (2021), the base earnings of UberEats delivery workers in Mexico are a percentage of the delivery cost.[35] Together with estimated driving times from the coordinates of the pickup and dropoff locations of orders, this information allows me to calculate implied hourly wages from the transaction data. This is a rough approximation, as there

[33] Based on Figure 5, food delivery workers work more on days above 36C. I group together the 36-39°C and >39°C bins to increase precision for my estimates, given a lower sample size from moving from daily to weekly data.

[34] This sample is identical to the alternative sample of workers used in Figure A23 and includes all "delivery workers of merchandise" and couriers in the food industry as well as self-employed motorcycle drivers in the food industry. I show an increase in the labor supply of these workers on hot days.

[35] These depend on the means the workers use to make deliveries and are: 35% for bicycle, 30% for motorcycles, and 25% for cars. I use 30% in my calculations, as the majority of delivery workers in Mexico use motorcycles (Tejada et al. 2021).

may be additional rewards for picking up orders and for completing a certain number of trips.

I calculate hourly wages by dividing 30% of the delivery fee associated with each order by the estimated driving time in hours. The average hourly wage calculated from UberEats transaction data using these steps is \$3.0, compared to \$2.8 in the ENOE labor force survey and \$2.6 in the survey of food delivery workers in Mexico City (Tejada et al. 2021), suggesting that while the approximation is rough, it is a useful benchmark. Column (5) of Table 3 shows the effect of a day with maximum temperatures above 36°C, relative to the baseline bin (24-27°C). I find results similar to those using the labor force survey data: a decrease of 6.9% ($p = 0.095$) in hourly wages on hot days, relative to moderate days. Figure A30 shows the results for the entire temperature distribution.

Table 3: Delivery Worker Wages

	Main Sample			Alternative Sample	Transaction Data		
	Dependent variable (logs):						
	Income	Hours	Wages	Wages	Wages		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
>36C	0.032	0.133*	−0.100	−0.066***	−0.069*	-0.043	-0.006
	(0.147)	(0.072)	(0.208)	(0.017)	(0.038)	(0.035)	(0.035)
	[0.828]	[0.079]	[0.633]	[0.000]	[0.095]	[0.243]	[0.878]
Base Tip					No	10%	10%
Extra Tip					No	+10%	No
Efficiency					No	No	+5%
Obs.	280	280	280	1,221	14,433	14,433	14,433

Notes: Table shows the relationship between daily maximum temperature and monthly income, hours worked, and implied hourly wages (estimated according to equation 6). **Columns (1)-(4):** Use ENOE labor force survey data. The main explanatory variable is the number of days in the reference week with maximum temperatures above 36°C, compared to the reference bin of all days between 24 and 27°C. Dependent variables are based on one observation per reference week and weekly hours worked; flexible controls (mean of the daily maximum temperatures and its square and cube and total precipitation and its square and cube) are included for the first three weeks of the relevant month in order to isolate variation in temperatures in the reference week. **Columns (5)-(7)**: Implied wages calculated from UberEats transaction data. The main explanatory variable is an indicator for days above 36°C. Regressions are weighted by number of observations in main ENOE sample in each municipality. **All columns:** Standard errors (clustered by municipality and month) are shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01). Figures A29 and A30 show the unweighted wage results for the entire temperature distribution for all samples.

I also incorporate conservative assumptions about consumer tips and efficiency. In column (6) of Table 3, I add 10% of the total food cost to the pay workers receive for each trip and include an increase of this tip to 11% on hot days. This is likely to overestimate tips, as consumers in Mexico generally round up or tip a fixed amount. In Column (7), I include tips and also an increase of 5% efficiency in the driving time on hot days. Again, this is likely to overestimate wages, as I do not find changes in delivery speed in response to temperatures (Table A8). However, even with these additions, implied hourly wages decrease in response to high temperatures.

As this setting is one in which hourly wages have the potential to respond to shocks rapidly due to the structure of platform-based pay, null or negative results are meaningful. Peak-pay is one way platforms advertise attracting workers during high demand times. I show that hourly wages increased meaningfully in response to the COVID-19 pandemic. Table A11 shows that the hourly wages of food delivery workers increased by 24-74% per 100 local deaths during the pandemic. I find increases in wages in both the labor force survey data and the UberEats transaction data.

Together, these results show that although food delivery workers work more on average on days with extreme temperatures and higher demand, their hourly wages are not higher. Even using a wage elasticity on the high end of existing estimates for men (0.3), hourly wages would have to increase by 44% to result in the observed increases in hours worked. This is outside the 99% confidence intervals of even the imprecisely estimated wages in Table 3, showing other mechanisms are responsible for the large increases in food delivery labor supply during extreme temperatures.

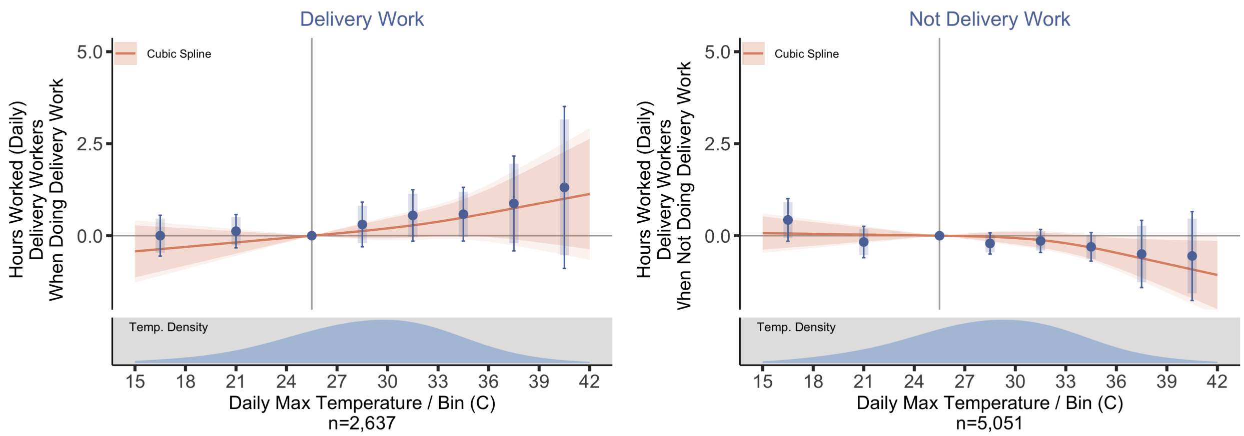
Despite the increase in hours worked, the rise in total daily income is minimal, given the observed changes in wages. Table 3, column (1) shows a statistically insignificant 3.2% increase in daily income ($p = 0.828$). Similarly, when using the transaction data to calculate the wage decrease and applying it to the change in hours worked, I find a 5.5% increase in total daily income.

6.3 The Role of Platforms

What is the role of platforms in the increase in labor supply on days with high temperatures? In this section, I provide evidence that the increase in labor supply, without increases in wages, is specific to platform-based self-employment.

I first show that food delivery platform workers are not indifferent to working in the heat and *do decrease* hours worked when they are not working delivery jobs. I select a group of food delivery workers who hold other jobs in different quarters of the survey panel. For the same group of workers, I separately estimate the relationship between temperature and hours worked in quarters they are doing delivery and other work. I find that while these workers are working as delivery workers they work more hours on hot days relative to moderate days (left panel of Figure 7), but when they are not working in food delivery, they work *fewer* hours (right panel of Figure 7).

Figure 7: Labor Supply of Food Delivery Workers in Mexico - Delivery vs. Other Work



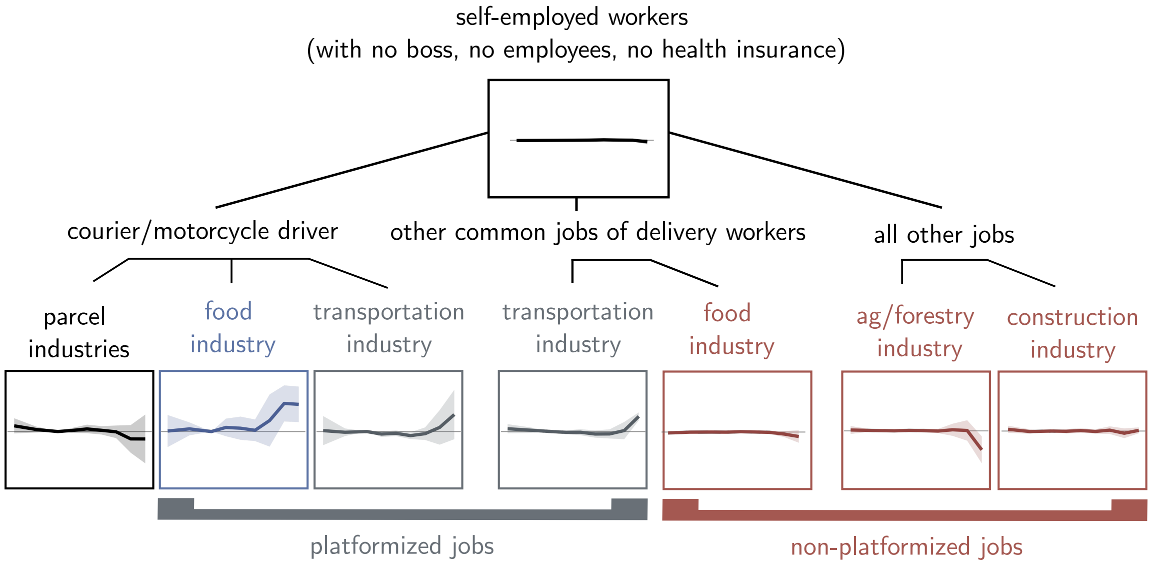
Notes: Figure shows the relationship between daily maximum temperature and hours worked (estimated according to equation 6) for a group of food delivery platform workers in Mexico who, during different quarters, perform both delivery and other work. Left panel shows sample when they are doing food delivery work, while right panel shows sample when they are *not* doing food delivery work. Figure shows estimates for both binned temperatures (blue) and cubic spline temperatures (red); relative to the baseline bin (24-27C) or temperature (25.5C). Graphs below coefficient plots show the distribution of daily maximum temperatures in the sample. Standard errors clustered by municipality & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline).

The relative increase in labor supply on hot days may be characteristic of self-employment in general, rather than specific to platform-based work. I next show that this is not the case. Figure 8 illustrates the temperature-labor supply relationship for various groups of self-employed workers in Mexico. The top row of Figure 8 shows that self-employed workers, on average, do not work more on hot days.[36] However, for self-employed workers in industries where platforms are prevalent, including the transportation industry (e.g., ride-hailing platforms), I demonstrate the same increase in labor supply on hot days, relative to mild days. For work less associated with platforms, such as food work outside of delivery (e.g., street food) or agricultural work, I observe the usual decrease in labor supply in response to high temperatures shown in the literature (bottom row of Figure 8).

To further investigate the role of platforms, I compare two jobs that involve driving passengers: transportation platform workers and private chauffeurs. The occupations differ significantly in their employment structures as transportation platform workers represent a common type of gig economy job, typically operating through app-based ride-hailing services (e.g., Uber, Ola, and Didi in Mexico). In contrast, private chauffeurs work in a traditional, non-platform-based employment model. Hours worked increase for both (Columns (2) and (5) of Table A12), but while hourly wages fall for transportation platform workers (in line with earlier results for food delivery workers), it increases significantly for private chauffeurs (Columns (3) and (6) of Table A12).

[36]Neither do self-employed couriers/motorcycle drivers, workers with jobs commonly held by delivery workers outside of quarters working in food delivery, or self-employed workers with other jobs (middle row of Figure 8, not shown).

Figure 8: Self-Employed Workers in Platformized vs. Non-Platformized Jobs



Notes: Figure illustrates the relationship between daily maximum temperature and hours worked (estimated according to equation 6) for various groups of self-employed workers in Mexico. Blue plot shows the relationship for self-employed food delivery workers, while gray plots show the same for self-employed transportation workers (also likely to be platformized). In red, the temperature-work relationship is shown for self-employed workers unlikely to be on platforms (e.g., in agriculture or construction). Figure shows estimates for binned temperatures relative to the baseline bin (24-27°C), with >42°C as the highest bin; y-axis has the same scale across all plots. Standard errors clustered by municipality & month; 95% confidence intervals shown.

Mechanisms: Together, the results shown in Figures 5-8 and Table A12 demonstrate that the combination of increased hours but flat or lower wages is unique to platform work. But why do platform workers work more if their wages do not increase? Revisiting the theoretical framework from Section 3, I have ruled out as motivators changes in prices, fees, tips, and delivery times in response to temperatures (Figure A9 and Table A8). Rearranging equation 7, I write the platform's future opportunities expectations effect as

$$\left(\varepsilon_{H,E} \cdot \varepsilon_{E,T}\right) = \varepsilon_{D,T}\left(1 - m \cdot \varepsilon_{S,D}\right) - \varepsilon_{S,T} - \varepsilon_{w,T} \tag{7}$$

The previously described results suggest that $\varepsilon_{Q,T}$ is positive (from the demand results), $\varepsilon_{H,T}$ is likely negative (from workers' labor supply adjustment when not working for platforms, see Figure 7), and $\varepsilon_{w,T}$ is negative or zero (from the wage results, see Table 3). Therefore, the future earnings expectations effect is positive in this setting: workers increase their labor supply in response to changes in their expectations to future earnings due to extreme temperatures. This means that there is an indirect labor supply effect through the future opportunities mechanisms.

What are these future opportunities mechanisms? First, intertemporal substitution may play a role. If workers expect that the extreme temperatures today will continue for the next few days, they might work more today in order to be able to rest in the following days. However, I find no evidence of meaningful intertemporal substitution by workers. While there is a decrease in hours worked on days following those with maximum temperatures above 36°C, this effect is not statistically significant and is only about half the magnitude of the increase observed on the high-temperature days themselves (Figure A26). When aggregating at the weekly level, I still observe an increase in hours worked (e.g., Column (2) of Table 3) and the effect of high temperatures in the three weeks prior to the survey reference week is *positive* on hours worked in that reference week. Platform workers work more in total, at least in the short term.

I find the key mechanism to be worker beliefs about platform practices. As independent contractors, platform workers do not have set schedules, but their future earnings may depend on their priority in the platform's algorithm. The sociology literature has coined this "algorithmic management" or "soft control" (Schor et al. 2020; Griesbach et al. 2019). Reputational and psychological concerns may both play a role. For example, workers may believe that lower ratings will influence the quality of future opportunities. Similarly, workers may believe that turning down orders during high-demand periods (such as days with high extreme temperatures) will adversely affect their priority for future opportunities. There is extensive qualitative evidence on the behavior nudges and gamification employed by platforms (e.g., Scheiber 2021; Lei 2019).

I first provide suggestive evidence of this "algorithmic management" future earnings channel in Mexico using the labor force survey data. I separate food delivery platform workers into workers who just started working on platforms, and all others. I define workers who just started on platforms as those who had a job in the prior quarter that was not platform-based. I find that the large increase in hours is concentrated among workers new to platform work (Figure A31). For these workers, the marginal impact of each hour of work on their overall performance is higher. Additionally, these workers are also likely to have less experience and understanding of the algorithms. Indeed, new workers respond more to hot days, though the difference between the two groups is not statistically significant, so these results are only suggestive.

Platforms with greater market power may have more ability to influence worker behavior through algorithmic management, as workers' beliefs about algorithmic penalties for declining work become more salient when they have fewer alternative platforms. Platforms can leverage their dominant position to implement nudges, gamification, and performance metrics that shape workers' decisions. While the market timeline and lack of power do not allow me to test these hypotheses for food delivery workers,[37] I investigate them for rideshare workers,[38] whose beliefs about algorithmic management may also be relevant (as shown in Figure 8, the labor supply of these workers also increases on hot days relative to moderate days).

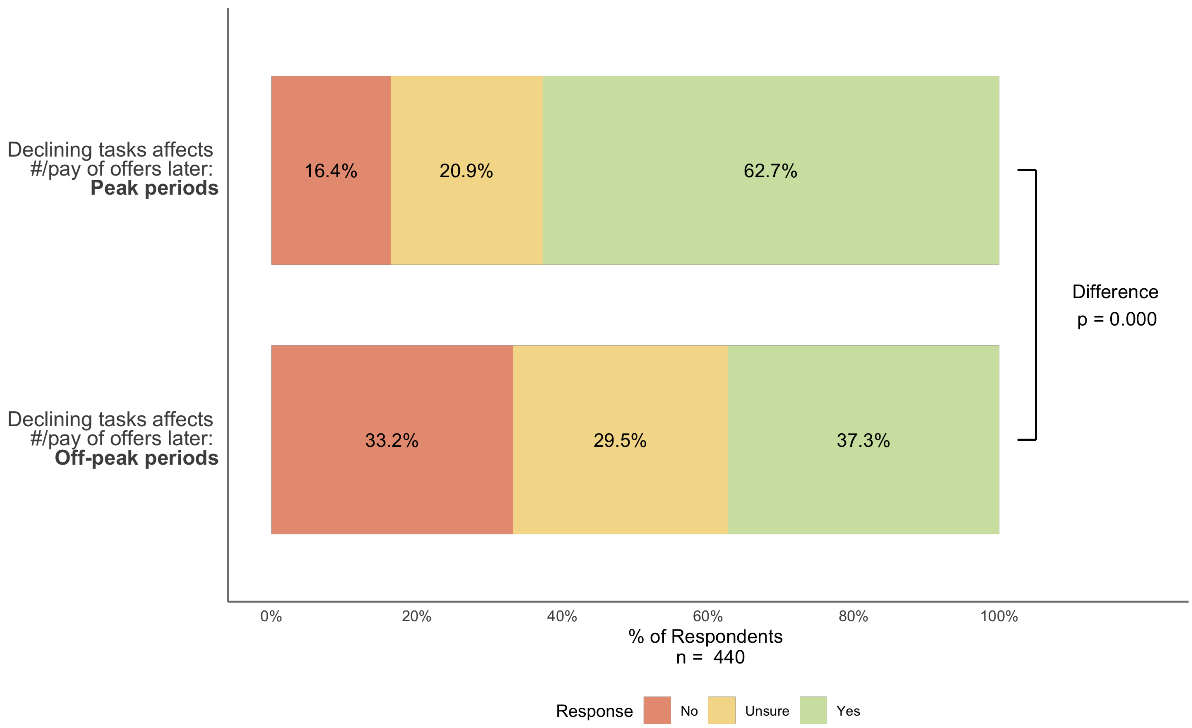
[37]Rappi and UberEats both launched in 2016 in Mexico. While a third major competitor, DiDi Foods, launched in 2019, most of my sample is from past 2019.

[38]These are self-employed workers without a boss, without employees, and without health insurance who work in land transportation of passengers (4850 for question `p4a`) and whose job description includes driving cars or motorcycles (8342 or 8344 for question `p3`).

Table A13 shows the temperature-labor supply and temperature-wages relationships for rideshare workers. Columns (1)-(3) show results for when Uber was the only major rideshare company in Mexico (almost 90% market share in mid-2017). During this time, hours worked by rideshare platform workers increased on hot days, relative to moderate days, while hourly wages decreased. For years after DiDi entered the market, there is no relationship between hours worked and extreme heat (Columns (4)-(6)).[39] This is further suggestive evidence of non-wage platform incentives.

Survey evidence: I next provide additional evidence of the worker belief mechanism through a survey conducted on Prolific with delivery and ride-hailing gig economy platform workers in both Mexico and the US. The survey reveals workers' strong beliefs about how their current work decisions affect future opportunities on the platforms.

Figure 9: Worker Survey - Effect of Actions Today on Future Platform Opportunities



Notes: Figure shows responses of platform workers from Prolific survey. Each bar shows the share of respondents answering "Yes", "Unsure", and "No", to whether each action today affects the number or pay of offers they receive in the future. For example, the first question asks workers: "Do you think saying no to jobs during busy times (like rush hour or special events) affects the number or pay of jobs the app offers you later (e.g., tomorrow)?". Figures A33 and A34 show the results separately for the US and Mexico.

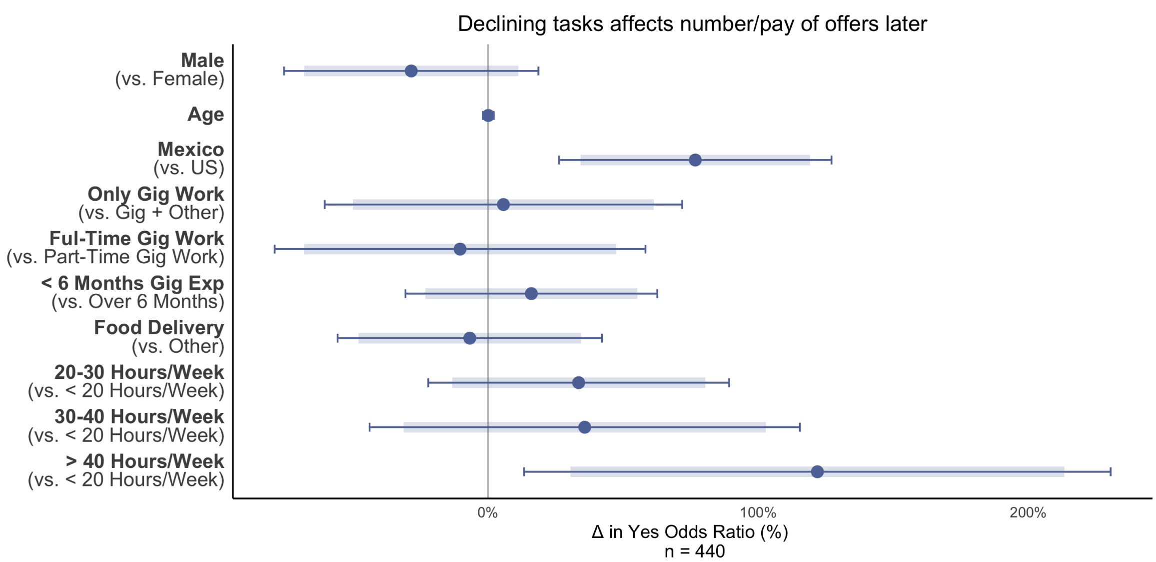
The substantial majority of gig workers believe the number of hours worked and declining jobs impact both the quantity and compensation of future job offers (Figure A32). Workers' concerns about future consequences vary by timing: 62.7% of platform workers believe that declining jobs during peak demand periods affects future opportunities, while only 37.3% hold this belief for less

[39] Results for Columns (4)-(6) are also similar excluding all of 2020 due to the pandemic.

busy periods (Figure 9). These proportions are statistically significantly different ($p < 0.001$), meaning that the beliefs of workers during peak time periods — such as hot days — are different from their beliefs during less busy times. While these results are pooled for all workers, Figures A33 and A34 show that they hold separately for Mexican and US platform workers.

Platform workers on Prolific may not be representative of gig workers in general. As described in Section 4, the average Prolific gig worker is more likely to be female, younger, and work only part-time or fewer hours on platforms than the sample from the public labor force surveys (Table A5). To address this potential concern, I compare responses to whether declining orders today affects future opportunities across various subgroups. These results are shown in Figure 10. Differences between most groups are not statistically significant. Full-time and part-time gig workers respond similarly as do those with and without other jobs. Workers new to platform work are slightly more likely to believe that their actions on the platforms influence future opportunities than those with more experience on platforms (though this difference is not statistically significant). This is consistent with the suggestive evidence in Figure A31. Gig workers in Mexico and those who work more than 40 hours a week — who make up the majority sample from the labor force survey used in the analyses in Section 6.2 — are more likely to believe that declining tasks affects the number or pay of their future opportunities.

