Who Bears Climate Change Damages? Evidence from the Gig Economy

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Climate adaptation on gig economy platforms

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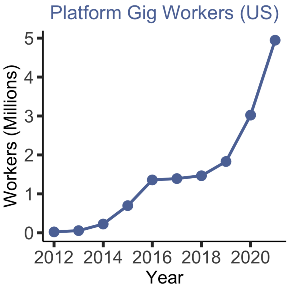
  - Algorithms/legislation of gig work increasingly important



Adapted from Garin et al. 2023

1: Source: (Public First 2024; Datta et al. 2023; Ramachandran and Kulandai 2024)

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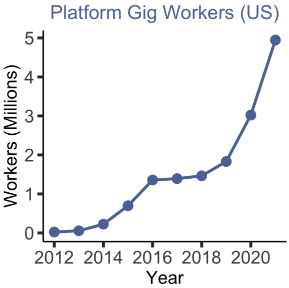
  - Potential margin of adaptation to climate change
  - Consumers: May enable adaptation through **avoidance**
  - Workers: Offer adjustable **working hours**/flexible **wages**



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- Weather data, transaction data, labor force survey data, and survey on gig worker beliefs
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Findings:

1. Increase in food delivery spending at extreme (hot or cold) temperatures
2. Increase in hours worked by delivery workers at extreme temperatures
3. No change in hourly wages of workers; survey points to beliefs abt. platforms as key mechanism

Outline

Data

1. **Weather data**
   - Station-level, inverse-distance weighted (HadISD) and reanalysis (CHIRPS, ERA5-Land) data
   - Locality-by-day spatiotemporal aggregation (population-weighted when appropriate)

▸ Weather summary stats ▸ Transaction summary stats ▸ LFS summary stats ▸ LFS comparison ▸ Prolific summary stats

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4. **Survey on gig worker beliefs**
   - Conducted on Prolific; sample of 440 workers with delivery/ridesharing experience (US and Mexico)

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Introduction

Data

Empirical Strategy

Results

Summary and Discussion

Empirical Strategy

Use exogenous variation in realized daily maximum temperature to recover the causal effect on:

- delivery spending / hours worked / hourly wages

$$y_{ict} = f(\mathbf{T}_{ct}) + g(\mathbf{P}_{ct}) + h(\mathbf{W}_{ct}) + \mathbf{X}_i\lambda_i + \omega_i/\alpha_c + \psi_{ys} + \delta_{ws} + \phi_d + \epsilon_{ict} \tag{1}$$

- y_{ict}: outcome for individual i, in locality c, at time t
- $f(\mathbf{T}_{ct})$: function of daily maximum temperature in locality c, at time t
- $g(\mathbf{P}_{ct})$: function of daily precipitation in locality c, at time t
- $h(\mathbf{W}_{ct})$: function of other weather variables (e.g., wind speed) in locality c, at time t
- $\omega_i/\alpha_c, \psi_{ys}, \delta_{ws}, \phi_d$: individual/locality, year-by-state, week-of-year-by-state, day-of-week FEs
- $\mathbf{X}_i$: individual-level characteristics such as gender, age, and education
- Standard errors clustered at the locality (municipality or postcode) and month level

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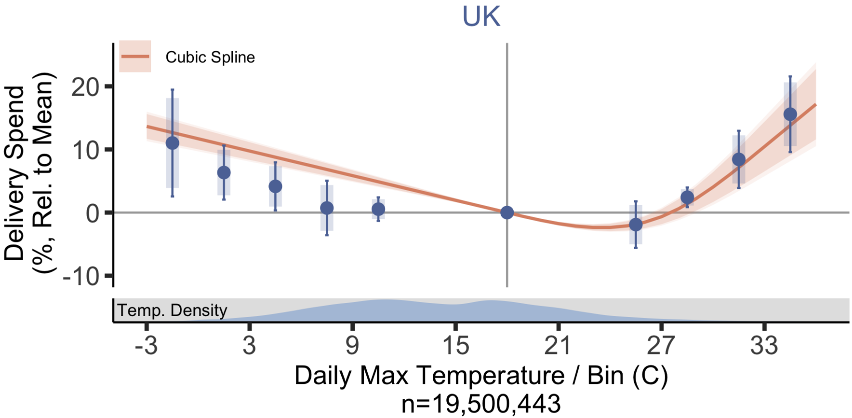
Demand: ↑ in delivery spending at extreme temperatures



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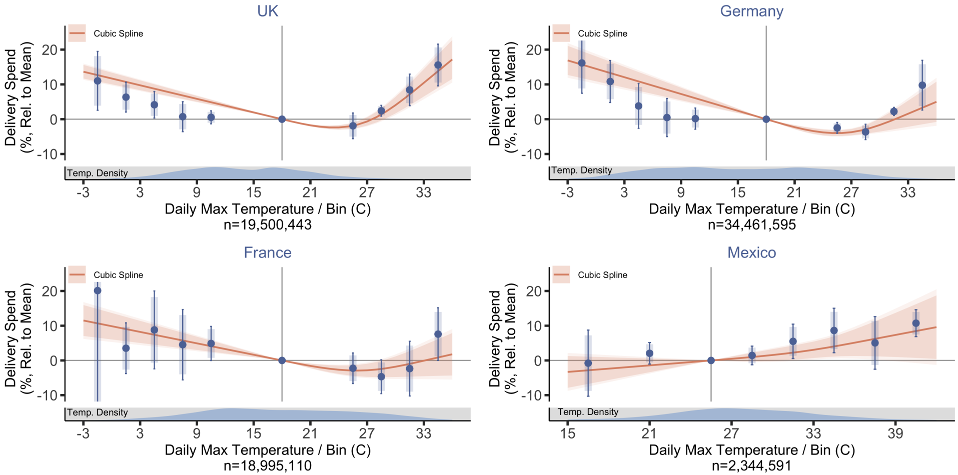

▸ Robustness ▸ Log results ▸ Google Trends results

Demand: More details

- Increase in delivery spending driven mostly by an increase in **orders**, not spending-per-order
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  ▸ Restaurant results

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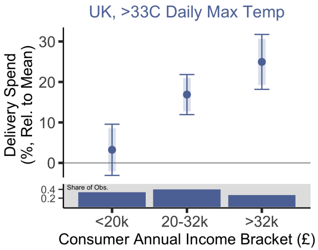
  - Restaurant results
- Evidence of disparities in access to this adaptation



Other Demand Results

- Delivery demand details
  - Delivery fees and estimated speed ▸ details
  - Intertemporal substitution ▸ details
- Other (non-delivery) demand
  - Other online food spending ▸ details
  - Consumer discretionary and non-food spending ▸ details
- Other shocks
  - Precipitation ▸ details
  - Pollution ▸ details
  - COVID-19 and paydays ▸ details

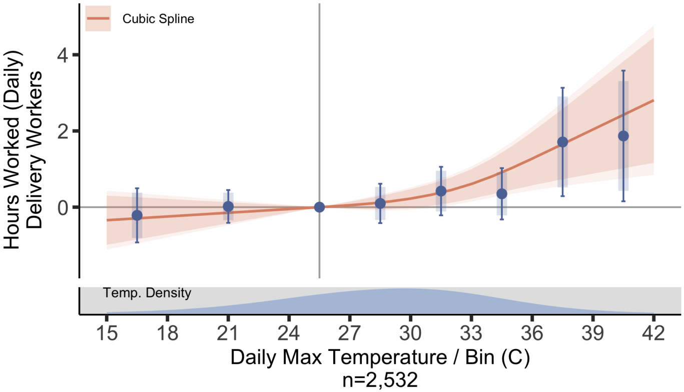
Outline

Labor Supply

- Increase in demand for platform services when conditions documented to be harmful for health. How does this affect workers?