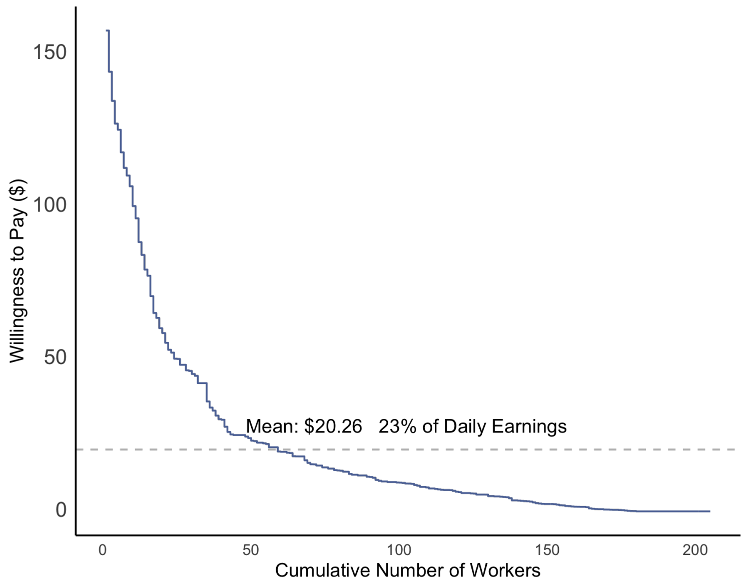
Figure 10: Survey Responses By Worker Characteristics



Notes: Figure displays results from a logistic regression examining which worker characteristics predict believing that declining tasks affects future job offers. Points show changes in odds ratios (%). The baseline worker is female, is in the US, does gig work alongside other jobs, works part-time (< 20 hours per week), and has over 6 months of experience. Age is measured in years. Thin (thick) line shows 95% (90%) CI. Figures A35 and A36 show the results separately for the US and Mexico.

To quantify workers' willingness to pay to avoid future algorithmic consequences of their current actions, I calculate the dollar amount they would sacrifice based on their self-reported earnings. I multiply each worker's reported average pay per task by their reported average count of daily tasks to obtain their daily earnings, then multiply this by the percentage they report being willing to give up. I find that on average, workers are willing to pay \$20.26 or 23% of their daily earnings for their actions today to not affect future offers by platform algorithms (Figure 11).

Figure 11: Willingness to Pay for Hours/Orders Today to Not Affect Future Offers



Notes: Figure plots the amount gig workers report they would give up for their actions on the platforms today to not affect their future earnings. This is calculated from workers' average pay per task, average tasks per day, and the response to the question "What percentage of your daily pay would you be willing to give up for your actions on the platform (e.g., hours worked or orders accepted) to not affect the number or pay of jobs the app offers you later (e.g., tomorrow)?." Figure A37 shows the results separately for the US and Mexico, while Figure A38 presents results for gig workers with food delivery specific experience.

Together, these results show four key findings that support worker beliefs regarding algorithmic management as the main mechanism for driving their increase in labor supply during extreme temperature days. First, the majority of platform workers believe that declining tasks influences the quantity and pay of future offers from platforms (Figure A32). Second, this belief is particularly strong regarding peak demand periods compared to off-peak hours (Figure 9). Third, this belief is also stronger for workers who work more hours on platforms (Figure 10). Lastly, gig economy workers report that they would be willing to sacrifice 23% of their daily earnings for their actions on the platform (e.g., hours worked or orders accepted) to not affect their future offers (Figure 11).

Beyond but consistent with these results, survey responses also reveal that workers believe platforms use gamification and behavioral nudges to encourage longer working hours. Appendix Section A.5.6 presents survey answers for other questions in the survey. These results show that most workers believe that descriptions of gamification and nudges describe their experience on the platforms and that platforms use these strategies mainly to get workers to work more and raise company profits.

All of these survey findings on algorithmic management strengthen the evidence that workers' decisions to increase hours during extreme temperature days, without receiving higher pay, are driven by concerns about maintaining future work opportunities on the platforms.

7 Welfare Calculations

How large are the shifts in climate burdens from consumers to workers? Using the temperature-mortality relationship in Mexico estimated in Wilson et al. (2024), I next present back-of-the-envelope calculations of the marginal mortality risk that delivery workers are exposed to on a hot day compared to a moderate day.

I first calculate a weighted mortality risk of a day with average temperatures of 30°C relative to 20°C based on the age distribution of delivery consumers and workers (Panel A of Table 4). Given that I use maximum daily temperatures in my main analysis (due to food delivery orders peaking approximately when daily temperatures do), I then re-estimate the temperature-delivery and temperature-labor supply relationships using mean temperatures and appropriate bins to match Wilson et al. (2024). Panel B of Table 4 shows that food delivery spending and hours worked by delivery workers both increase on days with mean temperatures of 30°or above, relative to days with mean temperatures of 20°C.

The labor supply of workers increases by an average of 1.7 hours (or 4.4 deliveries, given an approximate time of 22 minutes for each delivery) on these days, equivalent to an increase in mortality risk of 0.08 per million. Per order, this results in the increase of delivery worker mortality risk of 0.02 per million. Given the weighted per-hour mortality risk for consumers, this means that if each delivery order reduces consumer time spent outside by less than 0.41 hours (25 minutes) on average, total worker and consumer welfare *decreases*. These figures are likely to underestimate the true mortality risks for workers, given that the marginal risk of an hour of exposure to heat may depend on baseline hours spent outside. This is likely to be higher for food delivery workers who spend the majority of their working hours exposed to the elements.

I take these calculations further by estimating the number of heat-related deaths caused by the additional 1.7 hours worked by delivery workers on hot days relative to moderate days. By the end of this century, under the SSP 3-7.0 emissions scenario, Mexico is expected to experience mean daily temperatures above 30°C for 18% of days (Wilson et al. 2024). The increased labor supply on hot days could result in approximately 10 *additional* work-related deaths per year for food delivery platform workers alone.[40] This is a large increase relative to about 3,900 annual heat-related deaths in Mexico historically (Wilson et al. 2024) and likely an underestimate due to the aforementioned reasons.

[40] This is calculated as follows. At present, about 5% of person-days are above 30°C and there are about 400,00 delivery platform workers in Mexico. Multiplying 365 days with 5% and 400,000 results in 7.3 million delivery-person-days of exposure above 30°C. Multiplying this by the increase in mortality risk (Table 4) results in 0.6 additional deaths per year. Repeating these calculations with 18% of days above 30°C and 2 million delivery workers (assuming an annual growth rate of 2.5%) results in 10.5 *additional* deaths per year.

Table 4: Back-of-the-Envelope Mortality Calculations

Panel A: Mortality Risk (from Wilson et al. 2024, avg. daily temp of 30°C vs. 20°C, per million)

	Abs. Risk	Consumer	Worker
Age Group		Share	Share
18-35	0.41	47%	56%
35-49	0.55	27%	26%
50-69	-	26%	17%
Wtd. Risk (Per M)		0.34	0.37
Per Hour (Per M)		0.04	0.05

Panel B: Regression Results (Average daily temp of 30°C vs. 20°C)

	Food Delivery Spending (%)	Food Delivery Work	
		Hours	Deliveries
>30 °C	8.67*	1.66**	4.4
	(4.65)	(0.69)	
	[0.064]	[0.019]	

Panel C: Implied Increase in Mortality Risk (Average daily temp of 30°C vs. 20°C, per million)

	Eq. Outdoor Exp. (Hours)	Per Worker	Per Delivery
>30 °C	**0.41**	**0.08**	**0.02**

Notes: Table shows back-of-the-envelope calculations of mortality risk from exposure to heat. **Panel A** shows the increase in mortality risk (per million) for various age groups for a day with average temperatures of 30°C compared to 20°C in Mexico, as estimated by Wilson et al. 2024. Age-weighted risk per million is calculated based on the approximate share of food delivery consumers (from Statista) and workers (from ENOE used in main analysis) in each age group. An hour of exposure is assumed to be equivalent to an eight of the full day. **Panel B** shows regression results, repeating the analyses shown in Figure 2 and 5, except using mean daily temperatures and 2°C bins. The baseline bin is 20-22°C. Standard errors (clustered by municipality and month) are shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01). **Panel C** shows the implied increase in mortality risk for food delivery workers (0.08 per million), equivalent to the weighted risk per hour (0.05) times the additional hours worked (1.66). This panel also shows the average outdoor exposure that a food delivery order replaces for the food delivery trip to be welfare neutral, equivalent to the per-delivery decrease in welfare for workers (0.08) divided by the per-hour weighted risk for consumers (0.04).

8 Discussion and Conclusion

Climate change responses fall into two categories: mitigation and adaptation. While the unequal burden of mitigation efforts has been studied, less attention has been paid to how adaptation strategies may create or exacerbate inequalities. I study the distribution of climate adaptation burdens within labor markets, specifically in the rapidly growing gig economy. I examine how adaptation to extreme heat affects the demand for platform-based food delivery services and, in turn, how it impacts economic and environmental inequality.

I show that consumers in diverse markets and climates use app-based food delivery platforms to avoid exposure to extreme temperatures. This behavior is primarily driven by high-income consumers of all ages, highlighting a disparity in access to climate change adaptation along socioeconomic lines. This consumer adaptation behavior shifts climate burdens from high-income consumers to lower-income platform workers. I show that food delivery workers work more hours on days with high temperatures relative to mild days. While this increase is in line with the growth in consumer demand, it contrasts with existing literature that shows a decrease in labor supply during extreme temperatures for climate-exposed work (e.g., Graff Zivin and Neidell 2014; Rode et al. 2022). These novel findings demonstrate that time-sensitive increases in demand increase labor supply for gig economy workers during extreme temperatures.

Despite the heightened demand and risks of working in the heat, workers are not compensated through their hourly wages. I find that the increase in labor supply without wage increases is specific to self-employment on platforms. Workers in other industries, including those less associated with platforms, exhibit the usual downward-facing relationship between temperature and hours worked documented in previous work. Through a survey of platform workers, I show that this response is driven by worker beliefs about platform algorithms - workers believe their current choices, especially during high-demand periods, determine their future opportunities on the platform.

I show back-of-the-envelope calculations on the size of the climate burdens shifted from consumers to workers. Using age-specific temperature-mortality relationships from Wilson et al. (2024), I calculate the marginal mortality risk experienced by delivery workers on hot days compared to moderate days. I find that workers' mortality risk increases by 0.08 per million on days with average temperatures of 30°C compared to 20°C. If each delivery order reduces consumer time spent outside by less than 25 minutes on average, total worker and consumer welfare also decreases. The concentration of damages on lower-income workers may be of policy interest, regardless of the overall effect on consumer and worker welfare. Beyond increased mortality risk, the increased exposure to extreme temperatures also poses other health risks for delivery workers. Numerous studies have documented the negative health effects of working in high temperature, including heat-related illnesses and workplace accidents (e.g., Deschênes and Greenstone 2011; Dillender 2021).

My findings have important implications beyond the food delivery market. As climate change intensifies and the gig economy expands, consumers with the means to adapt may shift various tasks to workers. This suggests the need to carefully consider platform algorithms and regulations to protect gig workers who bear a disproportionate share of climate damages. Potential policy interventions may include ensuring adequate protections for platform workers and limiting the monopsony power of platforms. The paper also raises broader questions about how worker beliefs about platform algorithms may constrain the flexibility of gig work, particularly when environmental risks are high — an important consideration as algorithms mediate which workers face climate damages and how they are compensated. Ultimately, while digital platforms offer new opportunities for climate adaptation, they also create challenges in terms of environmental justice and labor rights.

References

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham. 2022. "Management and Shocks to Worker Productivity." *Journal of Political Economy* 130 (1): 1–47. https://doi.org/10.1086/717046. eprint: https://doi.org/10.1086/717046. https://doi.org/10.1086/717046.

Ahuja, Kabir, Vishwa Chandra, Victoria Lord, and Curtis Peens. 2021. *Ordering in: The rapid evolution of food delivery.* McKinsey & Company Report.

Angrist, Joshua D., Sydnee Caldwell, and Jonathan V. Hall. 2021. "Uber versus Taxi: A Driver's Eye View." *American Economic Journal: Applied Economics* 13 (3): 272–308. https://doi.org/10.1257/app.20190655. https://www.aeaweb.org/articles?id=10.1257/app.20190655.

Aroonruengsawat, Anin, and Maximilian Auffhammer. 2011. "Impacts of Climate Change on Residential Electricity Consumption: Evidence from Billing Data." In *The Economics of Climate Change: Adaptations Past and Present,* by Gary D. Libecap and Richard H. Steckel, 311–342. University of Chicago Press. http://www.nber.org/chapters/c11991.

Auffhammer, Maximilian. 2022. "Climate Adaptive Response Estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption." *Journal of Environmental Economics and Management* 114:102669. ISSN: 0095-0696. https://doi.org/https://doi.org/10.1016/j.jeem.2022.102669. https://www.sciencedirect.com/science/article/pii/S0095069622000432.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro. 2016. "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century." *Journal of Political Economy* 124 (1): 105–159. ISSN: 00223808, 1537534X, accessed January 30, 2023. https://www.jstor.org/stable/26549859.

Barwick, Panle Jia, Shanjun Li, Liguo Lin, and Eric Zou. 2019. *From Fog to Smog: the Value of Pollution Information.* Working Paper, Working Paper Series 26541. National Bureau of Economic Research. https://doi.org/10.3386/w26541. http://www.nber.org/papers/w26541.

Burke, Marshall, Sam Heft-Neal, Jessica Li, Anne Driscoll, Patrick Baylis, Matthieu Stigler, Joakim A. Weill, et al. 2022. "Exposures and behavioural responses to wildfire smoke." *Nature Human Behaviour* 6 (10): 1351–1361. ISSN: 2397-3374. https://doi.org/10.1038/s41562-022-01396-6. https://doi.org/10.1038/s41562-022-01396-6.

Camerer, Colin, Linda Babcock, George Loewenstein, and Richard Thaler. 1997. "Labor Supply of New York City Cabdrivers: One Day at a Time*." *The Quarterly Journal of Economics* 112 (2): 407–441. ISSN: 0033-5533. https://doi.org/10.1162/003355397555244. eprint: https://academic.oup.com/qje/article-pdf/112/2/407/5291730/112-2-407.pdf. https://doi.org/10.1162/003355397555244.

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, et al. 2022. "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits." *The Quarterly Journal of Economics* 137 (4): 2037–2105. ISSN: 0033-5533. https://doi.org/10.1093/qje/qjac020. eprint: https://academic.oup.com/qje/article-pdf/137/4/2037/51054116/qjac020.pdf. https://doi.org/10.1093/qje/qjac020.

Carreón Rodríguez, Víctor G., Miguel A. Guajardo Mendoza, Mauricio F. Coronado García, Julio Lezama Amastalli, and Francisco Rafael Suárez Ruiz. 2021. *Las Plataformas de Entrega a Domicilio en la Economia Mexicana [Home Delivery Platforms in the Mexican Economy].* Report. https://lnpp.mx/f/43efe283cc.

Chen, M. Keith, Judith A. Chevalier, Peter E. Rossi, and Lindsey Currier. 2024. *Suppliers and Demanders of Flexibility: The Demographics of Gig Work.* Working Paper. https://www.anderson.ucla.edu/faculty/keith.chen/papers/WP_Flexibility_Supply_and_Demand.pdf.

Chen, M. Keith, Judith A. Chevalier, Peter E. Rossi, and Emily Oehlsen. 2019. "The Value of Flexible Work: Evidence from Uber Drivers." *Journal of Political Economy* 127 (6): 2735–2794. https://doi.org/10.1086/702171. eprint: https://doi.org/10.1086/702171. https://doi.org/10.1086/702171.

Chu, Junhong, Haoming Liu, and Alberto Salvo. 2021. "Air pollution as a determinant of food delivery and related plastic waste." *Nature Human Behaviour* 5 (2): 212–220. ISSN: 2397-3374. https://doi.org/10.1038/s41562-020-00961-1. https://doi.org/10.1038/s41562-020-00961-1.

Colmer, Jonathan. 2021. "Temperature, Labor Reallocation, and Industrial Production: Evidence from India." *American Economic Journal: Applied Economics* 13 (4): 101–24. https://doi.org/10.1257/app.20190249. https://www.aeaweb.org/articles?id=10.1257/app.20190249.

Connolly, Marie. 2008. "Here Comes the Rain Again: Weather and the Intertemporal Substitution of Leisure." *Journal of Labor Economics* 26 (1): 73–100. https://doi.org/10.1086/522067. eprint: https://doi.org/10.1086/522067. https://doi.org/10.1086/522067.

Daly, Christopher, Michael Halbleib, Joseph I. Smith, Wayne P. Gibson, Matthew K. Doggett, George H. Taylor, Jan Curtis, and Phil Pasteris. 2008. "Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States." *International Journal of Climatology* 28 (15): 2031–2064. https://doi.org/10.1002/joc.1688. https://doi.org/10.1002/joc.1688.

Datta, Namita, Chen Rong, Sunamika Singh, Clara Stinshoff, Nadina Iacob, Natnael Simachew Nigatu, Mpumelelo Nxumalo, and Luka Klimaviciute. 2023. *Working Without Borders: The Promise and Peril of Online Gig Work.* World Bank Report. https://openknowledge.worldbank.org/handle/10986/40066.

Deschênes, Olivier, and Michael Greenstone. 2011. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." *American Economic Journal: Applied Economics* 3 (4): 152–185. ISSN: 19457782, 19457790, accessed November 2, 2022. http://www.jstor.org/stable/41288654.

Dillender, Marcus. 2021. "Climate Change and Occupational Health." *Journal of Human Resources* 56 (1): 184–224. ISSN: 0022-166X. https://doi.org/10.3368/jhr.56.1.0718-9594R3. eprint: https://jhr.uwpress.org/content/56/1/184.full.pdf. https://jhr.uwpress.org/content/56/1/184.

Doremus, Jacqueline M., Irene Jacqz, and Sarah Johnston. 2022. "Sweating the energy bill: Extreme weather, poor households, and the energy spending gap." *Journal of Environmental Economics and Management* 112:102609. ISSN: 0095-0696. https://doi.org/https://doi.org/10.1016/j.jeem.2022.102609. https://www.sciencedirect.com/science/article/pii/S0095069622000018.

Downey, Mitch, Nelson Lind, and Jeffrey G. Shrader. 2023. "Adjusting to Rain Before It Falls." *Management Science* 0 (0): null. https://doi.org/10.1287/mnsc.2023.4697. eprint: https://doi.org/10.1287/mnsc.2023.4697. https://doi.org/10.1287/mnsc.2023.4697.

Dubé, Jean-Pierre, and Sanjog Misra. 2023. "Personalized Pricing and Consumer Welfare." *Journal of Political Economy* 131 (1): 131–189. https://doi.org/10.1086/720793. eprint: https://doi.org/10.1086/720793. https://doi.org/10.1086/720793.

Einav, Liran, Chiara Farronato, Jonathan Levin, and Neel Sundaresan. 2018. "Auctions versus Posted Prices in Online Markets." *Journal of Political Economy* 126 (1): 178–215. https://doi.org/10.1086/695529. eprint: https://doi.org/10.1086/695529. https://doi.org/10.1086/695529.

Farber, Henry S. 2005. "Is Tomorrow Another Day? The Labor Supply of New York City Cabdrivers." *Journal of Political Economy* 113 (1): 46–82. https://doi.org/10.1086/426040. eprint: https://doi.org/10.1086/426040. https://doi.org/10.1086/426040.

———. 2008. "Reference-Dependent Preferences and Labor Supply: The Case of New York City Taxi Drivers." *American Economic Review* 98 (3): 1069–82. https://doi.org/10.1257/aer.98.3.1069. https://www.aeaweb.org/articles?id=10.1257/aer.98.3.1069.

Fisher, Jack. 2024. *Worker Welfare in the Gig Economy.* Working Paper. https://www.jackwfisher.com/worker_welfare.pdf.

Gaineddenova, Renata. 2022. *Pricing and Efficiency in a Decentralized Ride-Hailing Platform.* Working Paper. https://users.ssc.wisc.edu/~gaineddenova/Gaineddenova_JMP.pdf.

Garg, Teevrat, Matthew Gibson, and Fanglin Sun. 2020. "Extreme temperatures and time use in China." *Journal of Economic Behavior & Organization* 180:309–324. ISSN: 0167-2681. https://doi.org/https://doi.org/10.1016/j.jebo.2020.10.016. https://www.sciencedirect.com/science/article/pii/S016726812030384X.

Garin, Andrew, Emilie Jackson, Dmitri K Koustas, and Alicia Miller. 2023. *The Evolution of Platform Gig Work, 2012-2021.* Working Paper, Working Paper Series 31273. National Bureau of Economic Research. https://doi.org/10.3386/w31273. http://www.nber.org/papers/w31273.

Graff Zivin, Joshua, and Matthew Neidell. 2014. "Temperature and the Allocation of Time: Implications for Climate Change." *Journal of Labor Economics* 32 (1): 1–26. ISSN: 0734306X, 15375307, accessed May 3, 2023. http://www.jstor.org/stable/10.1086/671766.

Graff Zivin, Joshua, Yingquan Song, Qu Tang, and Peng Zhang. 2020. "Temperature and high-stakes cognitive performance: Evidence from the national college entrance examination in China." *Journal of Environmental Economics and Management* 104:102365. ISSN: 0095-0696. https://doi.org/https://doi.org/10.1016/j.jeem.2020.102365. https://www.sciencedirect.com/science/article/pii/S0095069620300887.

Griesbach, Kathleen, Adam Reich, Luke Elliott-Negri, and Ruth Milkman. 2019. "Algorithmic Control in Platform Food Delivery Work." *Socius* 5:2378023119870041. https://doi.org/10.1177/2378023119870041. eprint: https://doi.org/10.1177/2378023119870041. https://doi.org/10.1177/2378023119870041.

Hall, Jonathan V., John J. Horton, and Daniel T. Knoepfle. 2023. *Ride-Sharing Markets Re-Equilibrate.* NBER Working Paper No. 30883. https://www.nber.org/system/files/working_papers/w30883/w30883.pdf.

Hanna, Rema, and Paulina Oliva. 2015. "The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City." *Journal of Public Economics* 122:68–79. ISSN: 0047-2727. https://doi.org/https://doi.org/10.1016/j.jpubeco.2014.10.004. https://www.sciencedirect.com/science/article/pii/S0047272714002096.

Hoffmann, Bridget, and Juan Pablo Rud. 2024. "The Unequal Effects of Pollution on Labor Supply." *Econometrica* 92 (4): 1063–1096. https://doi.org/https://doi.org/10.3982/ECTA20484. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA20484. https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA20484.

Howard, Hilary. 2024. "The Dog Days of Summer Are Here Early. New York City Is Adapting." *The New York Times,* accessed July 23, 2024. https://www.nytimes.com/2024/06/21/nyregion/nyc-weather-heat-summer.html.