Labor Supply: ↑ in food delivery worker hours at extreme heat

- Focus on Mexico due to data availability



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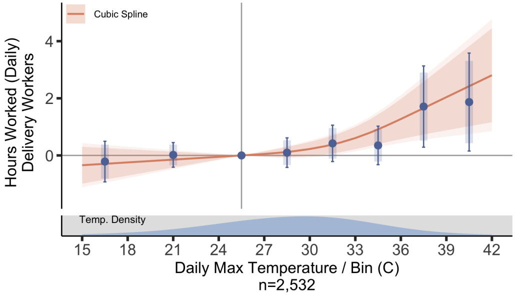

- In contrast to other food-industry and agricultural workers who work *less* on hot days
- Delivery workers work *less* in heat when doing **non-delivery** jobs
  - Consistent with literature (e.g., Graff Zivin and Neidell 2014; Garg et al. 2020; Rode et al. 2022)

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Other Labor Supply Results

- Labor supply details
  - Intertemporal substitution ▸ details
  - Secondary job ▸ details
  - Worker heterogeneity ▸ details
  - Delivery worker survey answers ▸ details

Labor Supply

- Are wages higher on hot days (given disamenity of working in the heat)?

Labor Supply: Hourly wages are not higher

- Evidence from two (imperfect) sources (w/ offsetting pros/cons):

Entire temperature range
COVID-19 wages

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Table: Delivery Worker Wages

	Main Sample
	Log Wages
	(1)
>36C	−0.100
	(0.208)
	[0.633]
Base/Extra Tip	
Efficiency	
Obs.	280

Notes: Standard errors (clustered by municipality and month) are shown in parentheses; p-values shown in brackets (* $p<0.1$; ** $p<0.05$; *** $p<0.01$).

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Table: Delivery Worker Wages

	Main Sample	Alternative Sample
	Log Wages	Log Wages
	(1)	(2)
>36C	−0.100	−0.066***
	(0.208)	(0.017)
	[0.633]	[0.000]
Base/Extra Tip		
Efficiency		
Obs.	280	1,221

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	Log Wages	Log Wages	Log Wages		
	(1)	(2)	(3)	(4)	(5)
>36C	−0.100	−0.066***	−0.069*	-0.043	-0.006
	(0.208)	(0.017)	(0.038)	(0.035)	(0.035)
	[0.633]	[0.000]	[0.095]	[0.243]	[0.878]
Base/Extra Tip			No	10%/+10%	10%/No
Efficiency			No	No	+5%
Obs.	280	1,221	14,433	14,433	14,433

Notes: Standard errors (clustered by municipality and month) are shown in parentheses; p-values shown in brackets (* $p<0.1$; ** $p<0.05$; *** $p<0.01$).

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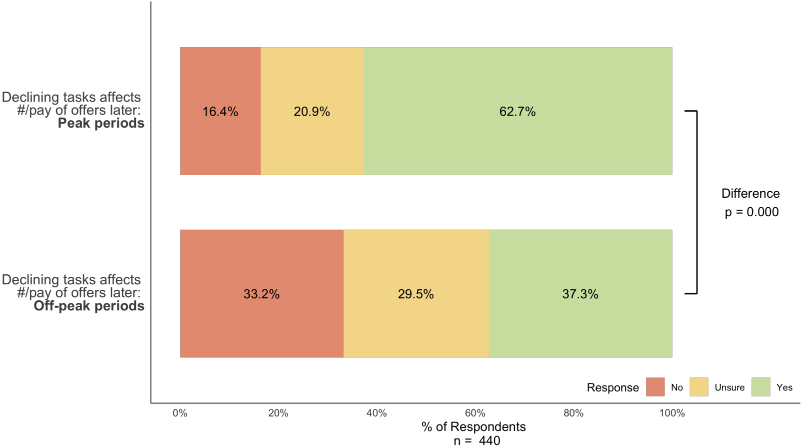
Worker Beliefs: Survey evidence

- Workers believe actions today affect future platform opportunities



▸ # of hours/declining tasks ▸ Mexico/US separately ▸ By worker characteristics ▸ Reason

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     - UK: JustEat (45%), UberEats (26%), Deliveroo (26%)
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- Algorithmic fairness and inequality in access to climate adaptation

Thank you!

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Outline

Appendix: Contributions to the literature

- Existence and extent of individual adaptation to environmental risks
  - Adaptation and avoidance behavior in response to rainfall, extreme temperatures, and air pollution (Connolly 2008; Barreca et al. 2016; Deschênes and Greenstone 2011; Aroonruengsawat and Auffhammer 2011; Auffhammer 2022; Neidell 2009; Barwick et al. 2019; Burke et al. 2022; Chu et al. 2021)
  - Inequalities in access to adaptation (Burke et al. 2022; Doremus et al. 2022)

→ Adaptation through platforms; shift in climate burdens from adaptive avoidance

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  - Inequalities in access to adaptation (; Burke et al. 2022; Doremus et al. 2022)

  → Adaptation through platforms; shift in climate burdens from adaptive avoidance

- Labor adaptations to environmental risks
  - Decrease in hours worked in response to heat and pollution exposure in outdoor-exposed industries (Graff Zivin and Neidell 2014; Garg et al. 2020; Rode et al. 2022; Hanna and Oliva 2015; Hoffmann and Rud 2022)
  - Longer-term adaptation to weather changes and climate uncertainty (Colmer 2021; Kala 2019; Downey et al. 2023)
  - Productivity and other on-the-job consequences of environmental hazards (Adhvaryu et al. 2022; Dillender 2021)

→ Extreme temps *increase* work hours for gig workers (when most detrimental to health)
→ Adaptation for **both** demand and supply in the same setting

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  → Extreme temps *increase* work hours for gig workers (when conditions are most detrimental to health)

  → Adaptation for **both** demand and supply in the same setting

- Empirical literature on gig economy labor markets
  - Pricing/allocation efficiency of algorithms (Wei and Lin 2017; Einav et al. 2018; Dubé and Misra 2023; Gaineddenova 2022)
  - Platform-initiated fare increases and gov't-imposed price-floors (Hall et al. 2023; Nakamura and Siregar 2024)
  - Pref. for flexibility; welfare & monopsony (Mas and Pallais 2017; Chen et al. 2019; Angrist et al. 2021; Fisher 2024b; 2024a)

→ Climate adaptation as a driver of app-based platform demand; limits to flexibility

Outline

Appendix: Heat-related mortality in Mexico

- Wilson et al. 2024: Increase in mortality from extreme temperatures in Mexico

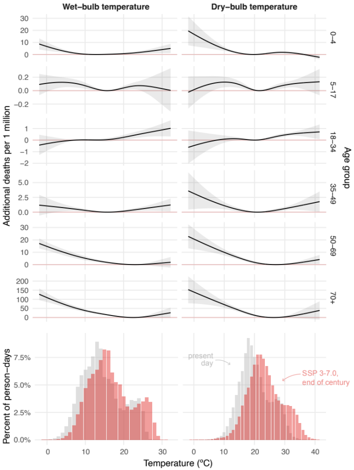

Figure S1: Relationships between mortality and exposure to wet- and dry-bulb temperature by age group in Mexico
This figure mirrors Figure 1, but expresses outcomes as absolute changes in deaths and adds a column for dry-bulb temperature. The top panels show the additional effects of 1 million person-days of exposure to the indicated daily average wet- and dry-bulb temperatures (x-axis) on mortality (y-axis); exposure and mortality are in terms of the indicated age group. Bands around each function indicate 95% confidence intervals. The bottom panel shows the distribution of daily average wet- and dry-bulb temperatures in Mexico throughout our sample period as well as the ensemble mean of projected temperatures under the SSP 3-7.0 emission scenario at the end of the century (2083–2099); we impose no change in population distribution or size.

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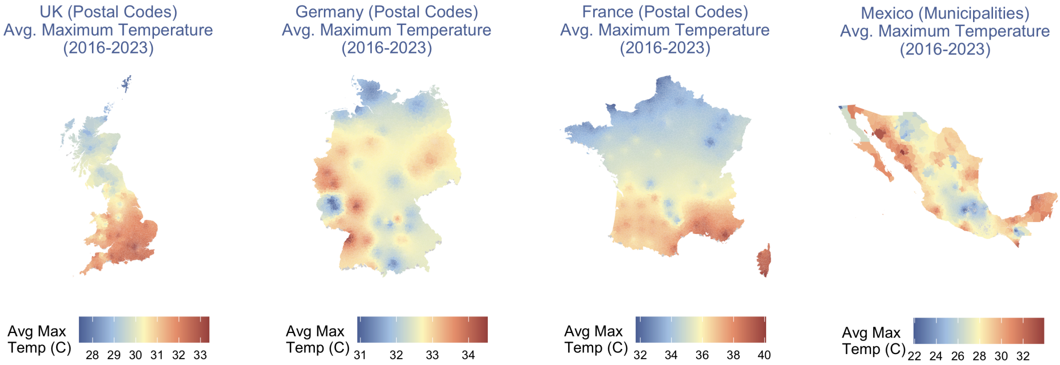
Appendix: Weather data summary statistics

Figure: Mean Daily Max. Temps. by Region



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

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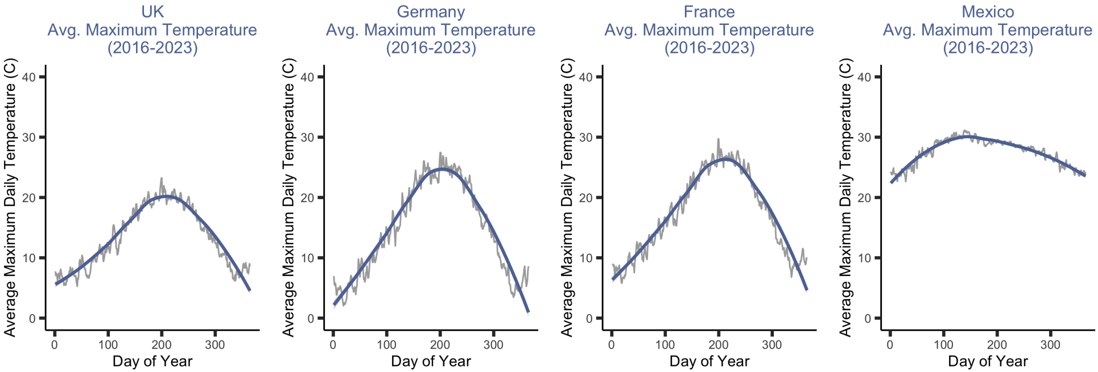
Appendix: Weather data summary statistics

Figure: Mean Daily Max. Temps. 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.

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Appendix: Consumer transaction data details

2. **Consumer transaction data**
   - Credit card data: Fable Data credit card transaction data for the UK, Germany, and France
     - Information from credit card companies (equivalent to data on credit card statement)
   - Transaction data from email receipts: Measurable AI Rappi and UberEats order data
     - Information from order confirmation receipts (consumers opt in to share for rewards)

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Appendix: Consumer transaction data details

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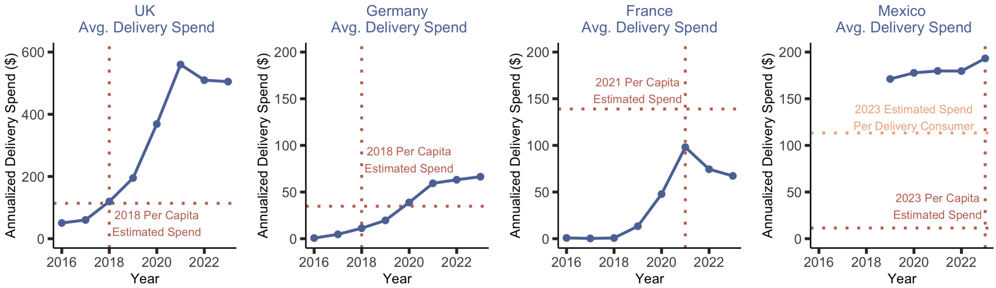
        - Information from order confirmation receipts (consumers opt in to share for rewards)

Figure: Transaction Data Comparison to Statistics



Notes: Figure shows mean annualized food delivery spend derived from transaction data. Red lines show comparisons to statistics on food deliver spend per capita from other sources. Orange line shows comparison to statistics on food delivery spend per delivery consumer for Mexico.

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Appendix: Labor force survey data details

Challenging to get data on gig workers, as conventional job descriptions often do not apply!