Kala, Namrata. 2019. *Learning, Adaptation, and Climate Uncertainty: Evidence from Indian Agriculture.* Working Paper. https://namratakala.files.wordpress.com/2020/01/kala_learning_dec2019.pdf.

Lei, Ya-Wen. 2019. *From Factories to Food Delivery Platforms: Contingent Contractual Relationships in China's Platform Economy.* Working Paper.

Mas, Alexandre, and Amanda Pallais. 2017. "Valuing Alternative Work Arrangements." *American Economic Review* 107 (12): 3722–59. https://doi.org/10.1257/aer.20161500. https://www.aeaweb.org/articles?id=10.1257/aer.20161500.

Mullins, Jamie T., and Corey White. 2019. "Temperature and mental health: Evidence from the spectrum of mental health outcomes." *Journal of Health Economics* 68:102240. ISSN: 0167-6296. https://doi.org/https://doi.org/10.1016/j.jhealeco.2019.102240. https://www.sciencedirect.com/science/article/pii/S016762961830105X.

Nakamura, Shotaro, and Rizki Siregar. 2024. *Gig Economy Regulation Meets Flexible Supply: Evidence from a Price Floor Policy in Indonesia.* Working Paper.

Neidell, Matthew. 2009. "Information, Avoidance Behavior, and Health: The Effect of Ozone on Asthma Hospitalizations." *The Journal of Human Resources* 44 (2): 450–478. ISSN: 0022166X, accessed November 2, 2022. http://www.jstor.org/stable/20648904.

NYC Consumer and Worker Protection. 2022. "A minimum pay rate for app-based restaurant delivery workers in NYC," https://www.nyc.gov/assets/dca/downloads/pdf/workers/Delivery-Worker-Study-November-2022.pdf.

Rode, Ashwin, Rachel E. Baker, Tamma Carleton, Anthony D'Agostino, Michael Delgado, Timothy Foreman, Diana R. Gergel, et al. 2022. *Labor Disutility in a Warmer World: The Impact of Climate Change on the Global Workforce.* Working Paper, SSRN Working Paper 4221478.

Scheiber, Noam. 2021. "How Uber Uses Psychological Tricks to Push Its Drivers' Buttons." *The New York Times,* accessed April 2, 2017. https://www.nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html.

Schor, Juliet B., William Attwood-Charles, Mehmet Cansoy, Isak Ladegaard, and Robert Wengronowitz. 2020. "Dependence and precarity in the platform economy." *Theory and Society* 49 (5): 833–861. ISSN: 1573-7853. https://doi.org/10.1007/s11186-020-09408-y. https://doi.org/10.1007/s11186-020-09408-y.

Tejada, Ana Heatley, Diego Alejo Vázquez Pimentel, Laura Arely Centeno Maya, Lucía Pacheco Fernández del Castillo, Alma Luisa Rodríguez Leal-Isla, Anahí Rodríguez Martínez, and Máximo Ernesto Jaramillo-Molina. 2021. "este futuro no applica," https://www.indesig.org/wp-content/uploads/2022/10/Este_futuro_no_applica_informe.pdf.

Wei, Zaiyan, and Mingfeng Lin. 2017. "Market Mechanisms in Online Peer-to-Peer Lending." *Management Science* 63 (12): 4236–4257. https://doi.org/10.1287/mnsc.2016.2531. eprint: https://doi.org/10.1287/mnsc.2016.2531. https://doi.org/10.1287/mnsc.2016.2531.

White, Corey. 2017. "The Dynamic Relationship between Temperature and Morbidity." *Journal of the Association of Environmental and Resource Economists* 4 (4): 1155–1198. https://doi.org/10.1086/692098. eprint: https://doi.org/10.1086/692098. https://doi.org/10.1086/692098.

Wilson, Andrew J., Daniel R. Bressler, Casey Ivanovich, Cascade Tuholske, Colin Raymond, Radley M. Horton, Adam Sobel, Patrick Kinney, Tereza Cavazos, and Jeffrey G. Shrader. 2024. *Age-dependent vulnerability to humid heat: Evidence from wet-bulb temperature exposure.* Working Paper.

Wood, Alex J., Nick Martindale, and Brendan Burchell. 2023. "Initial Findings from the Gig Rights Project: Labour Rights, Co-Determination, Collectivism and Job Quality in the UK Gig Economy," https://www.bristol.ac.uk/media-library/sites/business-school/documents/Gig%20Rights%20&%20Gig%20Wrongs%20Report.pdf.

A Appendix

A.1 Theoretical Framework Details

A.1.1 Derivation of Equation 7

I first show the details of the derivation of equation 7. I start with the log wage equation:

$$\ln(w_t) = \ln(A) + \ln(Q_d) - \ln(H_s) \tag{A1}$$

Where A is constant, $Q_d = Q_d(T)$, and $H_s = H_s(\phi(Q_d), T, E[w_{t+1}])$ given assumptions that all other factors do not vary with temperatures. Taking the total derivative with respect to $\ln(T)$:

$$\begin{aligned}\frac{d\ln(w_t)}{d\ln(T)} &= \frac{d\ln(A)}{d\ln(T)} + \frac{d\ln(Q_d)}{d\ln(T)} - \frac{d\ln(H_s)}{d\ln(T)} \\ &= 0 + \frac{\partial\ln(Q_d)}{\partial\ln(T)} - \frac{d\ln(H_s)}{d\ln(T)}\end{aligned} \tag{A2}$$

Expand $\frac{d\ln(H_s)}{d\ln(T)}$:

$$\frac{d\ln(H_s)}{d\ln(T)} = \frac{\partial\ln(H_s)}{\partial\ln(T)} + \frac{\partial\ln(H_s)}{\partial\phi} \cdot \frac{d\phi}{d\ln(Q_d)} \cdot \frac{d\ln(Q_d)}{d\ln(T)} + \frac{\partial\ln(H_s)}{\partial\ln(E[w_{t+1}])} \cdot \frac{d\ln(E[w_{t+1}])}{d\ln(T)} \tag{A3}$$

Substituting this back into equation A2:

$$\begin{aligned}\frac{d\ln(w_t)}{d\ln(T)} &= \frac{\partial\ln(Q_d)}{\partial\ln(T)} - \left(\frac{\partial\ln(H_s)}{\partial\ln(T)} + \frac{\partial\ln(H_s)}{\partial\phi} \cdot \frac{d\phi}{d\ln(Q_d)} \cdot \frac{d\ln(Q_d)}{d\ln(T)} + \frac{\partial\ln(H_s)}{\partial\ln(E[w_{t+1}])} \cdot \frac{d\ln(E[w_{t+1}])}{d\ln(T)}\right) \\ &= \frac{\partial\ln(Q_d)}{\partial\ln(T)} - \frac{\partial\ln(H_s)}{\partial\ln(T)} - \frac{\partial\ln(H_s)}{\partial\phi} \cdot \frac{d\phi}{d\ln(Q_d)} \cdot \frac{\partial\ln(Q_d)}{\partial\ln(T)} - \frac{\partial\ln(H_s)}{\partial\ln(E[w_{t+1}])} \cdot \frac{\partial\ln(E[w_{t+1}])}{\partial\ln(T)}\end{aligned} \tag{A4}$$

Defining and plugging in elasticities and $m = \frac{d\phi}{d\ln(Q_d)} \cdot \frac{\partial\ln(Q_d)}{\partial\phi}$, the final expression becomes:

$$\varepsilon_{w,T} = \varepsilon_{D,T}\,(1 - m\,\varepsilon_{S,D}) - \varepsilon_{S,T} - \left(\varepsilon_{S,E} \cdot \varepsilon_{E,T}\right) \tag{A5}$$

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A.1.2 Fees and Gratuity Depend on Temperatures

If delivery fees and consumer tips vary with temperatures, the elasticity of wages will also depend on direct fee (f) and gratuity (g) effects. For example, if fees and tips increase, wages will increase as well, through the amount (A) workers receive for each order. Furthermore, since fees enter the demand and supply functions, they will also indirectly affect wages through these channels. For example, an increase in fees with temperatures may lead to a decrease in demand (increasing wages) and an increase in labor supply (decreasing wages). These new terms are highlighted in blue:

$$\begin{aligned}\varepsilon_{w,T} = &\underbrace{\varepsilon_{f,T}}_{\text{direct fee effects}} + \underbrace{\varepsilon_{g,T}}_{\text{direct gratuity effects}} \\ &+ (\varepsilon_{D,T} + \underbrace{\varepsilon_{D,f} \cdot \varepsilon_{f,T}}_{\text{indirect demand effects through fees}})(1 - m \cdot \varepsilon_{S,D}) - \varepsilon_{S,T} \\ &- \underbrace{(\varepsilon_{H,\gamma} \cdot \varepsilon_{\gamma,f} \cdot \varepsilon_{f,T})}_{\text{indirect labor effects through fees}} - (\varepsilon_{S,E} \cdot \varepsilon_{E,T})\end{aligned} \tag{A6}$$

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A.1.3 Wait and Delivery Times Depend on Temperatures

Changes in the estimated total delivery time (t) affect demand. Therefore, changes in consumer-driver matching times (θ) or the time it takes for workers to delivery orders (τ) due to a deviation from optimal temperatures may amplify or counteract changes in demand. For example, a decrease in matching times due to higher demand on hot days may further increase demand (increasing wages). On the other hand an increase in delivery times due to changes in worker efficiency may decrease demand (decreasing wages). This new term is highlighted in blue:

$$\varepsilon_{w,T} = (\varepsilon_{D,T} + \underbrace{\varepsilon_{D,t} \cdot \varepsilon_{t,T}}_{\text{indirect demand effects through estimated delivery times}})(1 - m \cdot \varepsilon_{S,D}) - \varepsilon_{S,T} - (\varepsilon_{S,E} \cdot \varepsilon_{E,T}) \tag{A7}$$

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A.2 Delivery Market Details

In this section, I provide more details about the food delivery markets studied in the paper.

Table A1: Delivery Market Summary

Country	Main Players	Market Size
United Kingdom	Just Eat, UberEats, Deliveroo	$48 billion
Germany	Lieferando, Wolt, UberEats, Delivery Hero	$18 billion
France	UberEats, Deliveroo	$15 billion
Mexico	Rappi, UberEats, Didi Food	$7 billion

Notes: Table summarizes UK, Germany, France, and Mexico food delivery markets. Market size shows estimated revenues for 2024 for European countries and 2023 for Mexico.

United Kingdom: The British government has worked with leading food delivery companies to implement stricter security controls on driver accounts to prevent illegal and underage work. Delivery workers have been on strike numerous times, protesting over pay and working conditions. App riders remain self-employed independent contractors, not legally classified as "workers".

Germany: Strict labor laws, high labor costs, and a strong union presence significantly impact the operations of food delivery platforms in Germany. Despite the challenges, the German market continues to expand as consumers increasingly prefer the convenience of delivery services. In late 2021, a German court ruled that food delivery services must provide couriers with bikes and phones or pay compensation for the use of these tools.

France: France has taken steps to regulate the gig economy, particularly concerning food delivery workers. In 2023, France introduced a minimum hourly wage for food delivery workers. However, the country still faces ongoing legal battles regarding the classification of gig workers. French courts have occasionally ruled that certain delivery workers (e.g., workers on the platform Stuart) should be classified as employees rather than independent contractors.

Mexico: The Mexican food delivery market has grown rapidly, but the regulatory environment remains underdeveloped. Some platforms like Rappi and Uber have proposed offering limited social security benefits to some workers working over 40 hours a week. The Mexican government and delivery companies continue to negotiate the terms of worker classification and benefits.

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A.3 Data Details and Summary Statistics

In this section, I provide further details on the processing of data used in my analysis as well as summary statistics.

A.3.1 Hadley Station-Level Data Details

My main temperature data come from station-level data. I download sub-daily data for weather stations available at https://www.metoffice.gov.uk/hadobs/hadisd/. I keep temperatures recorded in every third hour (e.g., 0, 3, 6 UTC), as most stations report data every three hours. To construct a balanced panel of station records, I select stations that report on at least 50% of the hours in the relevant time period in Mexico (2012-2023), and 90% of the hours in Europe (2016-2023). My final data is from 79 stations in Mexico, 105 stations in the UK, 47 stations in Germany, and 105 stations in France.

Then, I fill in missing station values by the distance-weighted average of the cumulative density function of the closest five stations (e.g., if the nearby stations are on average at their 50th percentile, the station with the missing value is set to the 50th percentile of its own readings for that hour). Finally, I calculate daily functions of temperature from sub-daily data (e.g., minimum, maximum, and average daily temperatures) and then interpolate to a 0.1° grid using inverse-distance weighting.

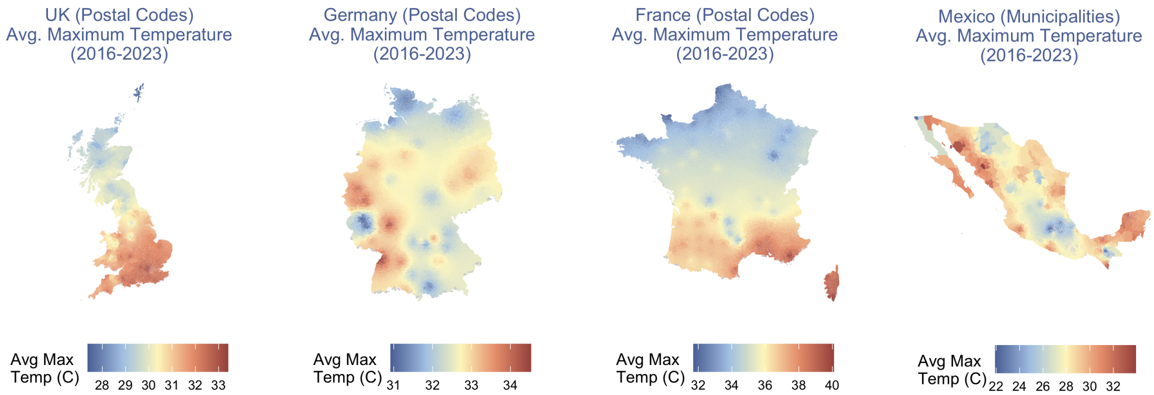
A.3.2 Reanalysis Weather Data Details

While my main temperature measures come from station-level data, I also use reanalysis products for robustness checks. Specifically, I use the ERA5-Land Daily Aggregated reanalysis product, available at a 0.1° spatial resolution and the Daymet V4 product, available at 1km spatial resolution for Continental North America. The former reanalysis data combines model data with observations using the laws of physics, while the latter is derived from selected meteorological station data and various supporting data sources. I aggregate the Daymet data to a 0.1° spatial resolution to match the rest of the data. I process and download these data through Google Earth Engine.

For my main precipitation measures, I use ERA5-Land (described above), as well as CHIRPS. CHIRPS (Climate Hazards Group InfraRed Precipitation with Station Data) uses satellite imagery and station data. For robustness checks, I use Daymet and PERSIANN-CDR products. The Daymet V4 product, which is available at 1km spatial resolution for Continental North America and is also based on station data. PERSIANN-CDR (Precipitation Estimation From Remotely Sensed Information Using Artificial Neural Networks-Climate Data Record) is an alternative source of precipitation data using satellite data and is available at an approximately 0.2° resolution. I reproject these data to a 0.1° spatial resolution to match the resolution of the rest of my data. I process and download the data through Google Earth Engine.

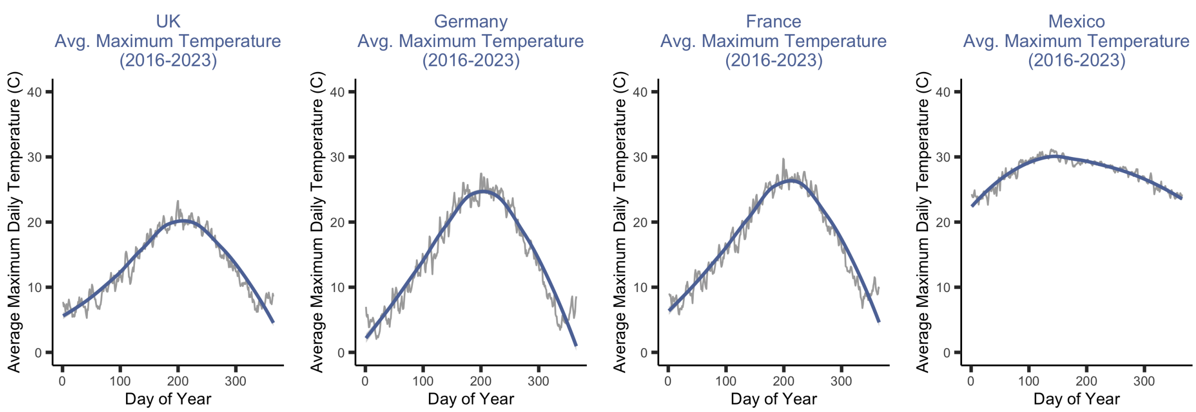
A.3.3 Weather Data Summary Statistics

Figure A1: Average Daily Maximum Temperatures by Region



Notes: Figure shows the daily maximum temperature, derived from station-level temperature data, averaged across 2016-2023, by municipality or postal code.

Figure A2: Average Daily Maximum Temperatures by Day-of-Year



Notes: Figure shows the daily maximum temperature, derived from station-level temperature data, averaged across 2016-2023, by day-of-year. Gray line shows average by day-of-year, blue line shows LOESS smoothed trend.

A.3.4 Fable Transaction Data Details

I start with the universe of users available as of March 7th, 2024 in the Fable Signal data product (37 million users). Only credit card users with information on their postal codes (9.8 million users) are kept. Then, I select users whose postal code does not change during their presence in the data. I drop those whose start and end dates in the data are less than 30 days apart. Finally, for Germany and France, I keep users whose age group and income bands are not missing, while for the UK, I keep users whose age group is not missing (as income bands are only available for a more recent sample of users). Transaction data is processed for approximately 3.2 million users in the UK, 2.2 million users in Germany, and 700,000 users in France.

Next, using the transaction data, I calculate the monthly spend for all users. I keep users who have at least one transaction per month between when they enter and exit the panel. Finally, I filter for users with at least one year of continuous data to aid classification based on consumption patterns in later steps. This results in 109,078 users in the UK, 91,971 in Germany, and 34,679 in France.

To classify transactions, I use merchant codes and categories provided by Fable. As of March 7th, 2024, there are 3,668 merchants tagged in the credit card transaction data. 564 of these merchants are identified as "Food and Beverage" and "Groceries" merchants by Fable. I manually read through each of these merchant descriptions to classify food merchants into five food-related categories: food delivery merchants (e.g., Deliveroo, Wolt), grocery delivery merchants (e.g., Amazon Prime Fresh), restaurants (e.g., Le Pain Quotidien), grocery stores (e.g., Casino), and other food (merchants that cannot be categorized).

For each user, I also construct an indicator for whether they are likely to own an air conditioner. I select the primary electricity providers in the three countries (British Gas, E.on, Scottish Power, EDF, N Power, Bulb, Engie, Ilterna, C Discount, and Direct Energie). I calculate the average summer (June - August) and winter (November - January) expenditure for all consumers across these electricity providers. Consumers who have non-zero spending in both periods and for whom summer spending on these categories is higher than winter spending, I flag as likely to own an air conditioner. However, I note that credit cards may not typically be used to pay utility bills. When customers do use credit cards for utilities, it may indicate financial strain, making ownership of air conditioners less probable. These results, therefore, should be interpreted with caution.

A.3.5 Measurable AI Email Transaction Data Details

I start with the universe of Rappi and UberEats orders available for 2019-2023 from Measurable AI data. There are 112,329 Rappi and 140,671 UberEats transactions in the raw data. For each transaction, I have the city and state and in some cases, the dropoff coordinates, for the order. Based on this information, I match each order to a Mexican municipality and state. I drop orders without identifiable geographic information and those with an order total of 0 MXN. This leaves me with 94,838 Rappi and 138,634 UberEats transactions.

For a small subset of orders for which both pickup and dropoff coordinates are available, I calculate the driving and biking distance and time between the pickup (the restaurant) and the dropoff (the customer's location) using the Google Maps API. I have this information for 11,123 Rappi and 36,914 UberEats orders.

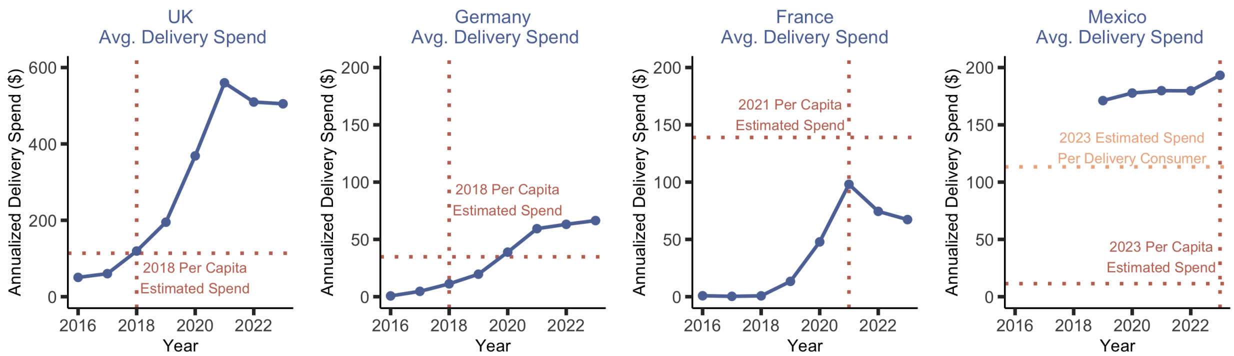
A.3.6 Transaction Data Summary Statistics

Table A2: Transaction Data User and Spend Summary Statistics

	UK (1)	**Germany** (2)	**France** (3)	**Mexico** (4)
Delivery ($, mean, std.dev)				
Total Order	29.38	25.33	29.02	11.09
	(16.52)	(14.99)	(18.33)	(7.38)
Fee	-	-	-	1.16
	-	-	-	(0.96)
Daily Spend ($, mean, std.dev)				
Food	10.67	8.09	11.64	-
	(9.84)	(11.61)	(15.94)	-
Delivery	1.02	0.15	0.20	-
	(2.36)	(0.831)	(1.22)	-
Restaurants	1.04	0.23	0.32	-
	(1.47)	(0.56)	(0.68)	-
Consumer Gender (%)				
Men	4.5	-	54.9	-
Women	2.7	-	43.9	-
No Data	92.8	100	1.3	-
Consumer Age (%)				
< 30	22.5	16.2	5.2	-
30-39	28.4	21.8	15.2	-
40-49	22.6	18.2	21.2	-
50-59	16.5	20.3	24.2	-
≥ 60	7.2	15.1	18.1	-
Users	109,078	91,971	34,679	21,958
Months in Data (mean)	23.0	46.6	50.9	4.9
Year	2016-2023	2016-2023	2016-2023	2019-2023

Notes: Table shows summary statistics for credit card data (UK, Germany, and France - using Fable transaction data) and Rappi and UberEats transaction data (Mexico - using Measurable AI transaction data). Pounds, euros, and pesos are converted to US dollars. Back to main text (model).