3. **Labor force survey data**
    - Quarterly labor force surveys with rolling participants
    - Main source: Mexico ENOE labor force survey, National Institute of Statistics and Geography (INEGI)
        - Days and hours worked in reference week, week prior to survey date
        - Delivery workers: “delivery workers of merchandise”/“motorcycle drivers” w/o boss, in food industry
    - Additional source: UK Labour Force Survey
        - Days and hours worked in reference week, week prior to survey date
        - Delivery workers: “delivery drivers and couriers” and “delivery operatives” (only available post-2021) in “restaurant and mobile food service activities”
    - Additional source: US Current Population Survey
        - Days and hours worked in reference week, week prior to survey date
        - Delivery workers: self-employed “couriers and messengers”

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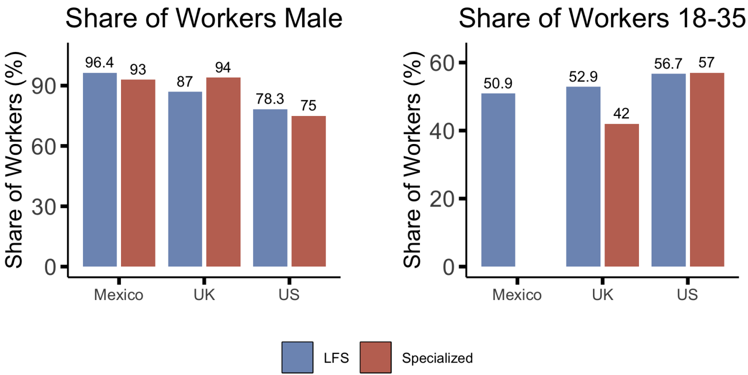
Appendix: Delivery workers in public labor force survey data

- Characteristics of food delivery workers in public LFSs very consistent with specialized surveys
  - Workers male and young (average age 36-37)



Specialized Surveys: Mexico: Tejada et al. 2021; UK: Wood et al. 2023; US: NYC Consumer and Worker Protection 2022.

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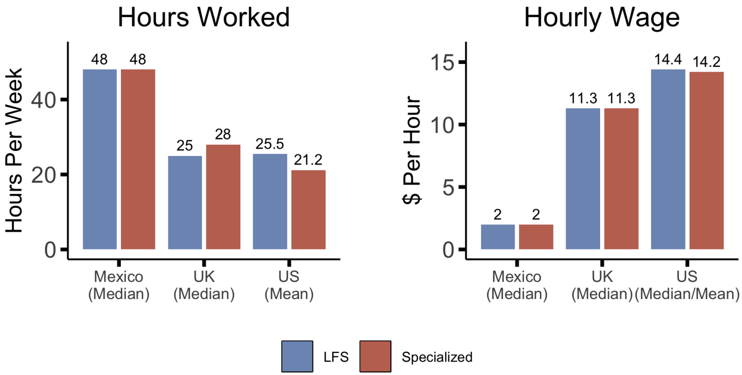
Appendix: Delivery workers in public labor force survey data

- Characteristics of food delivery workers in public LFSs very consistent with specialized surveys



Specialized Surveys: Mexico: Tejada et al. 2021; UK: Wood et al. 2023; US: NYC Consumer and Worker Protection 2022.

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Appendix: Prolific survey data details

Table: 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

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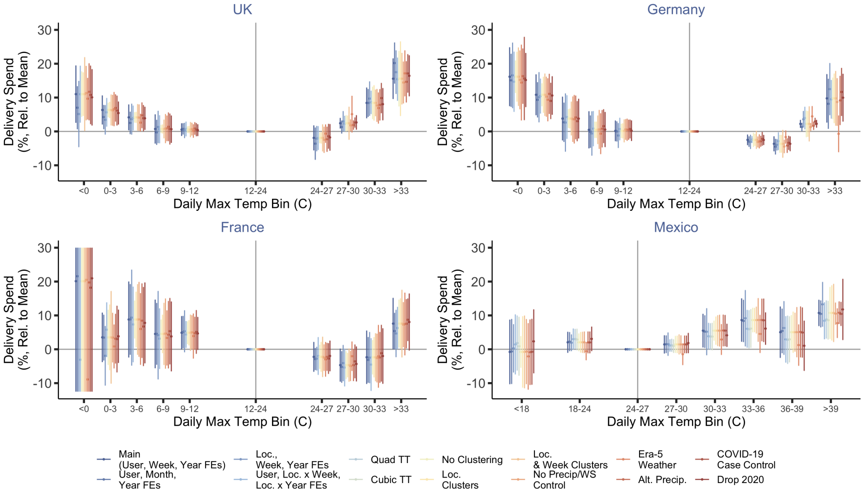
Appendix: Robustness of demand results



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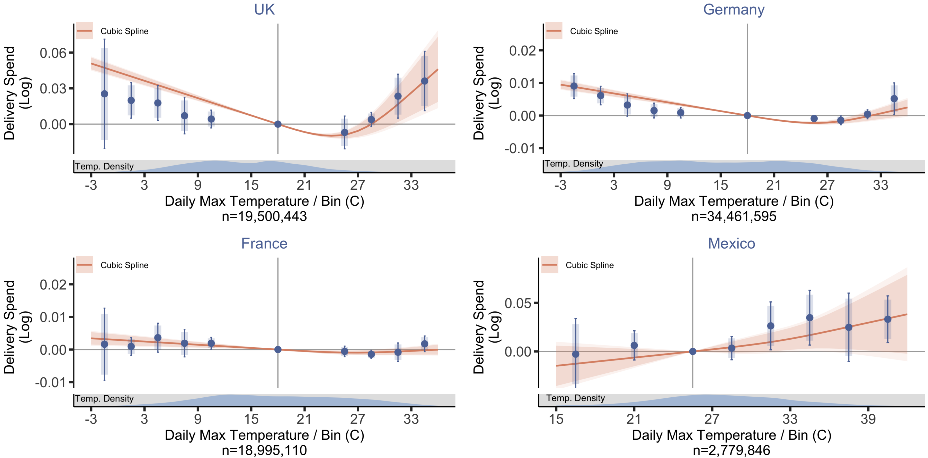
Notes: Dep. variable is delivery spend, divided by avg. spend per day. Line shows 95% CI.

Appendix: Log demand results



Notes: Dep. variable is log of delivery spend. SEs clustered by region & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline).

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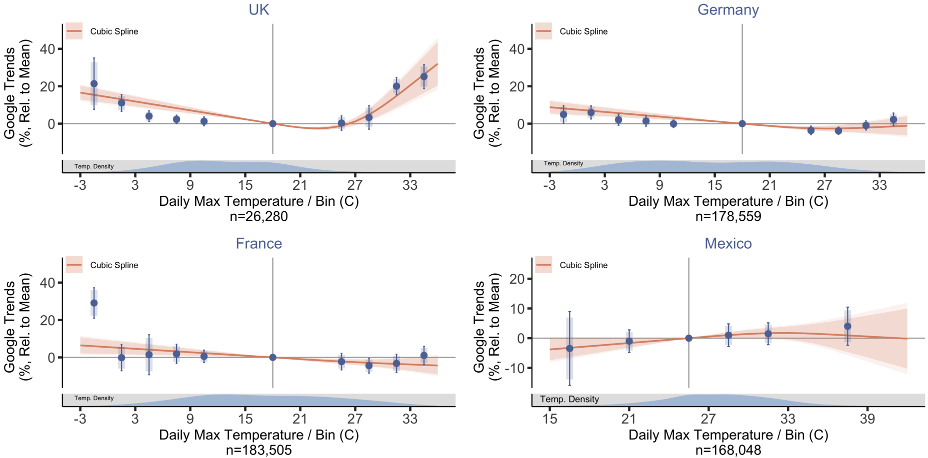
Appendix: Google Trends demand results



Notes: Dep. variable is Google Trends search volume. SEs clustered by region & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline).