Figure A3: Trends in Transaction Data Food Delivery Spending and Comparison to Statistics

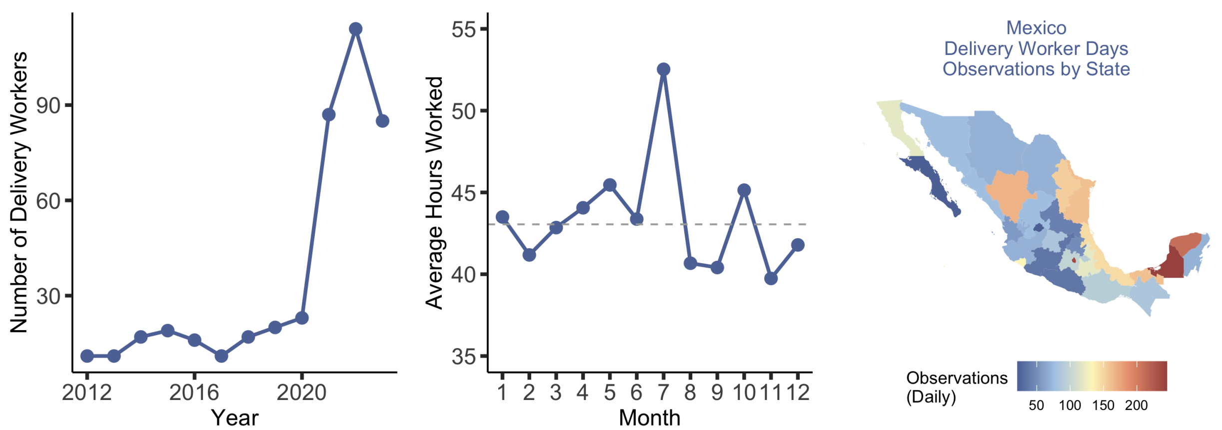


Notes: Figure shows mean annualized food delivery spending derived from transaction data (Fable Data for the UK and Measurable AI for Mexico). Average daily food delivery spending is calculated for each user and year, and then averaged across years. Pounds, euros, and pesos are converted to US dollars. Red lines show comparisons to statistics on food deliver spend per capita from other sources (Euromonitor for the UK and Germany (2018), and Statista for France and Mexico (2021)). Orange line shows comparison to statistics on food delivery spending per delivery consumer for Mexico (based on approximately 10% of the population using delivery apps, according to Trecone).

A.3.7 Mexico ENOE Labor Force Survey Details

I start with the universe of responses from the surveys conducted between the first quarter of 2012 and the fourth quarter of 2023. Note that due to the COVID-19 pandemic, no surveys were conducted in the second quarter of 2020. I keep the employed population (`clase2` $= 1$) in urban areas (`ur` $= 1$). Across all years, this leads to approximately 5.1 million survey responses. Figure A4 shows summary statistics for delivery workers (according to criteria in Section 4.3).

Figure A4: ENOE Labor Force Survey - Delivery Worker Summary Statistics



Notes: Figure shows number of food delivery platform workers over time (leftmost panel), the average number of hours worked throughout the year (middle panel), and the number of observations by Mexican state (rightmost panel). The main sample includes 2015-2023 (3,213 days worked; 414 unique workers).

A.3.8 Prolific Survey Details

In this section, I provide further details on the gig worker belief survey that I implement on Prolific. The survey was advertised as a general "Work Experience Survey". The estimated time of completion was 25 minutes and the reward was $5 per completed response, in line with Prolific's compensation guides. Respondents who were screened out were paid $0.30 for their time spent answering the screening questions. Tables A3 and A4 show the questions asked on the survey.

Table A3: Complete Survey Questions, Part 1

Question Text	Response
Screening Questions (7)	
1. Have you ever worked in a job where you set your own hours?	Yes/No
2. How many different jobs have you held in the last 3 years?	0-1, 2-3, 4-5, 6+
3. Have you ever used a smartphone app as part of your job?	Yes/No
4. In the past year, how often have you worked from home?	Never to Always
5. **Have you ever worked for a delivery, ridesharing, or other similar gig economy app?** *(Actual screening question)*	Yes/No
6. Have you ever worked for a fast-food or fast-casual restaurant?	Yes/No
7. How important to you is flexible work scheduling in what jobs you want to do?	Scale 1-5
Gig Economy Experience (12)	
1. How long have you worked in the gig economy?	Time ranges
2. What type of gig work have you mostly done?	Multiple select
3. Which of the following gig economy platforms have you ever worked for?	Multiple select
4. Have you worked for multiple gig economy platforms simultaneously? b) How many platforms have you worked for at the same time?	Yes/No + Write-in
5. When you were most active in gig work, how many hours per week did you spend on gig economy work on average?	Hour ranges
6. Which of the following times do you typically work?	Multiple select
7. Do you consider your gig economy work to be (or have been): [Full-time, Part-time, Occasional]	Work type
8. Besides gig economy work, do you (or did you) have other forms of employment?	Emp. type
9. In the past year, have you switched between different types of gig work? b) What prompted the switch?	Yes/No + Reasons
10. How much control do you feel you have had over your work schedule? b) Why do you feel you have [No/Little/Moderate] control over your work schedule on gig economy platforms?	Scale + Write-in
11. To what extent do you believe your earnings in gig work are influenced by each of the following? [Your own efforts and skills, Customer demand, Luck or chance, The platform's algorithms, Competition from other gig workers]	Multiple 1-5 scales
12. How satisfied were/are you with your gig economy work overall?	Scale 1-5

For questions 19 and 20, participants were asked to read excerpts from an article that describes behavioral nudges by Uber (Scheiber 2021). For question 24, they were shown screenshots from a DoorDash worker's post on Reddit ("Catalogue of DoorDash Manipulation Tactics").

Table A4: Complete Survey Questions, Part 2

Question Text	Response
Work Perceptions (6)	
13. How open do you feel gig economy platforms are about factors that influence your earning opportunities?	Scale 1-5
14. Do you think the number of hours you spend working on the app today affects the number or pay of jobs you're offered later? b) To what extent do you believe this affects future jobs?	Yes/No/Unsure + Scale
15. Do you think saying no to jobs today affects the number or pay of jobs the app offers you later? b) To what extent do you believe this affects future jobs?	Yes/No/Unsure + Scale
16. Do you think saying no to jobs during busy times affects the number or pay of jobs the app offers you later? b) To what extent do you believe this affects future jobs?	Yes/No/Unsure + Scale
17. Do you think saying no to jobs during less busy times affects the number or pay of jobs the app offers you later? b) To what extent do you believe this affects future jobs?	Yes/No/Unsure + Scale + Write-in
18. In your experience, which of the following do you think might affect the number or pay of jobs the app offers you later? [Customer ratings, Acceptance rate, Completion rate, Speed, Hours of availability, Other]	Multiple 1-5 scales
Company Practices (10)	
19. [**New York Times Screenshot**] What does 'gamification' mean in how Uber tries to keep drivers working?	Multiple choice
20. [**New York Times Screenshot**] Do you believe these descriptions represent your experience working on gig economy platforms? b) To what extent do these descriptions represent your experience?	Yes/No/Unsure + Scale
21. Why do you think gig economy platforms may use nudges and gamification in their apps? [Help workers earn more, Increase company profits, Improve worker satisfaction, Get workers to work more, Create fun experience, Better match workers with consumers, Other]	Multiple 1-5 scales
22. To what extent does the following quote from Uber's research director represent your experience: "The optimal default we set is that we want you to do as much work as there is to do. You're not required to by any means. But that's the default."	Scale 1-5
23. Companies like Uber have publicly said that they don't use tricks (e.g., gamifying) to get you to work more. Do you agree?	Yes/No/Unsure
24. [**Reddit Screenshot**] Do you believe these descriptions represent your experience working on gig economy platforms? c) To what extent do these descriptions represent your experience?	Yes/No/Unsure + Scale

Table A5 shows summary statistics for Prolific respondents in the final sample (not screened out), separately for the US and Mexico.

Table A5: Prolific Gig Worker Survey Summary Statistics

Question	Mexico	United States
All Respondents	1,262	738
Final Sample (Gig Experience)	174	266
Gig Experience (%)	13.8%	36.0%
Percent Male	66.7%	44.7%
Mean Age	30.60	36.12
Full-time (Primary Source of Income)	19.5%	24.1%
Gig Work Only Form of Employment	17.8%	17.3%
Mean Hours Worked Per Week	21.09	21.00
Median Hours Worked Per Week	20.00	20.00
Food Delivery Experience (Yes)	29.9%	25.2%
Rideshare Experience (Yes)	62.6%	69.5%
Grocery Delivery Experience (Yes)	27.0%	38.3%
Multiple Platforms at Same Time (Yes)	48.9%	53.8%
Switch between Different Gig Work Type (Yes)	33.9%	32.0%
Mean Satisfaction with Gig Work (Out of 5)	3.46	3.48
Median Satisfaction with Gig Work (Out of 5)	3.00	3.00

Back to main text.

A.4 Additional Demand Results

A.4.1 Main Results - Table Form

Table A6: Delivery Demand Results - Europe

	Dependent variable:					
	Total Food Delivery Spend (£/€)					
	UK		Germany		France	
	(1)	(2)	(3)	(4)	(5)	(6)
<0C	0.084**	0.054	0.016**	0.017**	0.017	0.003
	(0.038)	(0.041)	(0.006)	(0.006)	(0.024)	(0.021)
	[0.049]	[0.216]	[0.015]	[0.026]	[0.497]	[0.892]
0-9C	0.014	0.010	0.003	0.0003	0.005	0.003
	(0.017)	(0.018)	(0.003)	(0.004)	(0.004)	(0.005)
	[0.429]	[0.593]	[0.424]	[0.927]	[0.266]	[0.619]
9-12C	0.004	0.003	−0.0001	−0.002	0.004*	0.003
	(0.008)	(0.011)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.658]	[0.767]	[0.971]	[0.421]	[0.082]	[0.143]
24-27C	−0.016	−0.016	−0.003***	−0.003***	−0.002	−0.001
	(0.015)	(0.017)	(0.001)	(0.001)	(0.002)	(0.002)
	[0.311]	[0.371]	[0.008]	[0.007]	[0.339]	[0.635]
27-30C	0.019**	0.024*	−0.004***	−0.002	−0.004*	−0.002
	(0.007)	(0.012)	(0.001)	(0.001)	(0.002)	(0.002)
	[0.016]	[0.064]	[0.007]	[0.105]	[0.087]	[0.293]
30-33C	0.067***	0.084***	0.002***	0.009***	−0.002	−0.002
	(0.019)	(0.011)	(0.001)	(0.002)	(0.003)	(0.003)
	[0.005]	[0.000]	[0.005]	[0.002]	[0.570]	[0.645]
>33C	0.126***	0.144***	0.011**	0.014***	0.006*	0.008*
	(0.025)	(0.030)	(0.004)	(0.004)	(0.003)	(0.004)
	[0.000]	[0.001]	[0.023]	[0.003]	[0.077]	[0.059]
Mean Daily Spend	0.81	0.81	0.12	0.12	0.08	0.08
Individual, Year FEs, WoY FEs	Y	-	Y	-	Y	-
Post-Area-by: -Year, -WoY FEs	-	Y	-	Y	-	Y
Quad TT	-	Y	-	Y	-	Y
Day-of-Week FEs	Y	Y	Y	Y	Y	Y
Observations	19,500,443	19,500,443	34,461,595	34,461,595	18,995,110	18,995,110

Notes: Table shows the relationship between daily maximum temperature and food delivery spending in Europe based on Fable credit card data, estimating according equation 5. Results are relative to the baseline bin (12-24°C). Back to main text.

Table A7: Delivery Demand Results - Mexico

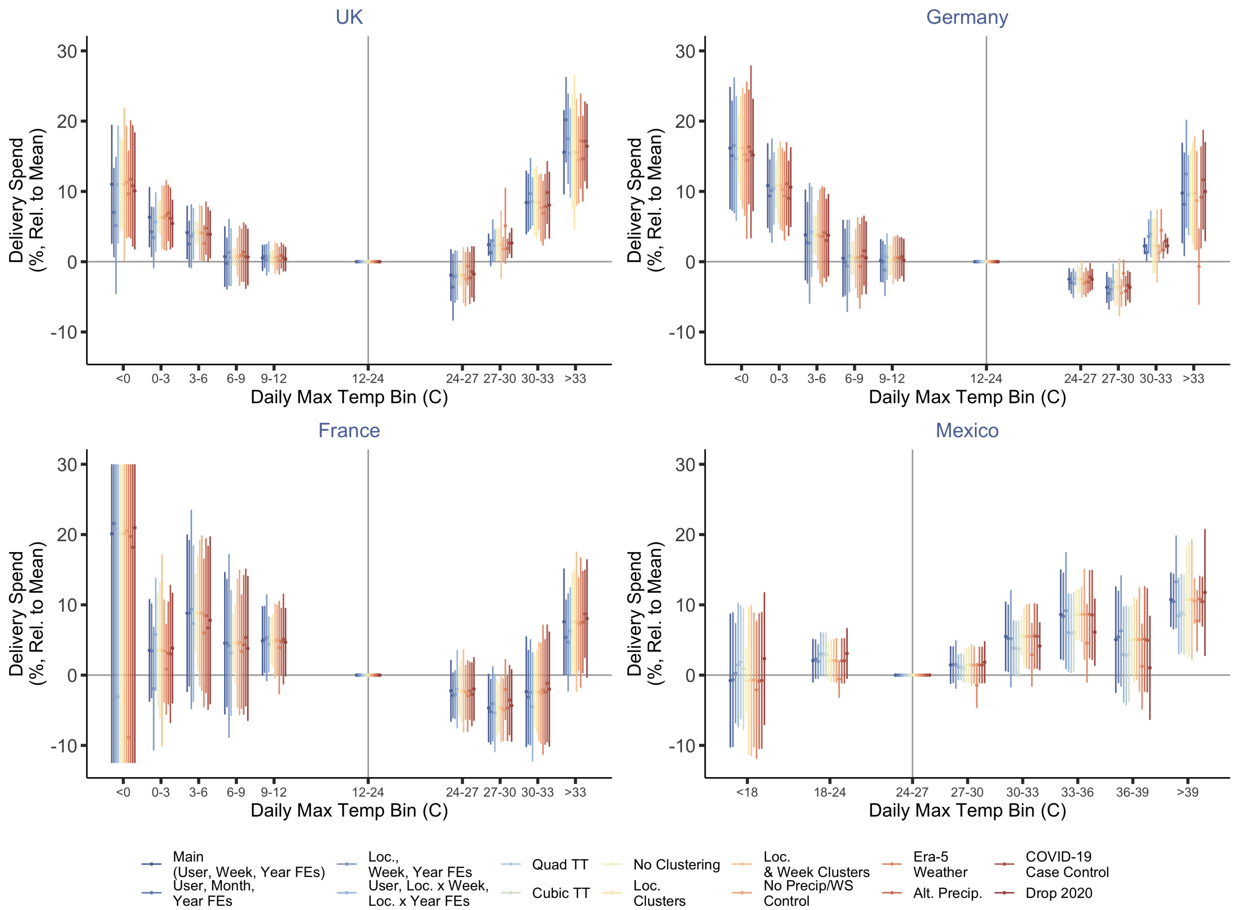
	Dependent variable:			
	Total Food Delivery (Rappi/UberEats) Spend ($)			
	(1)	(2)	(3)	(4)
<18C	−0.003	−0.001	0.001	0.010
	(0.020)	(0.020)	(0.018)	(0.017)
	[0.874]	[0.964]	[0.955]	[0.569]
18-24C	0.009	0.002	0.005	0.006
	(0.007)	(0.007)	(0.006)	(0.007)
	[0.192]	[0.837]	[0.375]	[0.435]
27-30C	0.006	0.006	0.002	−0.0002
	(0.006)	(0.009)	(0.004)	(0.006)
	[0.292]	[0.546]	[0.726]	[0.981]
30-33C	0.023**	0.011	0.006	0.002
	(0.010)	(0.011)	(0.009)	(0.010)
	[0.030]	[0.352]	[0.502]	[0.868]
33-36C	0.036***	0.023	0.021**	0.021
	(0.014)	(0.020)	(0.010)	(0.017)
	[0.009]	[0.268]	[0.048]	[0.238]
36-39C	0.021	0.011	0.011	0.005
	(0.016)	(0.021)	(0.016)	(0.021)
	[0.192]	[0.596]	[0.499]	[0.830]
>39C	0.045***	0.058**	0.033***	0.036**
	(0.008)	(0.020)	(0.011)	(0.016)
	[0.000]	[0.013]	[0.002]	[0.042]
Mean Daily Spend ($)	0.36	0.36	0.36	0.36
Version	W	W	UnW	UnW
Individual, Year, Week-of-Year FEs	Y	-	Y	-
Municip-by-Year-, Municip-by-WoY FEs	-	Y	-	Y
State-by-Quad-TT	-	Y	-	Y
Day-of-Week FEs	Y	Y	Y	Y
Platform FEs	Y	Y	Y	Y
Observations	2,344,591	2,344,591	2,779,846	2,779,846

Notes: Table shows the relationship between daily maximum temperature and food delivery (Rappi and UberEats) spending in Mexico, estimating according equation 5. Results are relative to the baseline bin (24-27°C). Columns 1 and 2 are weighted based on labor force survey data, while columns 3 and 4 are unweighted. Back to main text.

A.4.2 Main Results Robustness

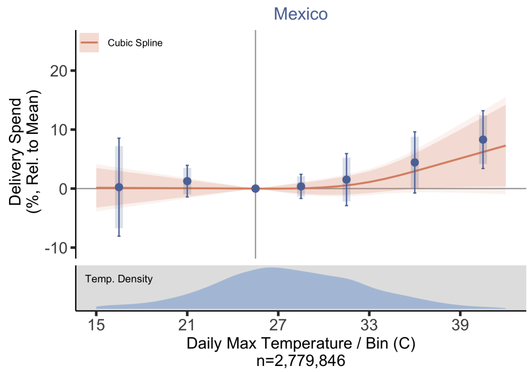
Figure A5 shows that the main demand results are robust to various alternative fixed effects and controls. The first six specifications show alternative spatiotemporal fixed effects, while the next three show alternative clustering. I also use different sources of temperature (ERA-5) and precipitation (PERSIANN-CDR) data. Lastly, I control for COVID-19 case counts.

Figure A5: Delivery Demand Results - Robustness to Alternative Spatiotemporal, Weather, and Other Controls and Alternative Clustering



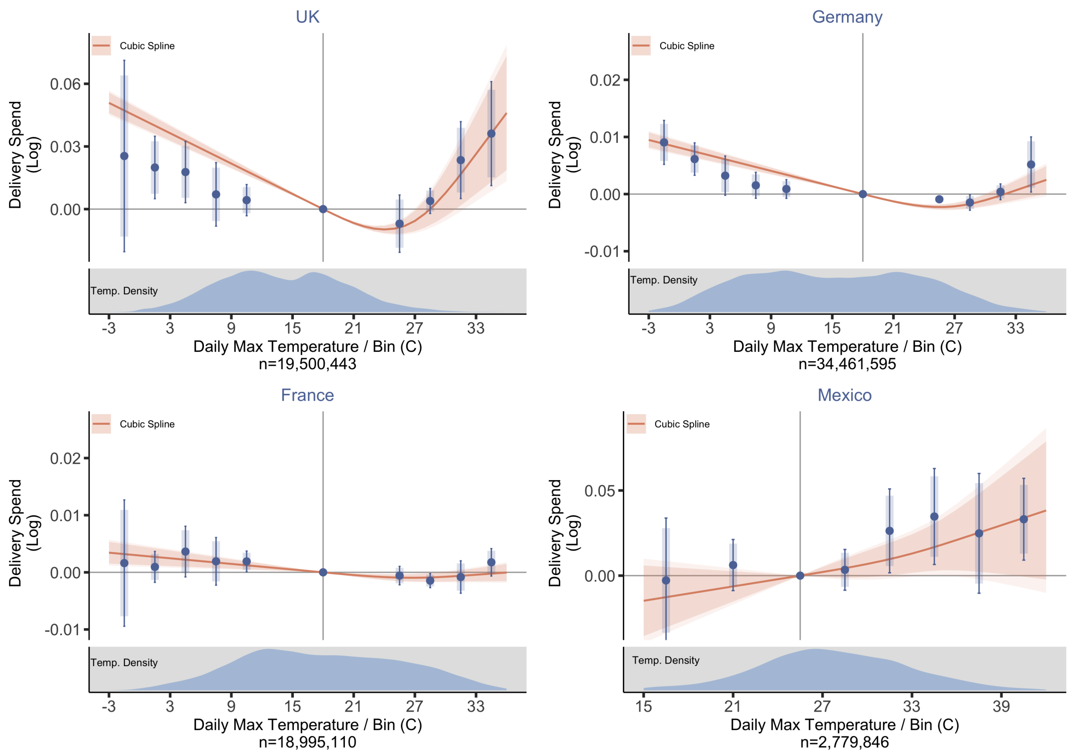
Notes: Figure shows the relationship between daily maximum temperature and food delivery spending in the UK, Germany, France (using Fable transaction data), and Mexico (using Measurable AI transaction data), estimated according to equation 5, but with alternative fixed effects, controls, clustering, and sampling. The dependent variable is delivery spend, divided by average spend per day for each country. Figure shows binned temperatures; all results are relative to the baseline bin (12-24°C in Europe; 24-27°C in Mexico). 95% confidence intervals shown. Back to main text.

Figure A6: Delivery Demand Results - Unweighted Mexico Results



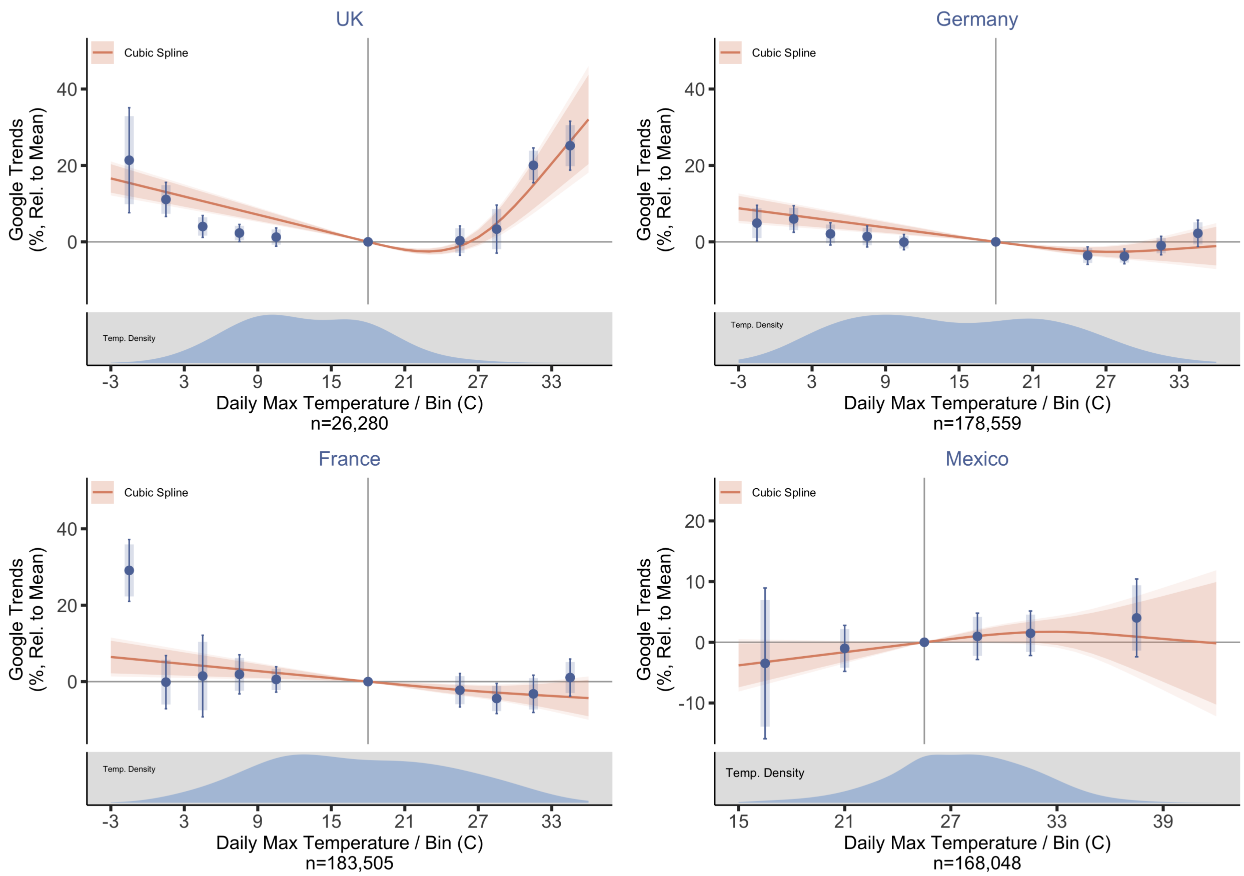
Notes: Figure shows the relationship between daily maximum temperature and food delivery spending in Mexico, estimated according to equation 5. The dependent variable is delivery spend, divided by average spend per day for each country. Figure shows binned temperatures; all results are relative to the baseline bin (24-27°C in Mexico). 95% confidence intervals shown. Back to main text.

Figure A7: Delivery Demand Results - Log Outcomes



Notes: Figure shows the relationship between daily maximum temperature and food delivery spending in the UK, Germany, France (using Fable transaction data), and Mexico (using Measurable AI transaction data), estimated according to equation 5. The dependent variable is log of delivery spending plus a small positive constant (note different y-axis scales across figures). Figures shows both binned temperatures (blue) and cubic spline temperatures (red). Results are relative to the baseline bin or temperature. Graphs below coefficient plots show the distribution of daily maximum temperatures in each sample. Standard errors clustered by municipality/postal-code & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline). Back to main text.

Figure A8: Delivery Google Trends Results



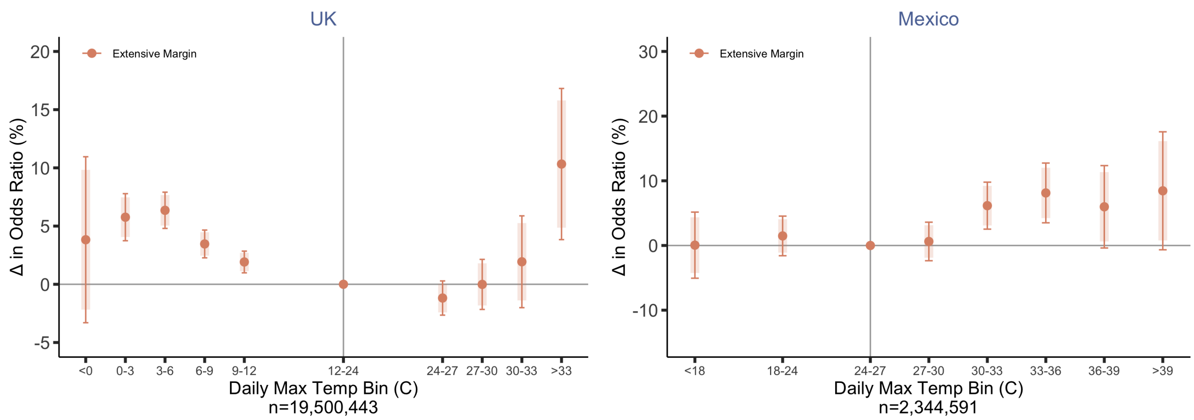
Notes: Figure shows the relationship between daily maximum temperature and Google Searches for popular food delivery platforms in the UK, Germany, France, and Mexico, estimated according to equation 5. The dependent variable is the normalized Google Trends search volume, divided by average search volume each country. For the UK, only country-level trends are available. For the rest of the countries, I use state-level search data. Search terms are the following. UK: Deliveroo, Just Eat, UberEats; Germany: Deliveroo, Lieferando, UberEats, Wolt; France: Deliveroo, Just Eat, UberEats; Mexico: Rappi, UberEats. Figure shows both binned temperatures (blue) and cubic spline temperatures (green). All results are relative to the baseline bin (12-24°C in Europe; 24-27°C in Mexico) or temperature (18°C in Europe; 25.5°C in Mexico). Density graphs below coefficient plots show the distribution of daily maximum temperatures in each sample. Standard errors clustered by region & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline). Back to main text.

A.4.3 Detailed Demand Results

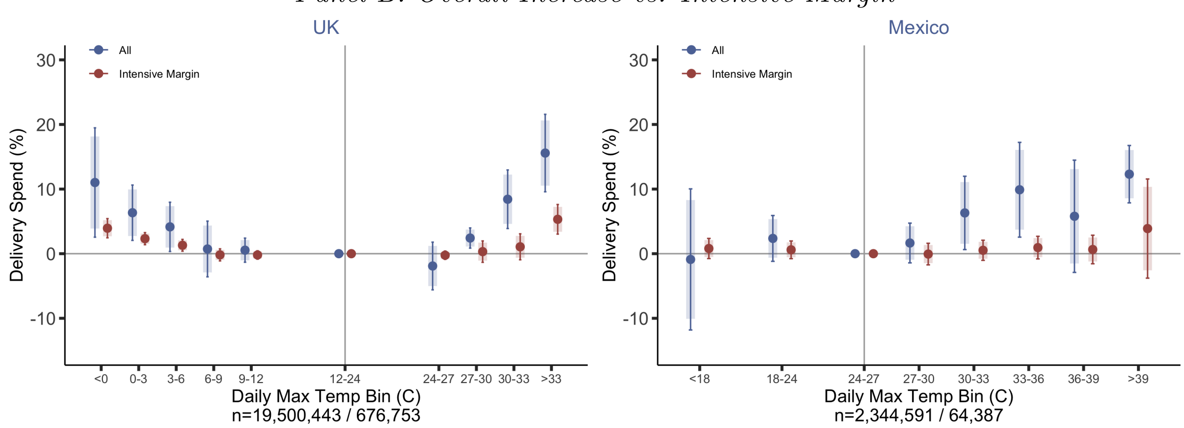
Extensive vs. Intensive Margin: Figure A9 shows that the increase in food delivery spending is primarily due to increases in the probability food delivery orders on hot days, or the extensive margin. A day with very high maximum temperatures (>33°C in the UK and >39°C in Mexico) corresponds to a 10.3% and an 8.5% increase in the odds ratio of food delivery orders relative to mild days in the UK and Mexico, respectively. In the UK, spend also increases, albeit much less (5.3% increase in intensive margin, vs. 15.6% increase overall). In Mexico, there is a small but noisy growth in total order size (3.9% vs. 12.5% increase in expenditures overall).[41]

Figure A9: Food Delivery Spending - Extensive vs. Intensive Margin

Panel A: Extensive Margin



Panel B: Overall Increase vs. Intensive Margin

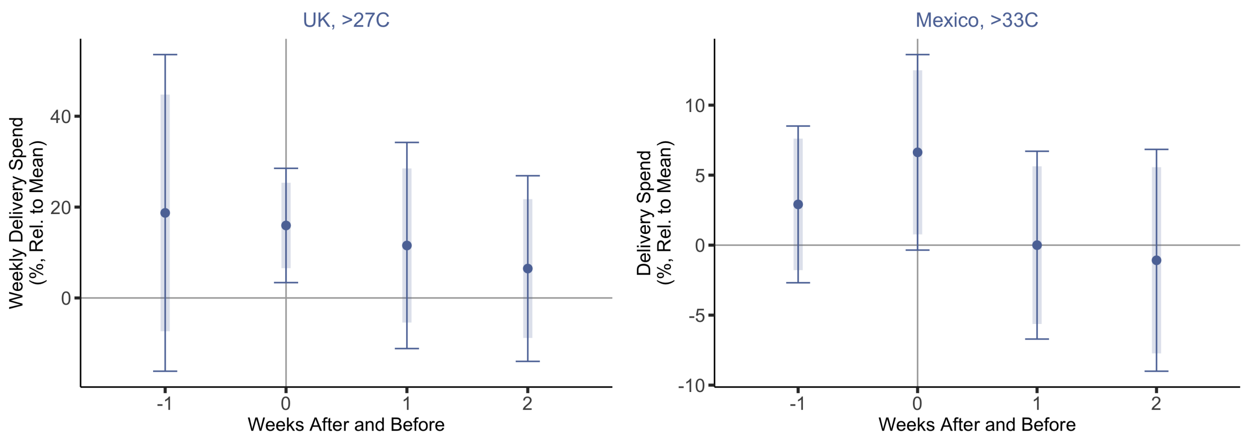


Notes: Figure shows the relationship between daily maximum temperatures and delivery probability (Panel A) or total spend and the intensive margin (Panel B) in the UK (using Fable transaction data) and Mexico (using Measurable AI transaction data), estimated based on equation 5 (for delivery probabilities, where the outcome variable is a binary indicator variable on days with delivery orders, I estimate a conditional logit model). All estimates are relative to the baseline bin. Standard errors clustered by postal-area & month. Thin (thick) line shows 95% (90%) CI. Back to main text.

[41] Results for Germany and France are not shown, but the increase in spend in Germany is driven entirely by the extensive margin, while for France, there are noisy increases in both the extensive and intensive margins.

Intertemporal Substitution: I aggregate transaction data to the weekly level in order to study intertemporal substitution. I run a version of regression 5, except including dummies for the average maximum temperature for the previous two weeks, the current week, and the next week. Figure A10 shows the results for the UK and Mexico for the >27°C and >33°C dummies. Since I use the *average* weekly maximum temperature, I use lower temperature thresholds, as an average daily maximum temperature of over 33°C or 39°C for an entire week is very uncommon. I do not find much evidence of intertemporal substitution.

Figure A10: Intertemporal Substitution Results



Notes: Figure shows the relationship between average weekly maximum temperatures and delivery spend in the UK (using Fable transaction data). The dependent variable is food delivery spend, divided by average spend. −1 is the week *after* the current week, while +1 is the week *before*. All estimates are relative to the baseline bin. Standard errors clustered by postal-area & month. Thin (thick) line shows 95% (90%) CI. Back to main text.

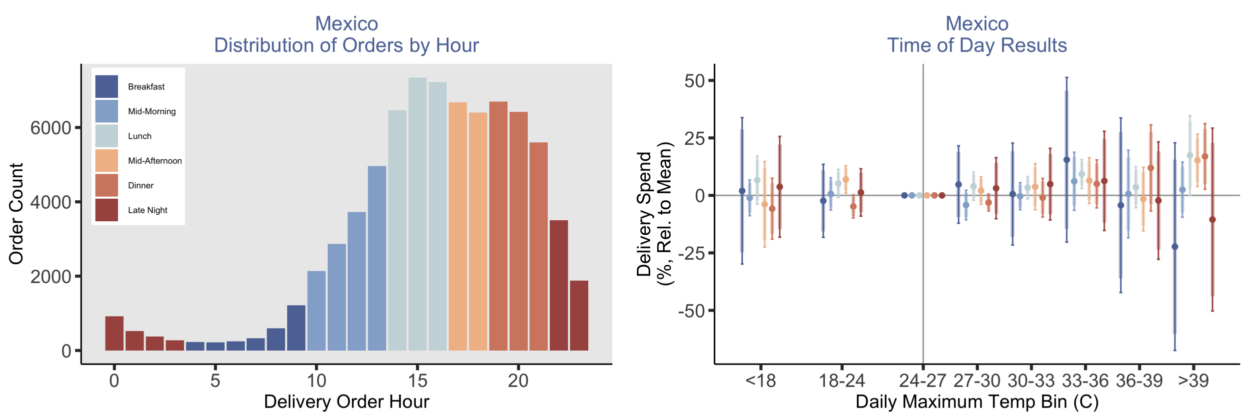
Delivery Fees and Times: MeasurableAI breaks out delivery fees from the order total. Therefore, I am able to examine the relationship between daily maximum temperature and food spend and delivery fees separately in Mexico. Column (1) of Table A8 show the change in food totals (in USD), while Columns (2)-(3) show the change in delivery fees on hot days, relative to moderate days. Column (2) shows results for all orders, while Column (3) restricts the analysis to orders with pickup and dropoff coordinates. While estimates are imprecise, if anything, delivery fees are lower on hot days. For a subset of orders, I also have pickup and dropoff coordinates and actual delivery times. Columns (4)-(5) of Table A8 show that neither the delivery distance nor the delivery time changes on hot days, relative to moderate days. If anything, there is a noisy decrease in delivery times on hot days (Column 5).

Table A8: Delivery Food Spend, Fees, and Estimated Speed

	Dependent variable:				
	Food Spend ($)	Delivery Fees ($)		Distance (km)	Time (min)
	(1)	(2)	(3)	(4)	(5)
36-39C	0.085	0.0003	-0.036^{***}	-2.806	-0.213
	(0.135)	(0.026)	(0.008)	(2.154)	(0.131)
	[0.529]	[0.992]	[0.001]	[0.220]	[0.134]
>39C	0.457	0.049	-0.059	0.216	-0.256
	(0.492)	(0.040)	(0.085)	(1.267)	(0.168)
	[0.353]	[0.218]	[0.501]	[0.868]	[0.156]
Mean	12.22	0.97	1.49	4.02	16.93
Observations	64,387	64,387	12,816	12,816	12,816

Notes: Table shows relationship between daily maximum temperatures and food totals (Column (1)), delivery fees (Columns (2)-(3)) as well as delivery distance and speed (Columns (4)-(5)) based on a subset of Rappi and UberEats transaction data with delivery times. Standard errors (clustered by municipality and month) are shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01). Back to main text.

Figure A11: Mexico Time-of-Day Results

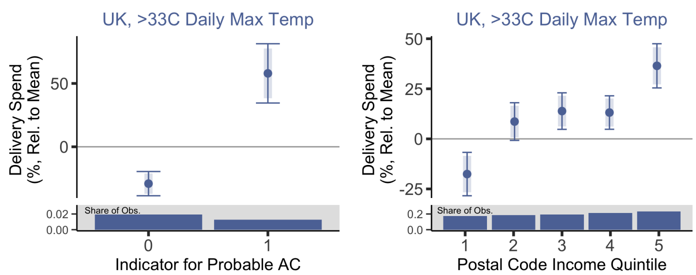


Notes: Left panel of Figure shows the distribution of Rappi and UberEats delivery orders by time of day. Right panel then shows the relationship between daily maximum temperature and delivery spend, estimated according to equation 5, separately for each part of the day. The dependent variable is food delivery spending, divided by average spend for each period. All estimates are relative to the baseline bin (24-27°C). Standard errors clustered by postal-area & month. Thin (thick) line shows 95% (90%) CI. Back to main text.

A.4.4 Heterogeneity Along Other Dimensions

The left panel of Figure A12 shows the effect of very hot days (>33°C) on food delivery expenditures in the UK, separately for consumers without and with an AC. The AC indicator is constructed from the spending on electricity bills, flagging consumers whose bills are much higher in the summer. I am only able to obtain this information for only a small share of all observations. Consumers who are likely to have an AC spend a lot more on delivery on hot days relative to moderate days; while the opposite is true for consumers without an AC. The right panel of the same figure breaks down results by postal code income quintile.

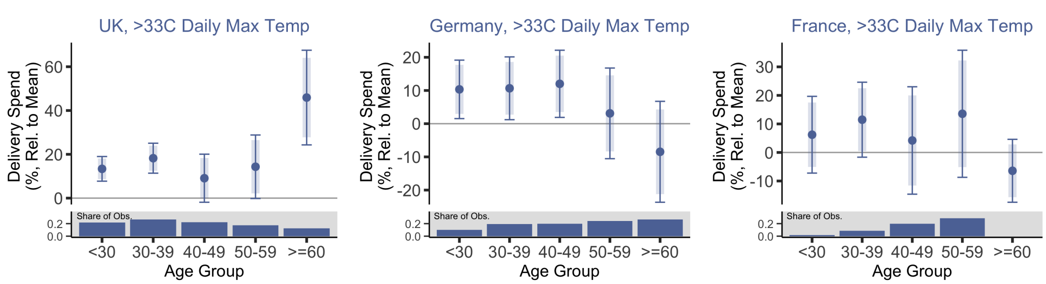
Figure A12: UK: AC Ownership and Postal Code Income



Notes: Panel shows the relationship between daily maximum temperature and delivery spending (estimated according to equation 5) separately for various groups of consumers in the UK (using Fable transaction data). The dependent variable is food delivery spend, divided by average spend for each period. All estimates are relative to the baseline bin (24-27C). Standard errors clustered by postal-area & month. Thin (thick) line shows 95% (90%) CI. Back to main text.

Figure A13 shows the temperature-delivery relationship – specifically the effects of very hot (>33°C) days – separately by age group for the UK, Germany, and France. Overall, younger consumers also use food delivery to adapt to extreme temperatures. In the UK, older consumers use this adaptation measure even more, while the opposite is true for Germany and France. I do not find meaningful differences in the temperature-delivery relationship by gender.

Figure A13: Europe: Consumer Age

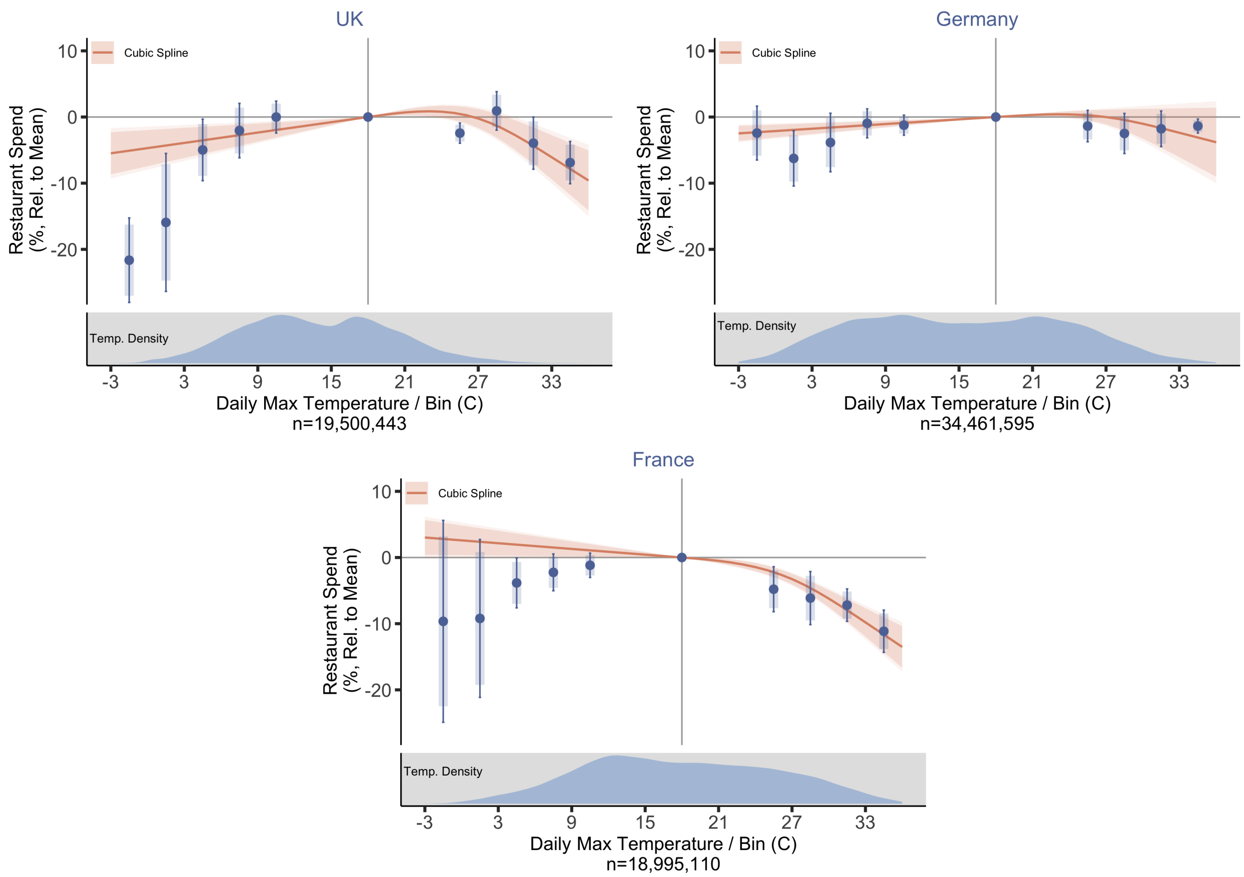


Notes: Panel shows the relationship between daily maximum temperature and delivery spending (estimated according to equation 5) separately for various groups of consumers in Europe (using Fable transaction data). The dependent variable is food delivery spend, divided by average spend for each period. All estimates are relative to the baseline bin (24-27C). Standard errors clustered by postal-area & month. Thin (thick) line shows 95% (90%) CI. Back to main text.

A.4.5 Other Temperature Demand Results

Restaurant Spending: The richness of the European credit card data provided by Fable data allows me to investigate how other categories of expenditures respond to extreme temperatures. Since food delivery may replace going out to eat at restaurants, I repeat my analysis with restaurant spending as the main outcome variable. Figure A14 shows the results. Instead of the U-shape curve, I recover an upside-down U-curve in all three European countries. In the UK, restaurant expenditures decrease by 6.9% on hot days relative to mild days.

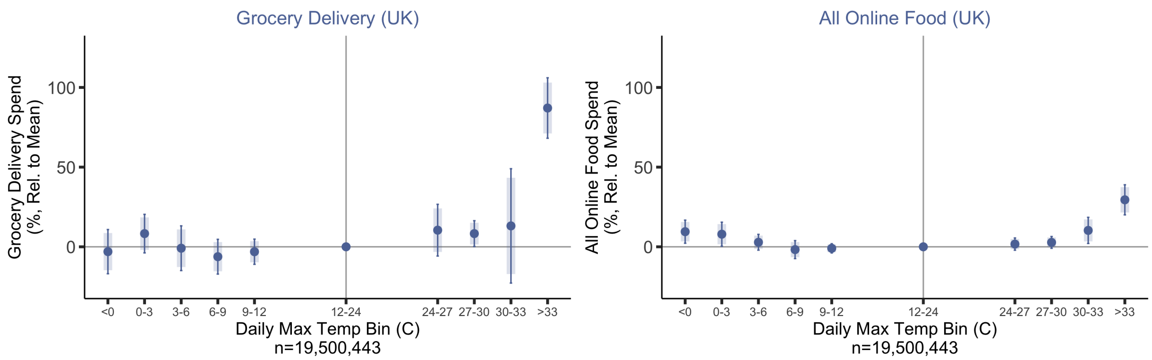
Figure A14: Restaurant Spend Results



Notes: Figure shows the relationship between daily maximum temperature and restaurant spend in the UK, Germany, and France (using Fable transaction data), estimated according to equation 5. The dependent variable is restaurant spend, divided by average spend per day for each country. Figure shows estimates both for binned temperatures (blue) and cubic spline temperatures (red); relative to the baseline bin (12-24C) or temperature (18C) Graphs below coefficient plots show the distribution of daily maximum temperatures in each sample. Standard errors clustered by postal-area & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline). Back to main text.