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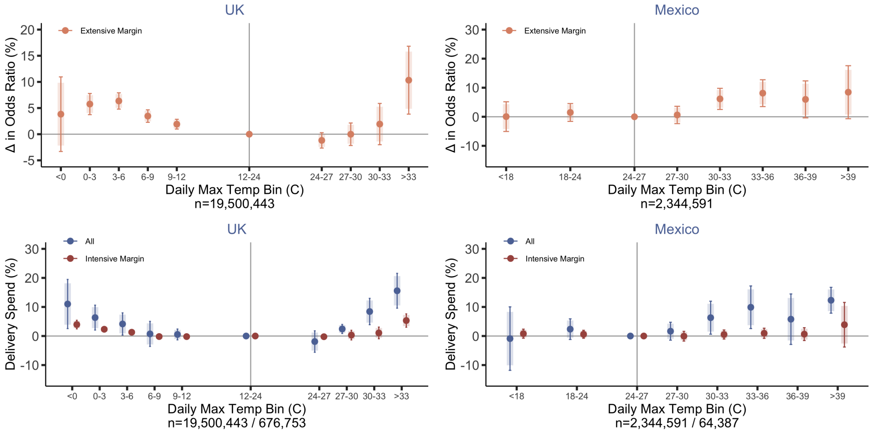
Appendix: Demand extensive vs. intensive margin

- Increase in delivery demand driven mostly by an increase in **orders**



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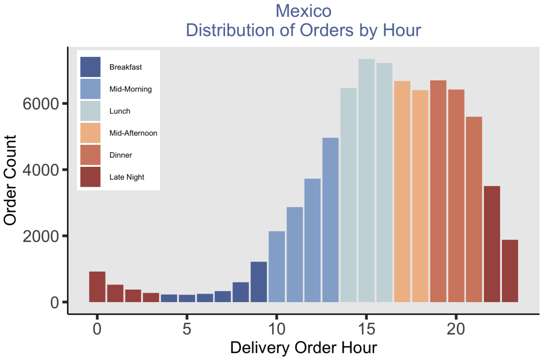
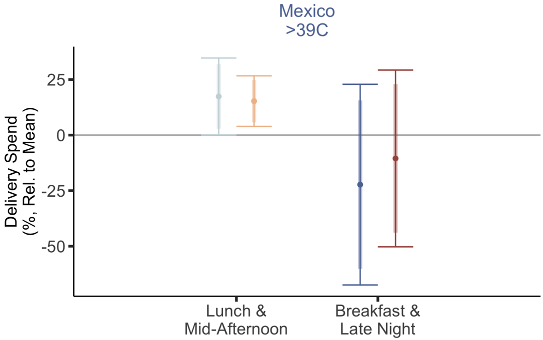
Appendix: ↑ in demand ∼ coincides with maximum temperatures

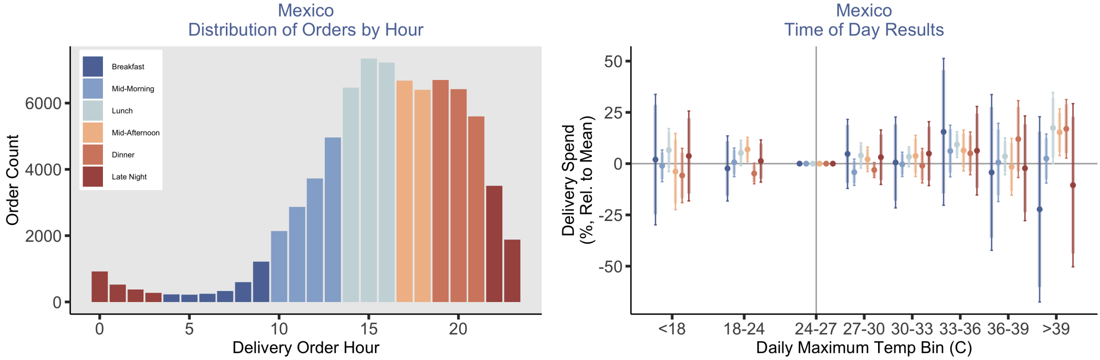
- Increase in lunch and mid-day spending
- But no change in breakfast and late night spending





▸ back ▸ Google Maps restaurant hours ▸ All temperatures

Appendix: Mexico hours



Notes: Left panel shows the distribution of Rappi and UberEats delivery orders by time of day. Right panel shows daily maximum temperature-delivery relationship, estimated separately for each part of the day. The dep. variable is food delivery spend, divided by average spend for each period. Standard errors clustered by postal-area & month. Thin (thick) line shows 95% (90%) CI.

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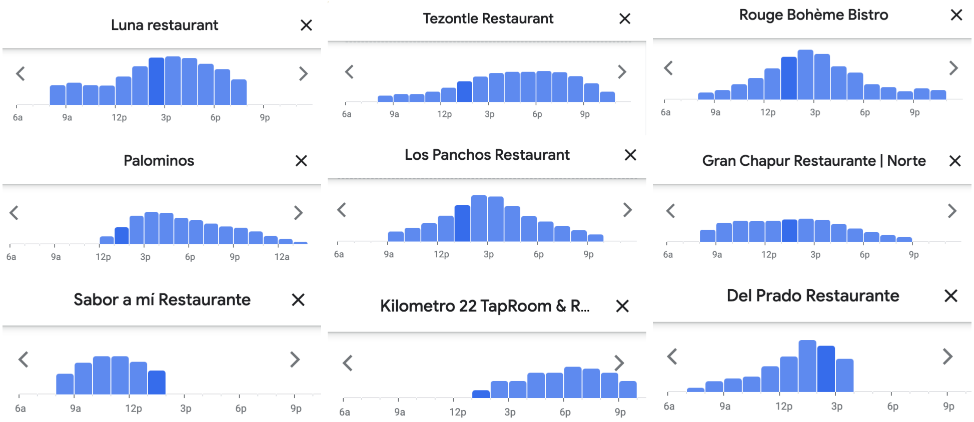
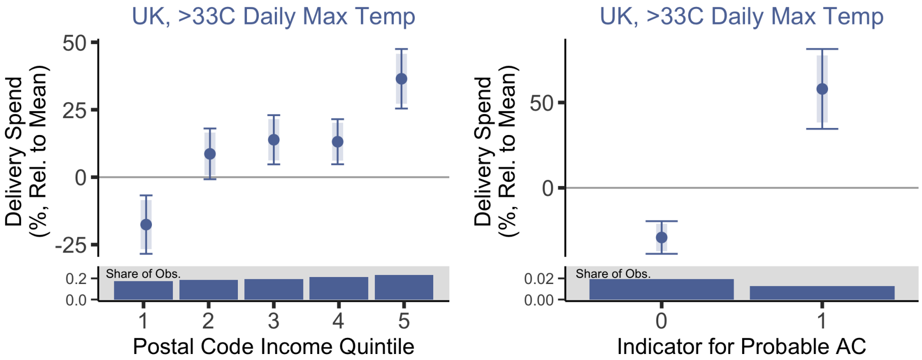
Appendix: Mexico dining hours



Notes: Peak hours for a random set of restaurants in Mexico on Google Maps.

▸ back

Appendix: Heterogeneity by postal code income and AC usage



Notes: Dep. variable is delivery spend, divided by avg. spend per day. SEs clustered by postal-code & month. Thin (thick) line shows 95% (90%) CI (binned).

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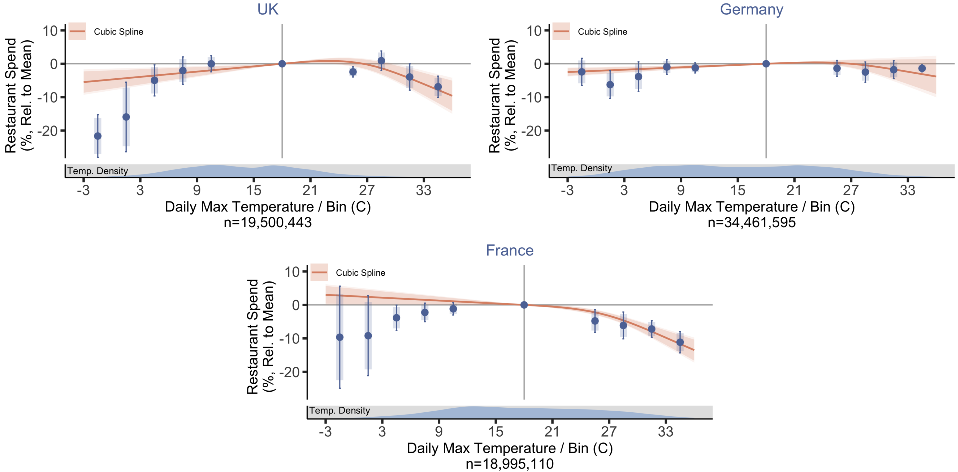
Appendix: Concurrent ↓ in restaurant spending



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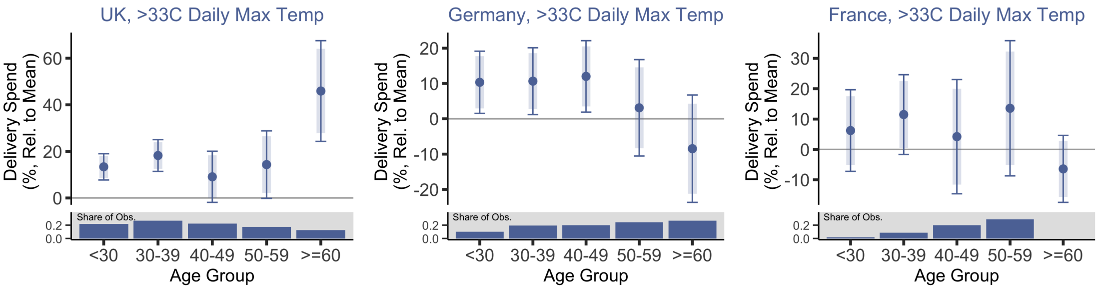
Appendix: Heterogeneity by age

- Differences across countries in heterogeneity by age
- Distribution of credit card users also differs
- No meaningful differences between men and women (evidence from France, not shown here)



Notes: Dep. variable is delivery spend, divided by avg. spend per day. SEs clustered by postal-code & month. Thin (thick) line shows 95% (90%) CI (binned).

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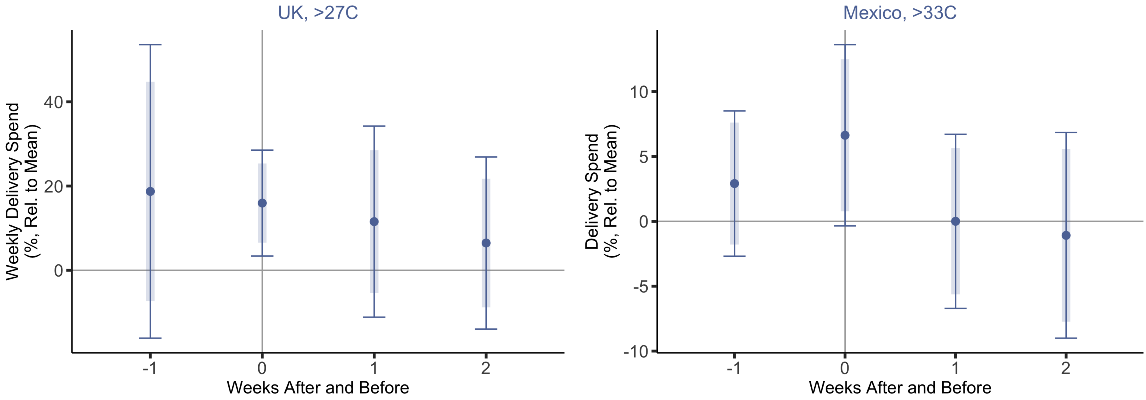
Appendix: Intertemporal substitution

- Aggregate transaction data to weekly level



Notes: Figure shows the relationship between average weekly maximum temperatures and delivery spend. 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.

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Appendix: Delivery fees and speed results

- For subset of orders, pickup/dropoff coords. and delivery timing available

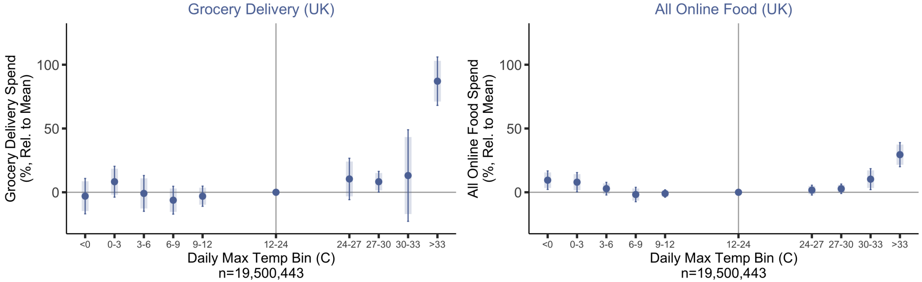
Table: Delivery Fees and Estimated Speed

	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 delivery fees (Columns (1)-(4)) as well as estimated delivery speed (Columns (5)-(6)) based on Rappi and UberEats transaction data. Estimated speed is calculated based on the Google Maps driving distance and time given pickup and dropoff coordinates. 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 (orders) ▸ back (other demand)

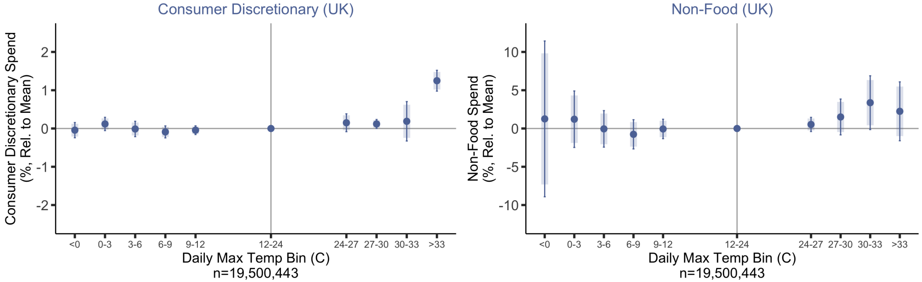
Appendix: Other online food spending



Notes: Dep. variable is grocery delivery and total online food spending, divided by avg. spend per day. SEs clustered by region & month (binned). Thin (thick) line shows 95% (90%) CI (binned).