Other Spending Results: I also look at the effects of extreme temperatures on other types of food delivery in the UK. Figure A15 shows the results for grocery delivery services (e.g., Amazon Prime Fresh) and all online food expenditures (the sum of food delivery, grocery delivery, and online grocery purchases). There is a very large (87.1%) increase in grocery delivery service spending on hot days relative to moderate days. Overall, online food spending increases by 29.5%.

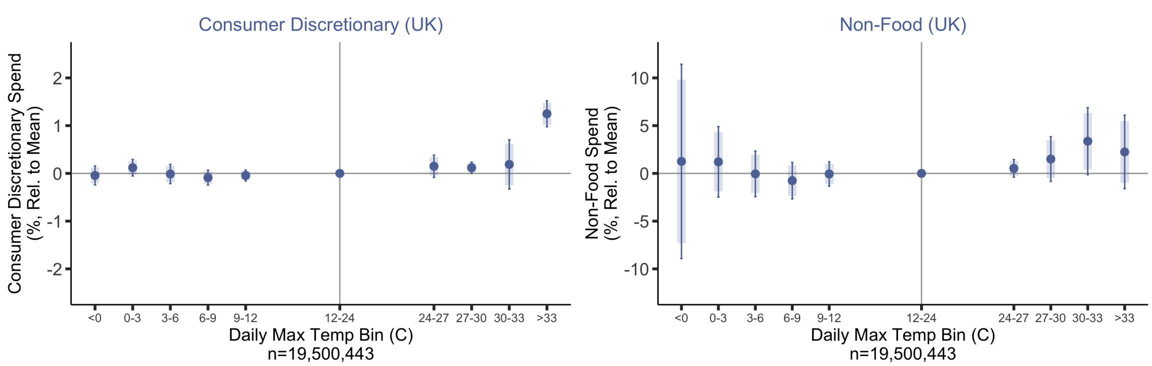
Figure A15: Other Delivery Results



Notes: Figure shows the relationship between daily maximum temperature and grocery delivery and online food spend in the UK (using Fable transaction data), according to equation 5. The dependent variable is grocery delivery or all online food (food delivery, grocery delivery, and online grocery) spend, divided by average spend per day for each category. Results are relative to the baseline bin (12-24C). Standard errors clustered by postal-area & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned). Back to main text.

In terms of other spending, consumer discretionary spending increases slightly (1.2%) on hot days. However, as numerous restaurants that specialize in delivery (e.g., Pizza Hut and Domino's) are categorized as consumer discretionary in the Fable data, this may be driven by food delivery expenditures. There is no significant change in non-food spending (Figure A16).

Figure A16: Other Spend Results



Notes: Figure shows the relationship between daily maximum temperature and consumer discretionary and non-food spend in the UK (using Fable transaction data), according to equation 5. The dependent variable is consumer discretionary or non-food spend, divided by average spend per day for each category. Results are relative to the baseline bin (12-24C). Standard errors clustered by postal-area & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned). Back to main text.

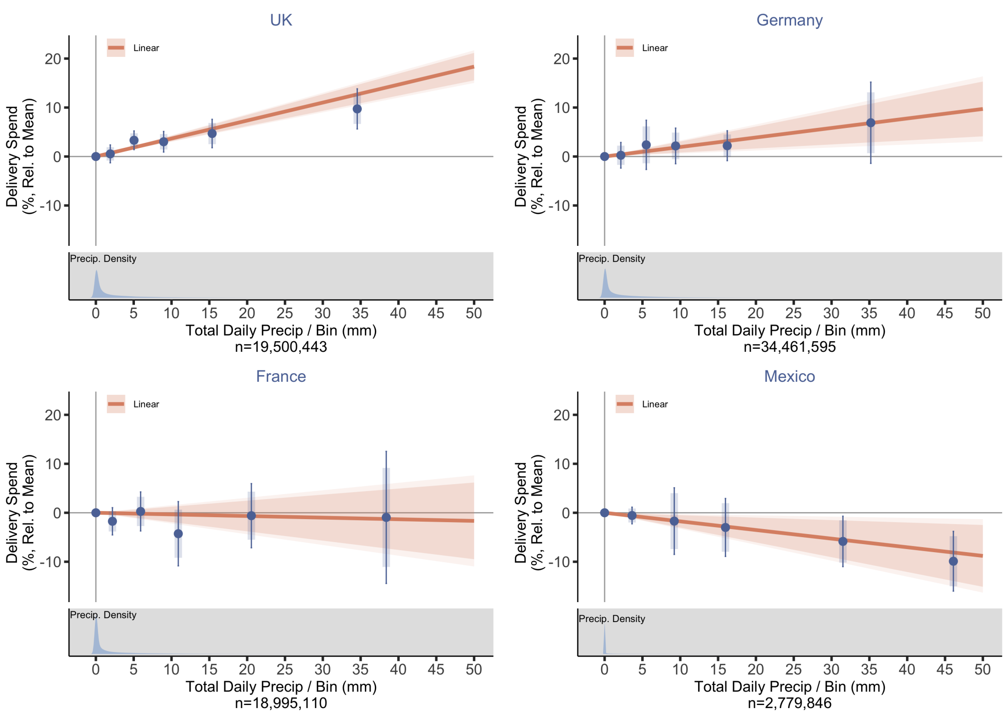
A.4.6 Other Shocks

In this section, I show additional results on how food delivery expenditures respond to other shocks.

Back to main text.

Rainfall: I study the relationship between rainfall and food delivery expenditures. Like extreme temperatures, rainfall may make it inconvenient and undesirable for consumers to leave their offices or homes. Figure A17 shows the relationship for the UK, Germany, France, and Mexico, which varies by country: in the UK and Germany, higher rainfall leads to higher delivery expenditures. In France, there is no statistically significant relationship. Finally, in Mexico, delivery spending actually *decreases* during extreme rainfall.

Figure A17: Food Delivery Spending Results - Rainfall

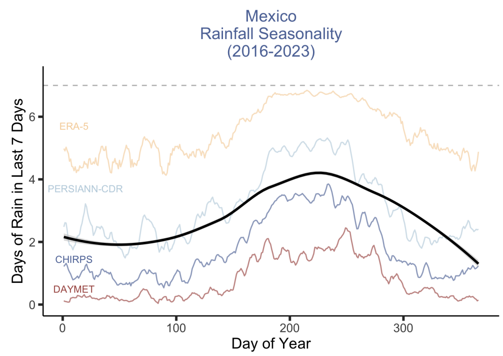


Notes: Figure shows the relationship between daily total precipitation and food delivery spending in the UK, Germany, France (using Fable transaction data), and Mexico (using Measurable AI transaction data), estimated according to equation 5. The dependent variable is delivery spend, divided by average spend per day for each country. Figure shows estimates both for binned precipitation (based on percentiles of rainfall, with 0-75th, 75-85th, 85-95th, 95-99th, and 99-100th percentiles as bins) relative to the baseline bin of no rain and for linear specification (higher order polynomials were tested as well, but the results were similar). Graphs below coefficient plots show the distribution of rainfall in each sample. Standard errors clustered by postal-area/municipality & month. Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline).

While this may seem counter-intuitive at first, there are two probable explanations for this pattern. First, as the climate of Mexico is much warmer, rainfall may be a welcome refresher on hot days.

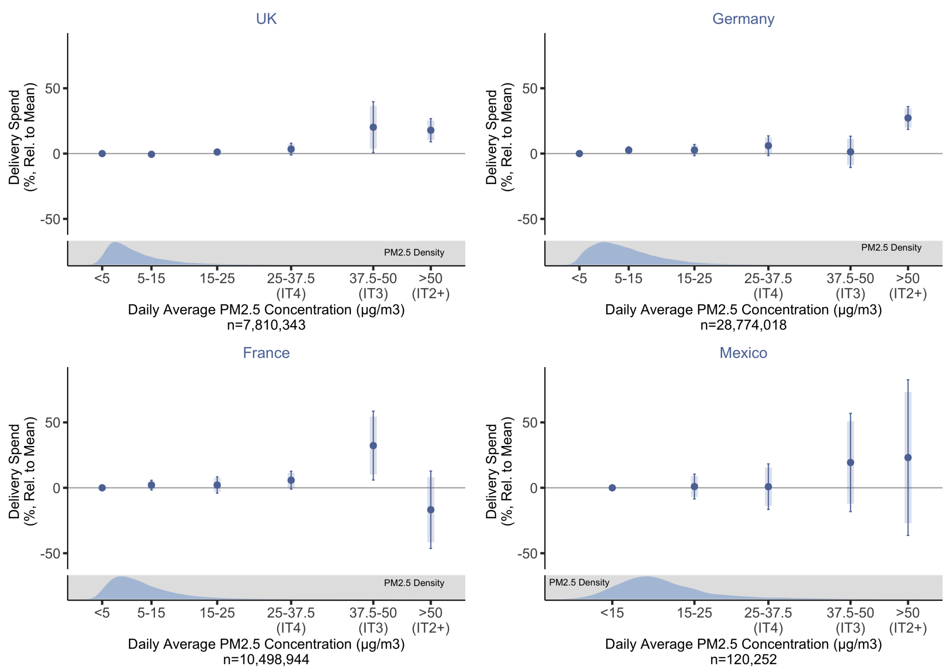
Second, precipitation in Mexico is very seasonal and predictable (see Figure A18). It rains most afternoons in the summer. Consumers may therefore be aware of and adapted to these patterns.

Figure A18: Mexico Rainfall Seasonality



Notes: Figure shows seasonality of precipitation in Mexico using four different reanalysis rainfall products. For each, the figure plots the average number of days of rain in the last 7 days for each day in the year. A day of rain is defined as rain higher than the 10th percentile of rain (on days with non-zero rain). Black line shows LOESS trend for the average of the four precipitation data.

Figure A19: Food Delivery Spending Results - Air Pollution



Notes: Figure shows the relationship between daily average particulate matter ($PM_{2.5}$) concentrations and food delivery spending in the UK, Germany, France (using Fable transaction data), and Mexico (using Measurable AI transaction data), estimated according to eq. 5. The dependent variable is delivery spend, divided by average spend per day for each country. Figure shows estimates both for binned temperatures relative to the baseline bin (12-24°C in Europe; 24-27°C in Mexico). Graphs below coefficient plots show the distribution of average $PM_{2.5}$ concentrations in each sample. Standard errors clustered by postal-area/municipality & month (binned). Thin (thick) line shows 95% (90%) CI.

Pollution: I examine the relationship between air pollution and food delivery expenditures. I note that ambient particulate matter concentrations may not be exogenous. For example, days with higher car use may be associated with higher pollution and lower food delivery orders. With that caveat, I rerun my main regressions with various dummy variables for daily $PM_{2.5}$ concentration levels based on World Health Organization (WHO) guidelines. In general, I find that food delivery spending is higher on days with average $PM_{2.5}$ concentrations above 37.5 and 50 $\mu g/m^3$ (WHO IT3 and IT2 levels, respectively), though results are noisy in Mexico where I have very limited data (Figure A19).[42] I also confirm that my estimates of the effects of extreme temperatures on food delivery expenditures are not biased by air pollution.

COVID-19 Pandemic and Payday in Mexico: Table A9 shows the relationship between confirmed COVID-19 cases, paydays, and food delivery demand. Higher local cases were associated with higher delivery spend. The increase in food delivery expenditures per 1,000 confirmed local cases was similar in magnitude to the increase seen on days with maximum temperatures above 39°C, compared to moderate days. Similarly, paydays on which most Mexicans get their paycheck (*la quincena*) are also correlated with higher food delivery spend.

Table A9: Food Delivery Demand - COVID-19 and Payday

	Dependent variable:	
	Delivery Spend ($)	
	(1)	(2)
Confirmed Cases (000s)	0.022**	0.049*
	(0.009)	(0.026)
	[0.022]	[0.057]
Payday	0.020***	0.020***
	(0.007)	(0.007)
	[0.005]	[0.006]
Max Temp >39C	0.034***	0.034***
	(0.011)	(0.011)
	[0.002]	[0.002]
Mean Spend ($)	0.36	0.36
Cases Squared	No	Yes
Observations	2,779,846	2,779,846

Notes: Table shows relationship between local COVID-19 cases, indicator for paydays, and daily maximum temperatures (above >39C), based on transaction data in Mexico (estimated according to equation 5).

[42]The intersection of the CAMS pollution data and Measurable AI Rappi and UberEats data mostly include the Mexico City area. Baseline particulate matter pollution is also much higher in Mexico than in Europe.

A.5 Additional Labor Supply Results

A.5.1 Main Results - Table Form

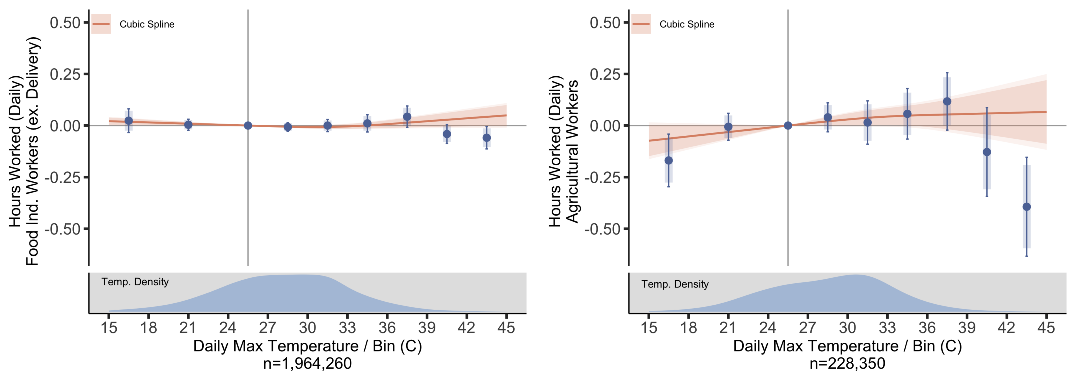
Table A10: Hours Worked Results - Mexico

	Dependent variable:				
	Hours Worked				
	(1)	(2)	(3)	(4)	(5)
<18C	−0.215	−0.220	−2.406***	0.527	−0.171
	(0.363)	(0.402)	(0.774)	(0.516)	(0.362)
	[0.557]	[0.587]	[0.003]	[0.311]	[0.638]
18-24C	0.019	0.013	1.036	0.188	0.030
	(0.220)	(0.235)	(0.759)	(0.227)	(0.219)
	[0.933]	[0.958]	[0.178]	[0.410]	[0.890]
27-30C	0.098	0.196	0.066	0.188	0.111
	(0.264)	(0.262)	(0.377)	(0.187)	(0.263)
	[0.712]	[0.458]	[0.862]	[0.320]	[0.675]
30-33C	0.422	0.364	0.569	0.141	0.435
	(0.325)	(0.328)	(0.573)	(0.251)	(0.322)
	[0.199]	[0.271]	[0.325]	[0.578]	[0.181]
33-36C	0.351	0.432	0.097	0.123	0.353
	(0.344)	(0.338)	(0.630)	(0.292)	(0.338)
	[0.311]	[0.207]	[0.878]	[0.676]	[0.301]
36-39C	1.711**	1.258*	2.324	1.275**	1.687**
	(0.725)	(0.650)	(1.881)	(0.581)	(0.724)
	[0.022]	[0.058]	[0.221]	[0.032]	[0.023]
>39C	1.869**	1.383	1.505**	1.314	1.813*
	(0.875)	(1.315)	(0.747)	(0.937)	(0.945)
	[0.037]	[0.297]	[0.049]	[0.166]	[0.060]
Mean Daily Hours	6.49	6.49	6.49	6.49	6.49
Municip, State-by-WoY, State-by-Year FEs	Y	-	-	-	Y
Municip-by-WoY, Municip-by-Year FEs	-	Y	-	-	-
State-by-Quad TT	-	Y	-	-	-
Municip, State-by-DoY, State-by-Year FEs	-	-	Y	-	-
Ind, Year, WoY FEs	-	-	-	Y	-
Avg. Daily Hours Worked (Municip)	-	-	-	-	Y
Individual (Worker) Characteristics	Y	Y	Y	-	Y
Day-of-Week FEs	Y	Y	Y	Y	Y
Observations	2,532	2,532	2,532	2,532	2,532

Notes: Table shows relationship between daily max. temperature and hours worked in Mexico estimating according equation 6 using ENOE data. Results relative to the baseline bin (24-27°C). Back to main text.

A.5.2 Main Results Falsification and Robustness Checks

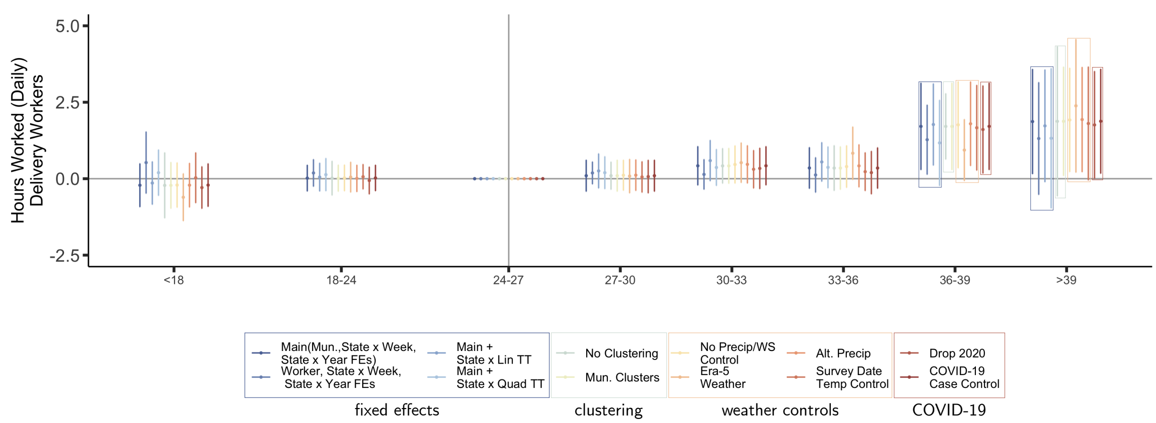
Figure A20: Hours Worked by Food Industry and Agricultural Workers in Mexico



Notes: Figure shows the relationship between daily maximum temperature and hours worked for food industry (non-delivery) workers (left panel) and agricultural workers (right panel) in Mexico, estimated according to equation 6. Figure shows estimates for both binned temperatures (blue) and cubic spline temperatures (red); relative to the baseline bin (24-27C) or temperature (25.5C). Graphs below coefficient plots show the distribution of daily maximum temperatures in the sample. Standard errors clustered by municipality & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline). Back to main text.

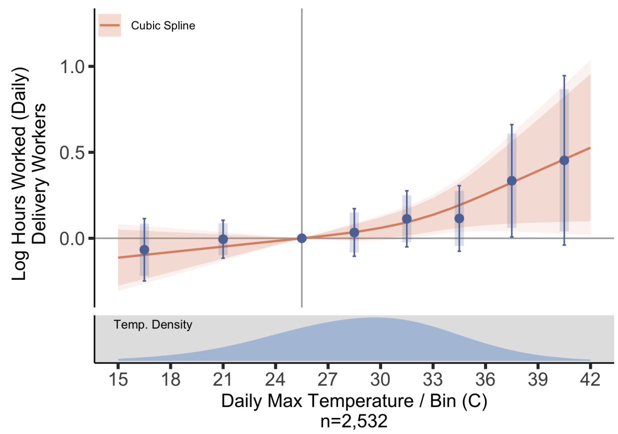
Figure A21 shows robustness of the main labor supply results to various alternative fixed effects and controls. The first four specifications show main results and alternative spatiotemporal fixed effects, while the next two show alternative clustering. I also drop non-temperature controls, use different sources of temperature and precipitation data, and flexibly control for the temperature on the day of the survey. Lastly, I drop 2020 and control for COVID-19 case counts.

Figure A21: Labor Supply Results - Robustness to Alternative Spatiotemporal, Weather, and Other Controls and Alternative Clustering



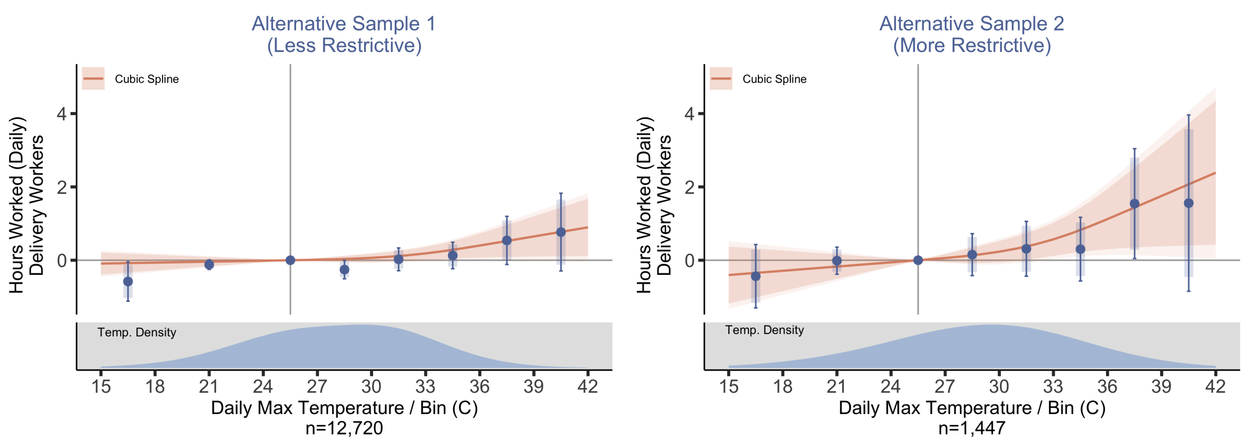
Notes: Figure shows the relationship between daily maximum temperature and hours worked for food delivery platform workers in Mexico, estimated according to equation 5, but with alternative fixed effects, controls, clustering, and sampling. Figure shows binned temperatures; all results are relative to the baseline bin (24-27C). 95% confidence intervals shown. Back to main text.

Figure A22: Labor Supply Results - Log Outcomes



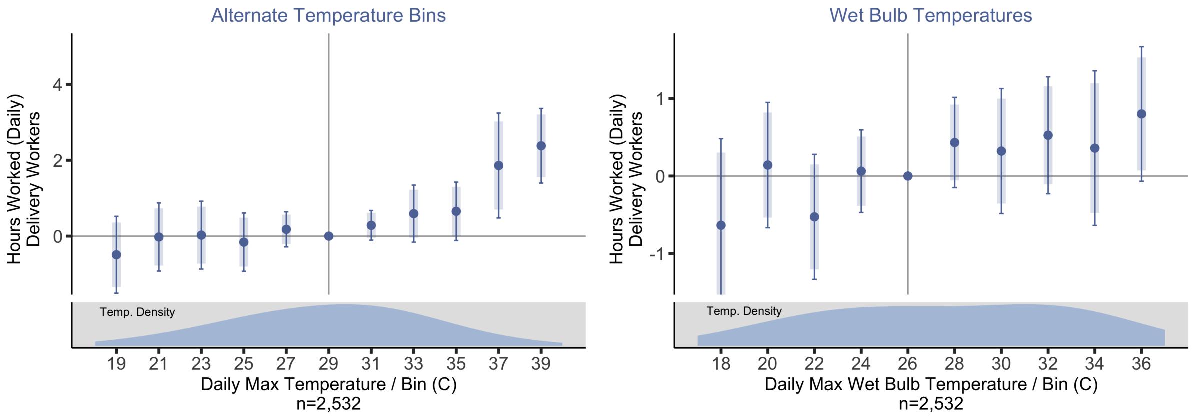
Notes: Figure shows the relationship between daily maximum temperature and hours worked (estimated according to equation 6) for food delivery platform workers in Mexico, with outcomes in logs. Figure shows estimates for both binned temperatures (blue) and cubic spline temperatures (red); relative to the baseline bin (24-27C) or temperature (25.5C). Graphs below coefficient plots show the distribution of daily maximum temperatures in the sample. Standard errors clustered by municipality & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline). Back to main text.

Figure A23: Labor Supply Results - Alternative Samples



Notes: Figures shows the relationship between daily maximum temperature and hours worked (estimated according to equation 6) for food delivery platform workers in Mexico, using alternative criteria for selecting workers. Left panel shows a less restrictive sample, including all "delivery workers of merchandise" and couriers in the food industry, as well as self-employed motorcycle drivers in the food industry. The right panel shows a more restrictive sample, including only self-employed "delivery workers of merchandise", couriers, and motorcycle drivers in the food industry, who do not have a boss, have no employees, and have no health insurance. Figures show estimates for both binned temperatures (blue) and cubic spline temperatures (red); relative to the baseline bin (24-27C) or temperature (25.5C). Graphs below coefficient plots show the distribution of daily maximum temperatures in the sample. Standard errors clustered by municipality & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline). Back to main text.

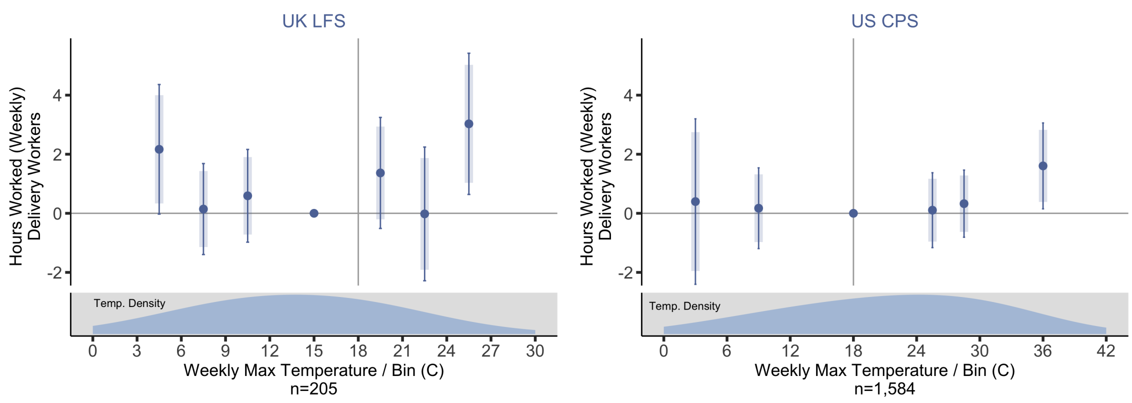
Figure A24: Labor Supply Results - Alternative Bins and Wet-Bulb Temperatures



Notes: Figures shows the relationship between daily maximum temperature and hours worked (estimated according to equation 6) for food delivery platform workers in Mexico, using alternative bins (left) and wet bulb temperatures (right). In left panel, temperature bins are 2°C bins, with the baseline bin at 28-30°C. Right panel also has 2°C bins, with the baseline bin at 25-27°C wet-bulb temperatures. Graphs below coefficient plots show the distribution of daily maximum temperatures in the sample. Standard errors clustered by municipality & month (binned). Thin (thick) line shows 95% (90%) CI. Back to main text.

Figure A25 shows the temperature-labor supply relationship for small samples of delivery workers in the UK and the US. These analyses are limited by industry and job characterizations and geographical identifiers available in the surveys.[43] Despite these limitations, I recover a similar overall temperature-labor supply relationship, with increases in the hours worked by food delivery workers on hot days.

Figure A25: Labor Supply Results - UK and US



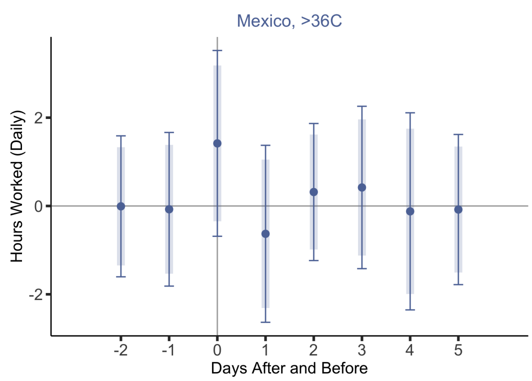
Notes: Figures show the relationship between daily maximum temperature and hours worked (estimated according to equation 6) for food delivery platform workers in the UK and US. Figures show estimates for binned temperatures; relative to the baseline bin (12-18°C in the UK; 12-24°C in the US). Graphs below coefficient plots show the distribution of daily maximum temperatures in the sample. Robust standard errors shown for the UK; standard errors clustered by CBSA and month for the US. Thin (thick) line shows 95% (90%) CI. Back to main text.

[43] For example, only a general region is available for the UK LFS, with 20 regions for all of the UK.

A.5.3 Detailed Labor Supply Results

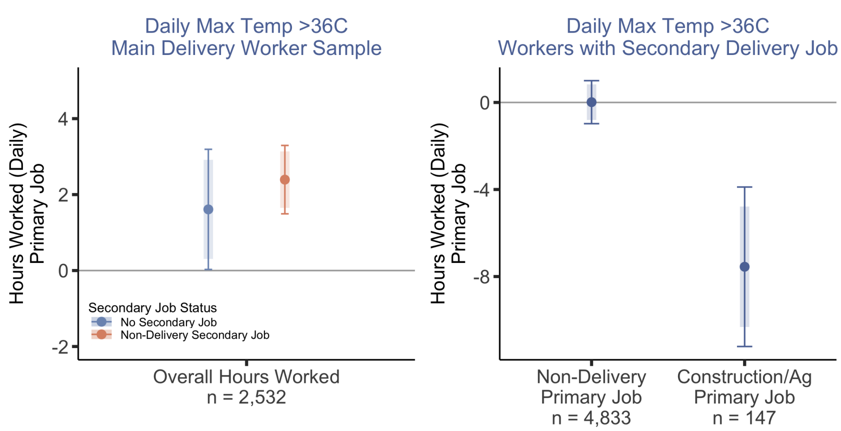
Figure A26 explores intertemporal substitution for labor supply. As temperatures are highly correlated across subsequent days, these results are less precise. However, when controlling for the maximum temperatures of the previous and following days, the main results remain roughly the same, though slightly less precise. High temperatures the day before lead to a smaller imprecise decrease in hours worked. Figure A27 explores the effects of temperatures on hours worked depending on secondary job status.

Figure A26: Labor Supply Results - Intertemporal Substitution



Notes: Figure shows the relationship between daily maximum temperature above 36°C and hours worked (estimated according to equation 6) for food delivery platform workers in Mexico. In addition to the main explanatory variables of binned temperatures, I also include binned temperature variables for the two days after and 5 days before: -1 is the day *after* the current day, while +1 is the day *before*. Standard errors clustered by municipality & month. Thin (thick) line shows 95% (90%) CI (binned). Back to main text.

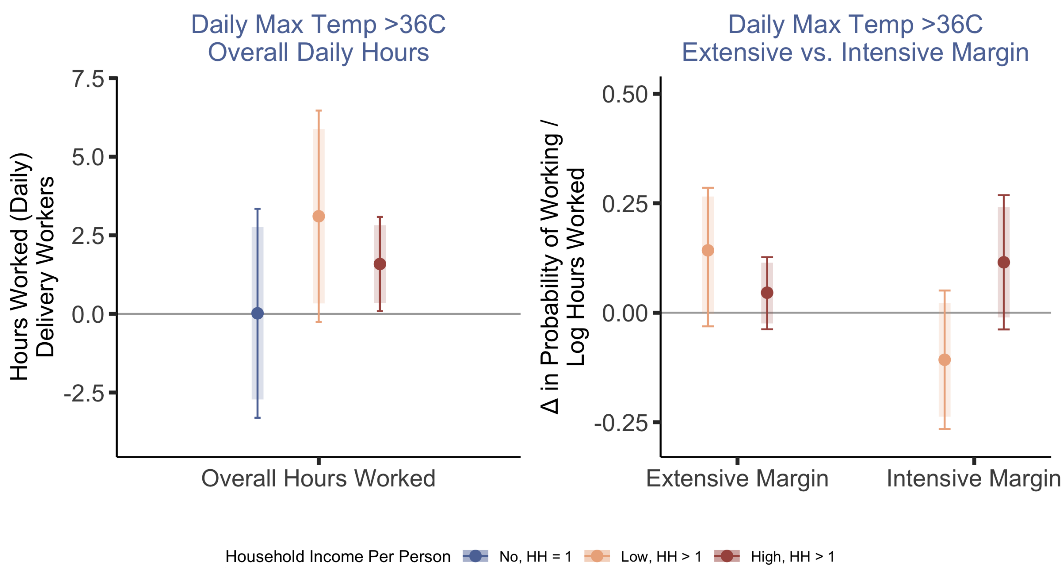
Figure A27: Labor Supply Results - Secondary Jobs



Notes: Figure shows the relationship between daily maximum temperatures above 36°C and hours worked (estimated according to equation 6) for food delivery platform workers in Mexico. Left panel is for main delivery worker sample, showing heterogeneity by whether workers have a secondary job. Right panel shows hours worked for those with secondary delivery jobs and non-delivery primary jobs. Standard errors clustered by municipality & month (binned). Thin (thick) line shows 95% (90%) CI. Back to main text.

The overall labor supply results reveal underlying heterogeneity, particularly when considering household size and income. I calculate the total income per person in each worker's household, excluding their own earnings.[44] Workers are then categorized into three groups: those in single households (with no other household income), and those with low and high household incomes per capita. Figure A28 illustrates that the increase in hours worked on hot days (>36°C) compared to moderate days is most pronounced for workers with lower household income per capita. This increase is primarily driven by a higher probability of working on hot days. Workers from households with higher income per capita also work more on days above 36°C (the difference is not statistically significant). Workers in single households do not work more hours on hot days relative to moderate days. However, this group represents a small fraction of the overall worker population.

Figure A28: Delivery Worker Labor Supply - Worker Heterogeneity

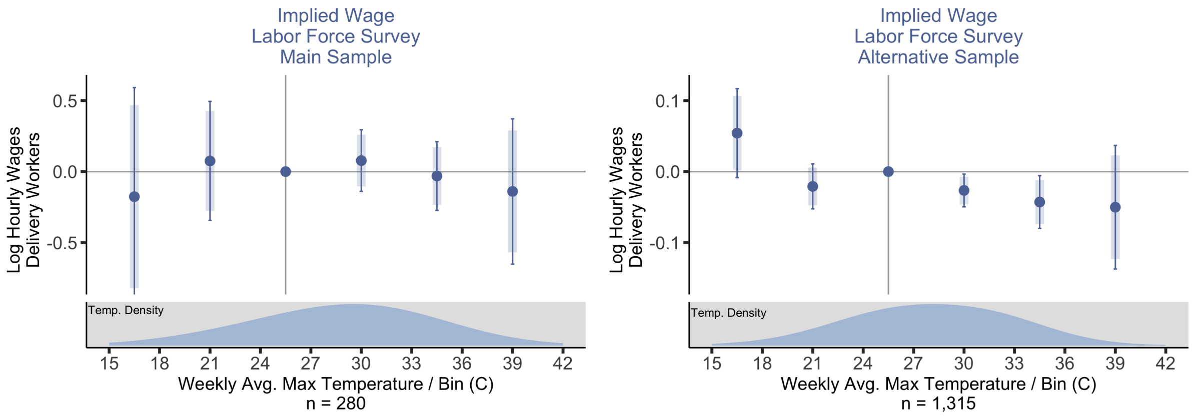


Notes: Figure shows the relationship between daily maximum temperature above 39°C (relative to baseline bin, estimated according to equation 6) and the extensive and intensive margin of hours worked, separately for workers with high and low household incomes per capita. Standard errors clustered by municipality & month. Thin (thick) line shows 95% (90%) CI (binned). Back to main text.

[44] Worker household income is defined as the total monthly income of individuals in the worker's household, *excluding* the worker's own income. I use the median monthly household income to define the threshold between low and high-income workers.

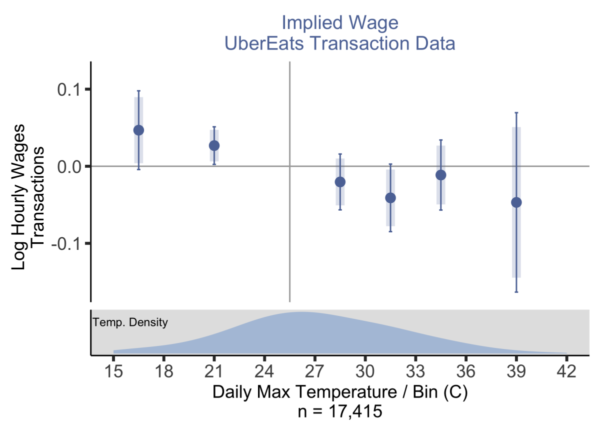
A.5.4 Additional Wage Results

Figure A29: Food Delivery Worker Hourly Wages



Notes: Figure shows the relationship between daily maximum temperature and implied hourly wages from the ENOE labor force survey data (estimated according to equation 6) for food delivery platform workers in Mexico. Figures show estimates for binned temperatures relative to the baseline bin (24-27C). Left panel shows results for entire sample, while right panel shows results for alternative sample (same as in Figure A23). Note different y-axes in two panels. Graph below coefficient plots show the distribution of the weekly average of daily maximum temperatures in the sample. Standard errors clustered by municipality & month. Thin (thick) line shows 95% (90%) CI. Back to main text.

Figure A30: Food Delivery Worker Hourly Wages



Notes: Figure shows the relationship between daily maximum temperature and implied hourly wages from UberEats transaction data (estimated according to equation 6) for food delivery platform workers in Mexico. Figures show estimates for binned temperatures relative to the baseline bin. Graph below coefficient plot shows the distribution of daily maximum temperatures in the sample. Standard errors clustered by municipality & month. Thin (thick) line shows 95% (90%) CI. Back to main text.

Table A11: Delivery Worker Wages - COVID-19 Pandemic

	Dependent variable:	
	Log Wages	
	Main Sample	Transaction Data
	(1)	(2)
COVID-19 Deaths (00s)	0.739	0.238*
	(0.611)	(0.119)
	[0.231]	[0.071]
Observations	1,221	10,792

Notes: Table shows the relationship between local (municipality) COVID-19 deaths and implied hourly wages (estimated according to equation 6) from the ENOE labor force survey data (left panel) and using UberEats transaction data (right panel) Main explanatory variable is the number of confirmed COVID-19 deaths within municipality. Standard errors (clustered by municipality and month) are shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01). Back to main text.

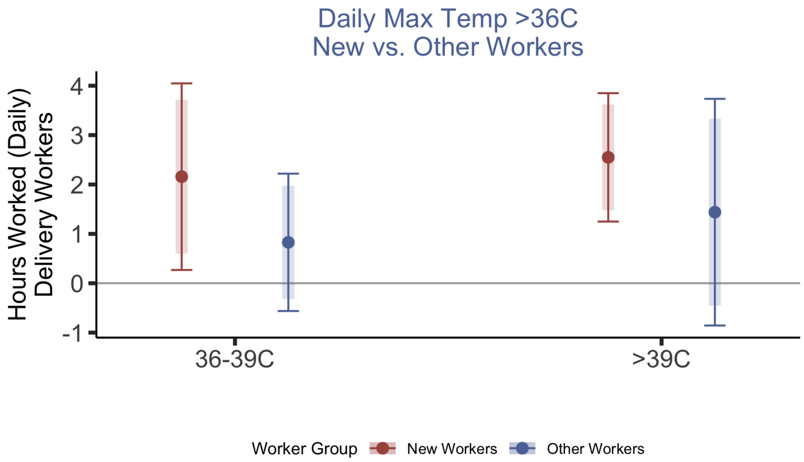
Table A12: Transportation Platform Worker and Private Chauffeur Results

	Transportation Platform Workers			Private Chauffeurs		
	Dependent variable (logs):					
	Income	Hours	Wages	Income	Hours	Wages
	(1)	(2)	(3)	(4)	(5)	(6)
36-42C	−0.010	0.009*	−0.019*	0.002	−0.027	0.030
	(0.009)	(0.005)	(0.010)	(0.025)	(0.019)	(0.021)
	[0.247]	[0.080]	[0.058]	[0.933]	[0.149]	[0.162]
>42C	−0.007	0.022*	−0.029	0.302***	0.068***	0.234***
	(0.043)	(0.013)	(0.051)	(0.032)	(0.020)	(0.036)
	[0.871]	[0.091]	[0.574]	[0.000]	[0.001]	[0.000]
Observations	21,646	21,646	21,646	2,976	2,976	2,976

Notes: Table shows the relationship between daily maximum temperature and monthly income, hours worked, and implied hourly wages (estimated according to equation 6) for transportation (ride-share) platform workers in Columns (1)-(3) and private chauffeurs in Columns (4)-(6). The main explanatory variable is the number of days in the reference week with maximum temperatures 36-42°C and above 42°C, compared to the reference bin of all days between 24 and 27°C. Dependent variables are based on one observation per reference week and weekly hours worked; flexible controls (mean of the daily maximum temperatures and its square and cube and total precipitation and its square and cube) are included for the first three weeks of the relevant month in order to isolate variation in temperatures in the reference week. Standard errors (clustered by municipality and month) are shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01). Figures A29 and A30 show the unweighted wage results for the entire temperature distribution for all samples. Back to main text.

A.5.5 Additional Mechanism Results

Figure A31: New Workers vs. Other Workers



Notes: Figure illustrates the relationship between daily maximum temperature and hours worked (estimated according to equation 6) for groups of food delivery workers in Mexico, based on their experience with platform work. Coefficients are relative to baseline temperature bin of 24-27°C. New workers are those who had a job in the prior quarter that was not platform-based; other workers are all other workers. Standard errors clustered by municipality & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned). Back to main text.

Table A13: Rideshare Workers Labor Supply and Wages

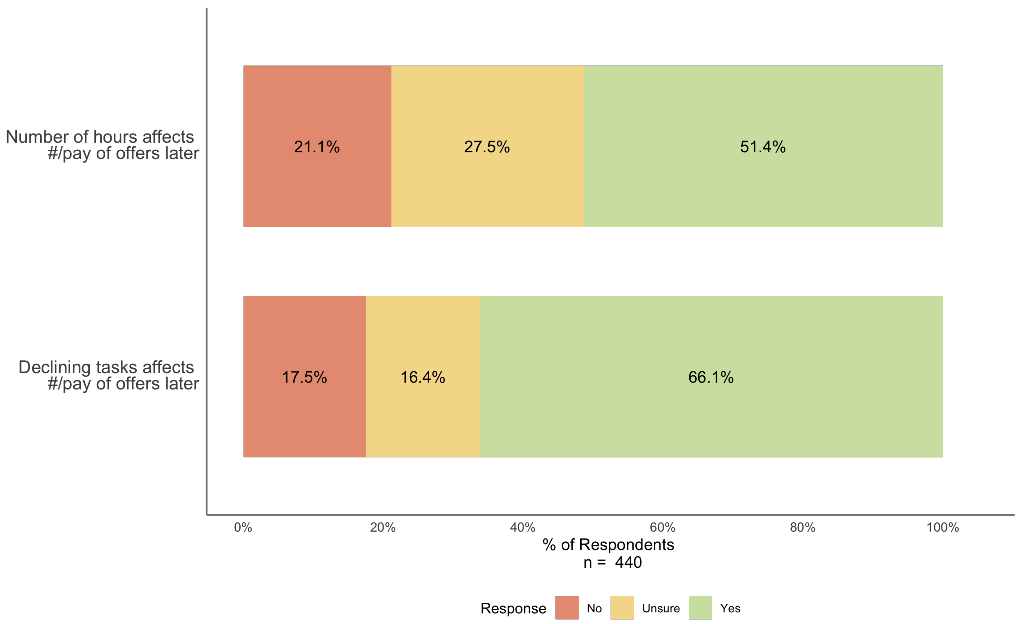
	Dependent variable:					
	Uber Only: 2013-2018			Uber and DiDi: 2019-2023		
	Log Income	Log Hours	Log Wages	Log Income	Log Hours	Log Wages
	(1)	(2)	(3)	(4)	(5)	(6)
33-36C	0.004	0.005	-0.002	0.004	0.004	-0.00004
	(0.008)	(0.004)	(0.007)	(0.008)	(0.006)	(0.008)
	[0.636]	[0.209]	[0.801]	[0.622]	[0.468]	[0.996]
>36C	-0.023^{*}	0.020^{***}	-0.043^{***}	-0.003	-0.0002	-0.003
	(0.012)	(0.005)	(0.012)	(0.009)	(0.006)	(0.010)
	[0.057]	[0.000]	[0.001]	[0.716]	[0.977]	[0.756]
Obs.	11,327	11,327	11,327	13,497	13,497	13,497

Notes: Table shows the relationship between daily maximum temperature and monthly income, hours worked, and implied hourly wages (estimated according to equation 6) for transportation (ride-share) platform workers. Columns (1)-(3) show results for 2013-2018, when Uber was the dominant company in the space (87% market share). Columns (4)-(6) show results for 2019 - 2023, after DiDi entered the market. The main explanatory variable is the number of days in the reference week with maximum temperatures 33-36°C and above 36°C, compared to the reference bin of all days between 24 and 27°C. Dependent variables are based on one observation per reference week and weekly hours worked; flexible controls (mean of the daily maximum temperatures and its square and cube and total precipitation and its square and cube) are included for the first three weeks of the relevant month in order to isolate variation in temperatures in the reference week. Standard errors (clustered by municipality and month) are shown in parentheses; p-values shown in brackets (*p<0.1; **p<0.05; ***p<0.01). Back to main text.