▸ back

Appendix: Other spending



Notes: Dep. variable is total consumer discretionary and non-food spending, divided by avg. spend per day. SEs clustered by region & month (binned). Thin (thick) line shows 95% (90%) CI (binned).

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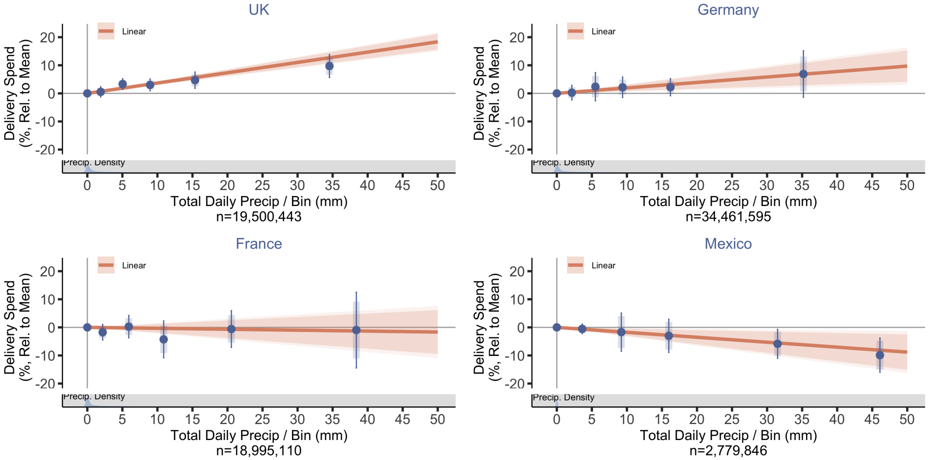
Appendix: Precipitation demand results



Notes: Dep. variable is delivery spend, divided by avg. spend per day. SEs clustered by region & month. Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline).

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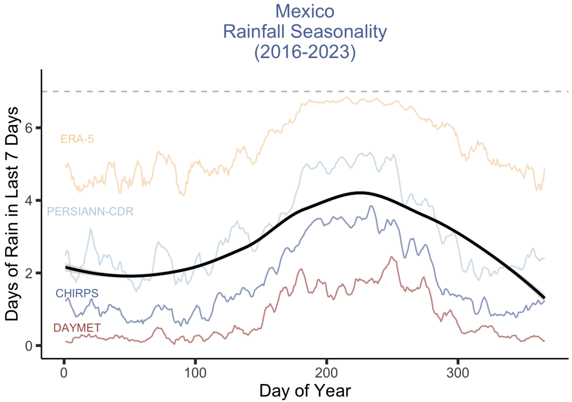
Mexico precipitation seasonality

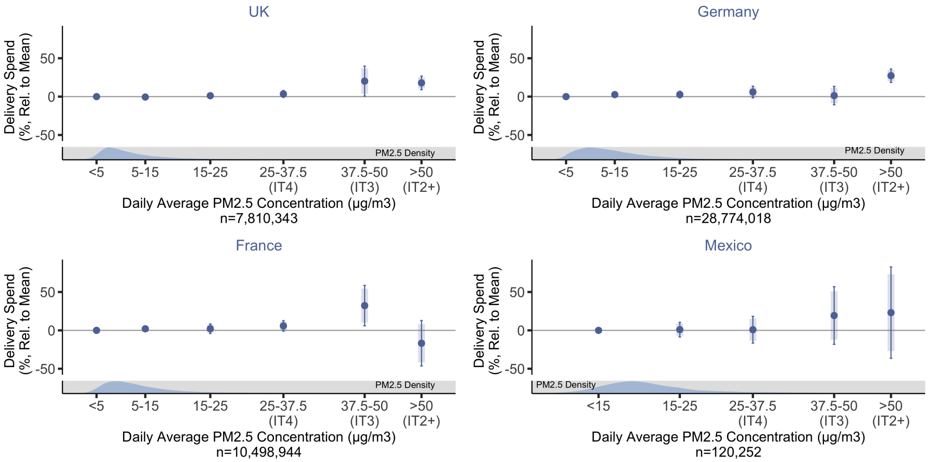
Appendix: Mexico precipitation seasonality



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.

back (precipitation) back (main)

Appendix: Pollution demand results



Notes: Dep. variable is delivery spend, divided by avg. spend per day. SEs clustered by region & month. Thin (thick) line shows 95% (90%) CI.

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Appendix: COVID-19 and payday demand results

Table: 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.

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Appendix: Back-of-the-envelope calculations

- Average delivery order takes 22 minutes to delivery
- 9.3-12.5% increase in delivery demand

  $\longrightarrow$ 2-2.8 minutes of additional work per consumer
  - Order size does not increase significantly on hot days
  - Approximately 60 delivery consumers per delivery workers

$\longrightarrow$ 2-2.8 hours of additional work per food delivery worker
  - Test this empirically next using labor force survey data

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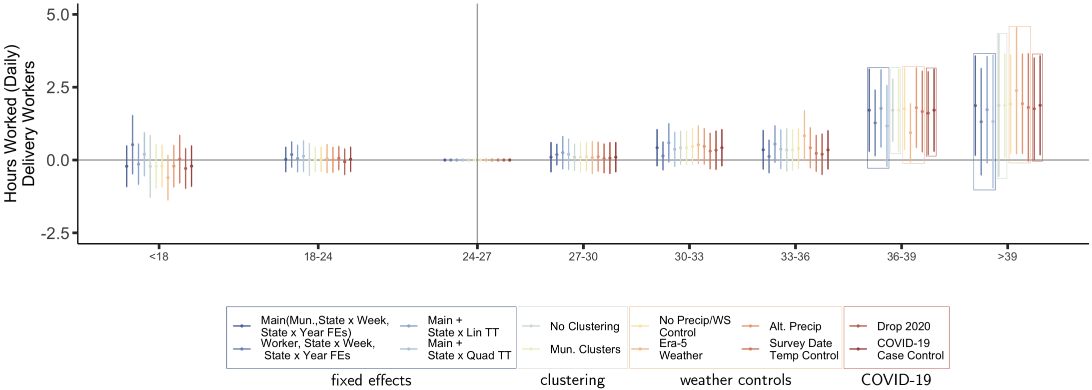
Outline

Appendix: Robustness of labor supply results

Results robust to various spatiotemporal, weather, and survey controls and clustering



Notes: Dep. variable is hours worked per day. Thin (thick) line shows 95% (90%) CI.