A.5.6 Additional Survey Results

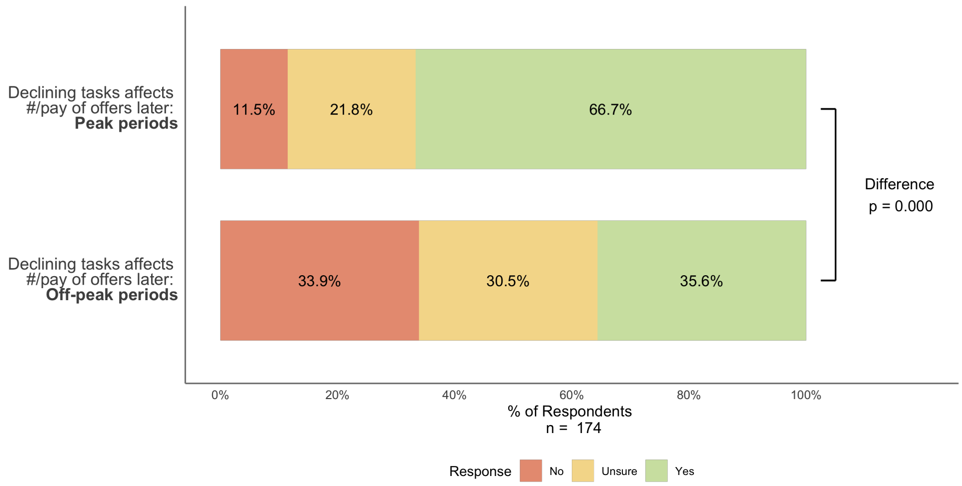
In this section, I present additional results from the worker belief survey. First, Figure A32 shows gig workers' responses to whether the number of hours they work or declining tasks affects future opportunities on platforms. Then, Figures A33 and A34 show the main results presented in Figure 9 separately for the Mexican and US gig worker samples. Similarly, Figures A35 and A36 show the results presented in Figure 10 separately for the Mexican and US gig worker samples. Finally, Figure A37 shows the demand curve (Figure 11) separately for Mexico and the US, while Figure A38 shows it only for gig workers with food delivery specific platform experience.

Figure A32: Worker Survey - Effect of Actions Today on Future Platform Opportunities



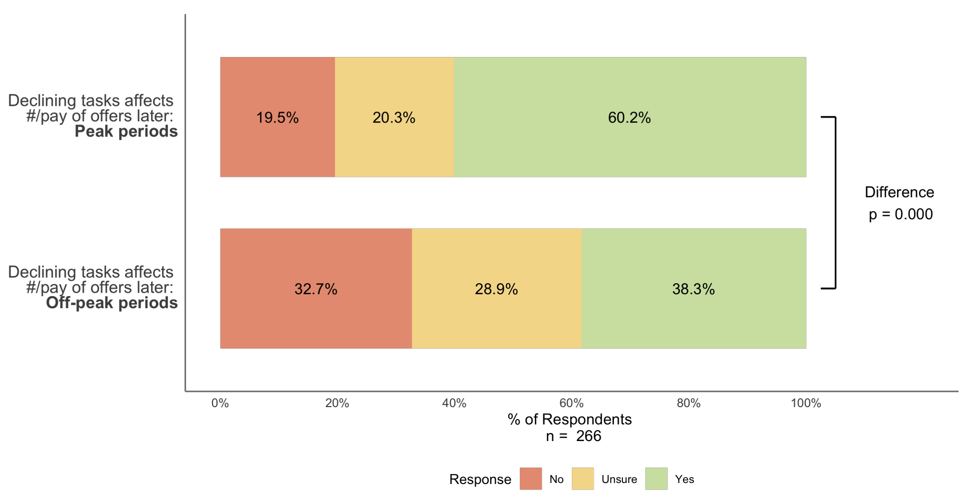
Notes: Figure shows responses of platform workers from Prolific survey. Each Figure shows the share of respondents answering "Yes", "Unsure", and "No", the whether each action today affects the number or pay of offers they receive in the future. For example, the first question asks workers: "Do you think the number of hours you spend working on the app today affects the number or pay of jobs you're offered later (e.g., tomorrow)?".

Figure A33: Worker Survey (Mexico) - Effect of Actions Today on Future Platform Opportunities



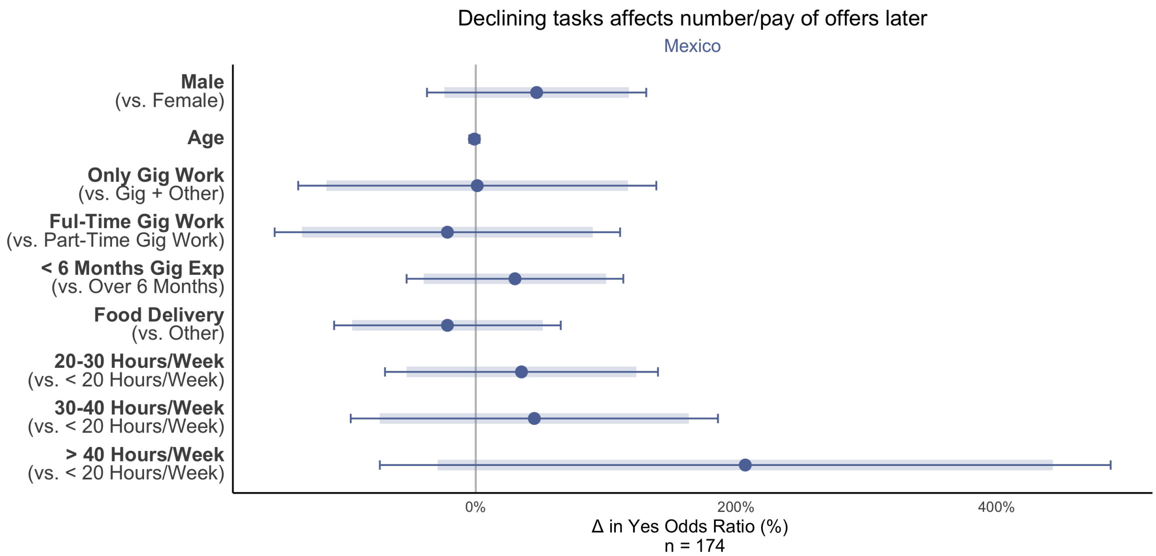
Notes: Figure shows responses of platform workers from Prolific survey, only for the sample from Mexico. Each bar shows the share of respondents answering "Yes", "Unsure", and "No", to whether each action today affects the number or pay of offers they receive in the future. For example, the first question asks workers: "Do you think saying no to jobs during busy times (like rush hour or special events) affects the number or pay of jobs the app offers you later (e.g., tomorrow)?".

Figure A34: Worker Survey (US) - Effect of Actions Today on Future Platform Opportunities



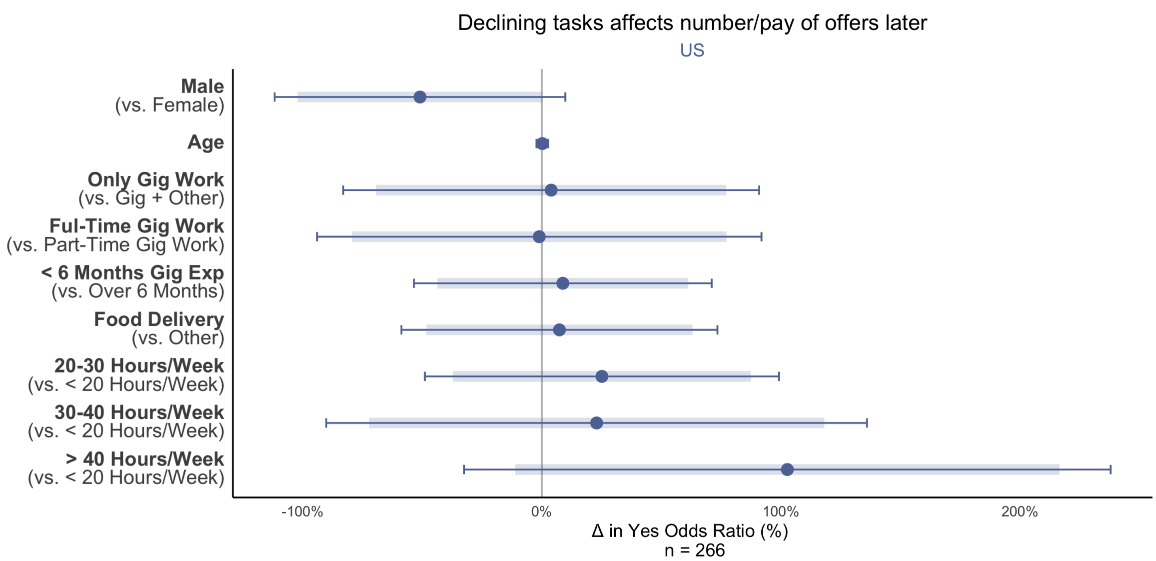
Notes: Figure shows responses of platform workers from Prolific survey, only for the sample from the US. Each bar shows the share of respondents answering "Yes", "Unsure", and "No", to whether each action today affects the number or pay of offers they receive in the future. For example, the first question asks workers: "Do you think saying no to jobs during busy times (like rush hour or special events) affects the number or pay of jobs the app offers you later (e.g., tomorrow)?".

Figure A35: Survey Responses By Worker Characteristics (Mexico)



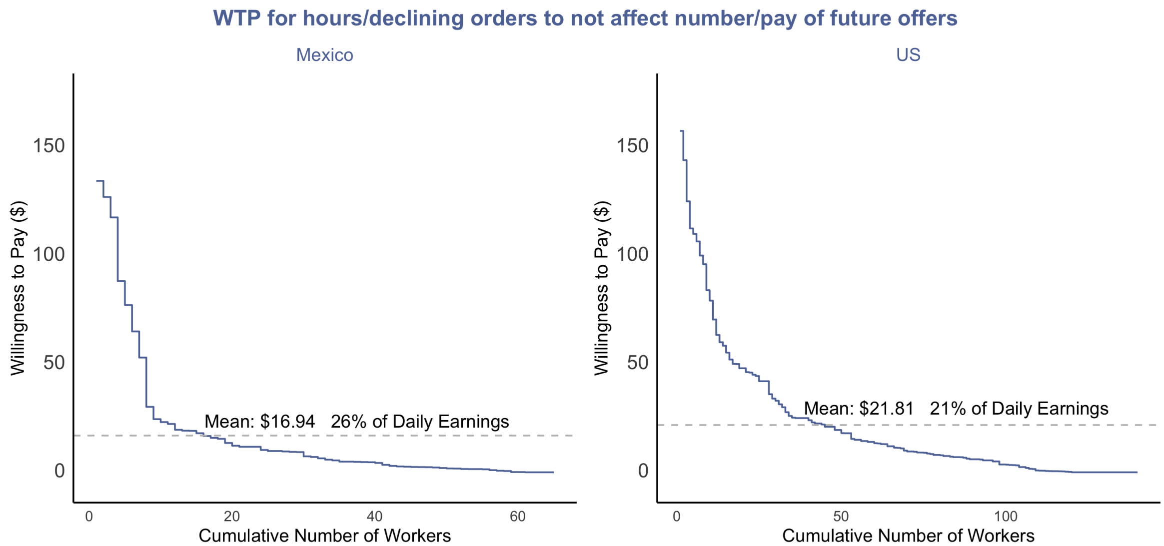
Notes: Figure displays results from a logistic regression examining which worker characteristics predict believing that declining tasks affects future job offers, for only the sample from Mexico. Points show changes in odds ratios (%). The baseline worker is female, does gig work alongside other jobs, works part-time (< 20 hours per week), and has over 6 months of experience. Age is measured in years. Thin (thick) line shows 95% (90%) CI.

Figure A36: Survey Responses By Worker Characteristics (US)



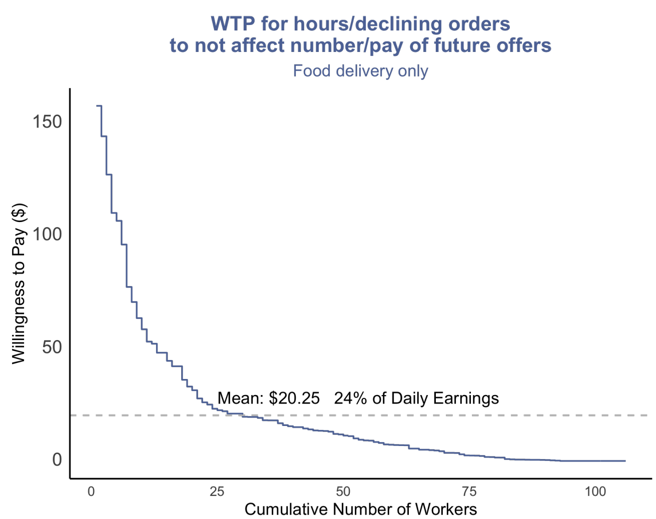
Notes: Figure displays results from a logistic regression examining which worker characteristics predict believing that declining tasks affects future job offers, for only the sample from the US. Points show changes in odds ratios (%). The baseline worker is female, does gig work alongside other jobs, works part-time (< 20 hours per week), and has over 6 months of experience. Age is measured in years. Thin (thick) line shows 95% (90%) CI.

Figure A37: Willingness to Pay for Hours/Orders Today to Not Affect Future Offers



Notes: Figure plots the amount gig workers report they would give up for their actions on the platforms today to not affect their future earnings, separately for Mexico and the US. This is calculated from workers' average pay per task, average tasks per day, and the response to the question "What percentage of your daily pay would you be willing to give up for your actions on the platform (e.g., hours worked or orders accepted) to not affect the number or pay of jobs the app offers you later (e.g., tomorrow)?."

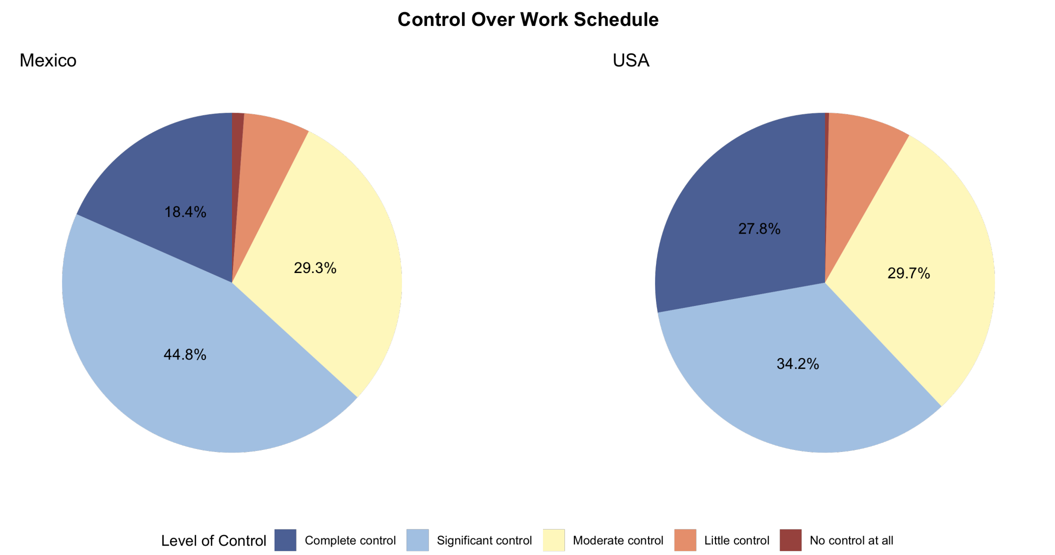
Figure A38: Willingness to Pay for Hours/Orders Today to Not Affect Future Offers



Notes: Figure plots the amount gig workers report they would give up for their actions on the platforms today to not affect their future earnings, separately for those workers with food delivery specific platform experience. This is calculated from workers' average pay per task, average tasks per day, and the response to the question "What percentage of your daily pay would you be willing to give up for your actions on the platform (e.g., hours worked or orders accepted) to not affect the number or pay of jobs the app offers you later (e.g., tomorrow)?."

Figure A39 shows that while most workers say they have significant control over their schedules on platforms, approximately a third report having moderate, little, or no control at all.

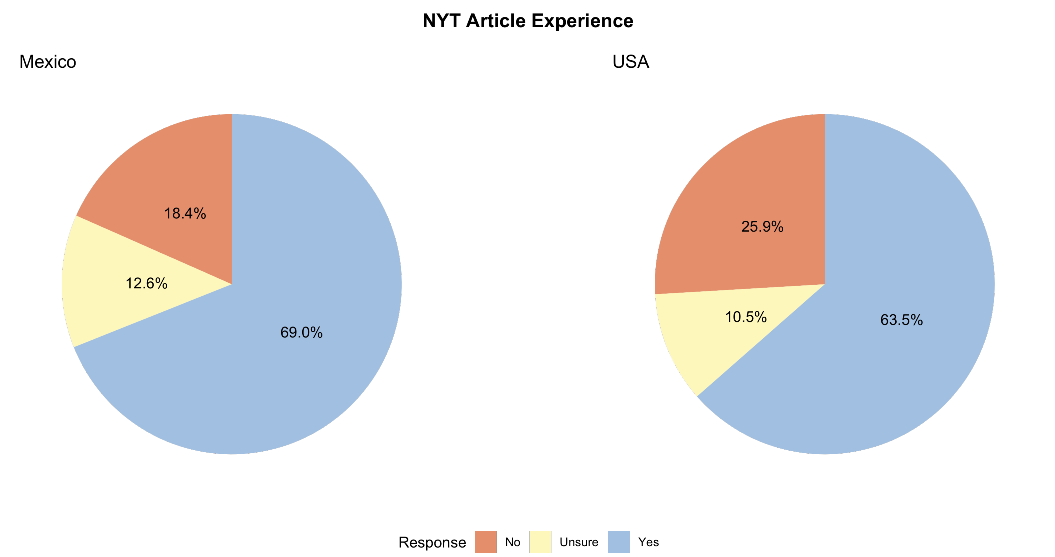
Figure A39: How much control do you feel you have had over your work schedule in gig economy jobs?



Notes: Figure shows the share of Prolific gig worker responses to a question about control over work schedules (question 10 in the survey), separately for Mexico and the US.

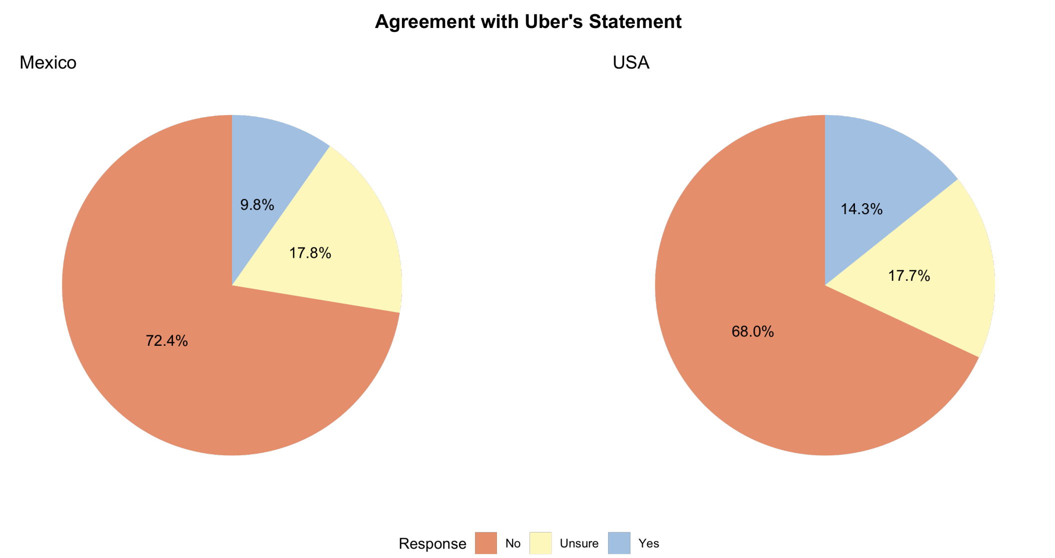
Participants were asked to read excerpts from an article that describes behavioral nudges by Uber (Scheiber 2021) and were also shown screenshots from a DoorDash worker's post on Reddit ("Catalogue of DoorDash Manipulation Tactics"). Additionally, they were asked whether they agree with Uber's statement that the company does not use tricks to get workers to work more. Figures A40-A42 show that most workers report that the *New York Times* article and the post by the DoorDash workers represent their experiences on gig economy platforms. The vast majority also disagree with Uber's statement that they don't use tricks to encourage workers to work more. Finally, when asked why platforms may use nudges and gamification in their apps, workers identify increasing worker supply and company profits as the reasons (Table A14).

Figure A40: Do you believe these descriptions [*New York Times* article excerpts] represent your experience working on gig economy platforms?



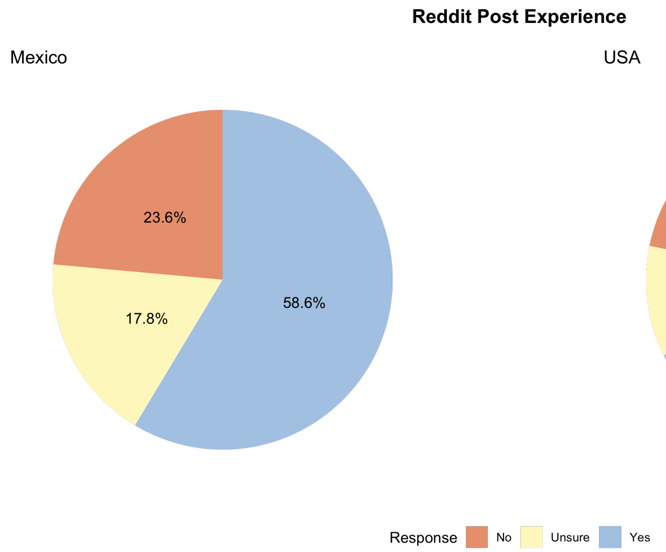
Notes: Figure shows the share of Prolific gig worker responses to a question about whether the *New York Times* article on gamification represents their experience on platforms (question 20 in the survey), separately for Mexico and the US.

Figure A41: Companies like Uber have publicly said that they don't use tricks (e.g., gamifying) to get you to work more. Do you agree?



Notes: Figure shows the share of Prolific gig worker responses to a question about whether they believe Uber that they do not use tricks to get workers to work more (question 24 in the survey), separately for Mexico and the US.

Figure A42: Do you believe these descriptions represent your experience working on gig economy platforms?



Notes: Figure shows the share of Prolific gig worker responses to a question about whether a Reddit post on DoorDash manipulation tactics represents their experience on platforms (question 24 in the survey), separately for Mexico and the US.

Table A14: Platform Motivations for Using Nudges and Gamification

	Mean (SD)	
Motivation	Mexico	USA
To help workers earn more money	2.97 (1.09)	2.90 (1.13)
To increase company profits	**4.54 (0.71)**	**4.47 (0.71)**
To improve worker job satisfaction	2.99 (1.07)	2.93 (1.14)
To get workers to work more	**4.47 (0.78)**	**4.27 (0.90)**
To create a fun work experience	2.93 (1.05)	2.84 (1.21)
To better match workers with consumers	3.02 (1.06)	2.76 (1.17)

Notes: Table shows the mean and standard deviation of Prolific gig worker responses to (question 21) “Why do you think gig economy platforms may use nudges and gamification (such as the features described in the New York Times article) in their apps? For each potential motivation below, please indicate how much you think it influences the company’s decision to use these features.” Each rating is on a scale of 1 to 5.

Back to main text.