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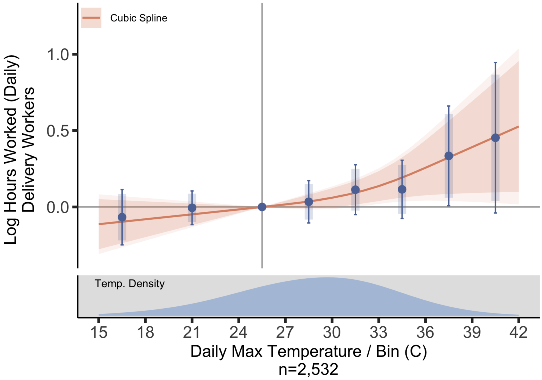
Appendix: Log labor supply results



Notes: Dep. variable is log hours worked per day. SEs clustered by municipality & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline).

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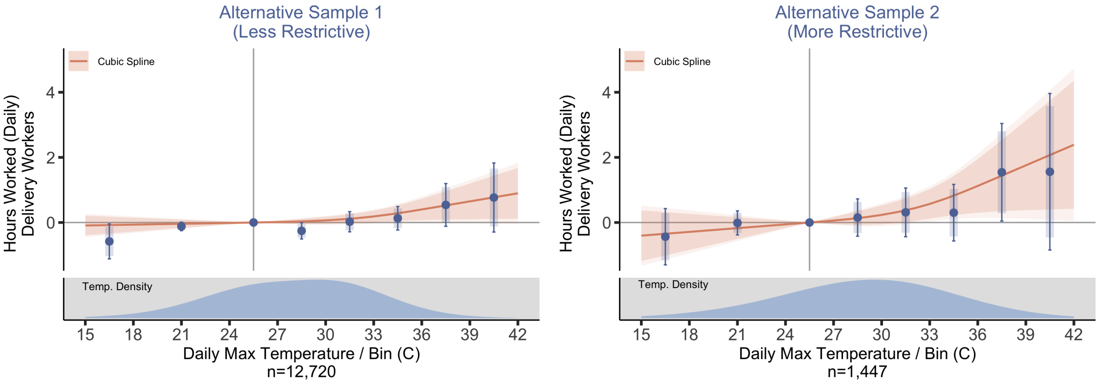
Appendix: Alternate delivery worker samples



Notes: Dep. variable is hours worked per day. SEs clustered by municipality & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline).

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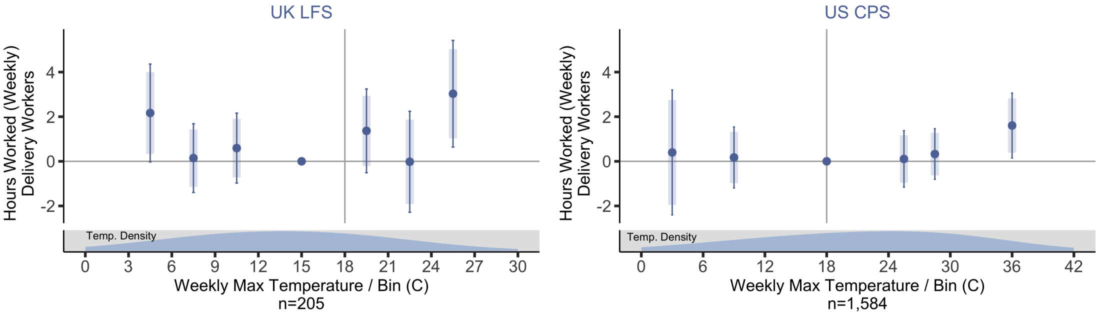
Appendix: UK and US results



Notes: Dependent variable is the hours worked per week. Thin (thick) line shows 95% (90%) CI (binned).

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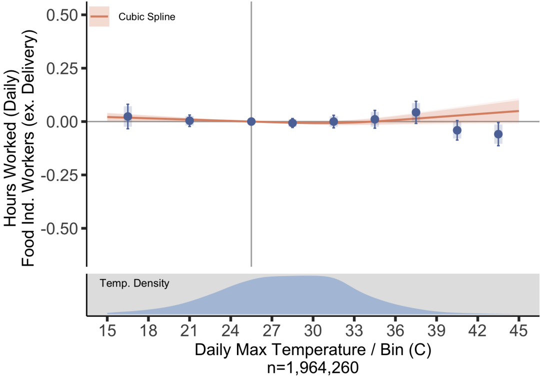
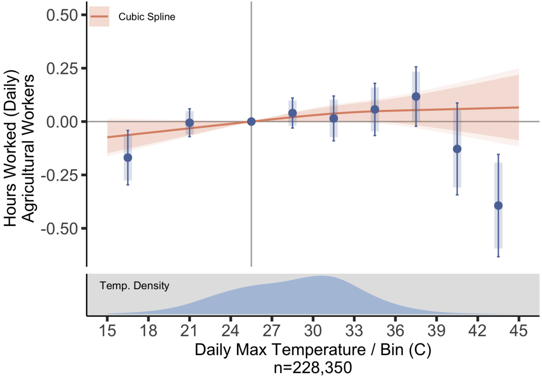
Appendix: Food industry and ag workers labor supply





Notes: Dep. variable is hours worked per day. SEs clustered by municipality & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline).

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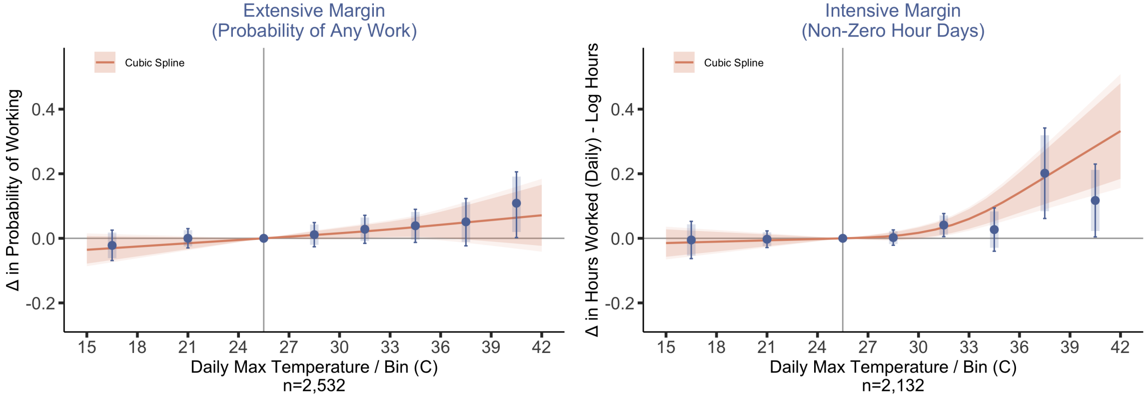
Appendix: Labor supply extensive vs. intensive margin



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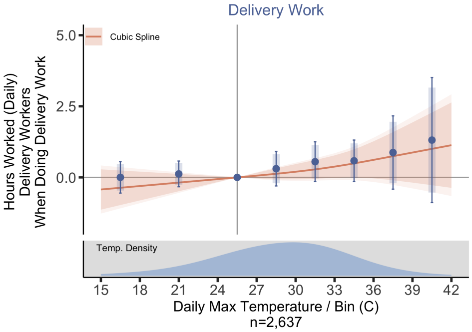
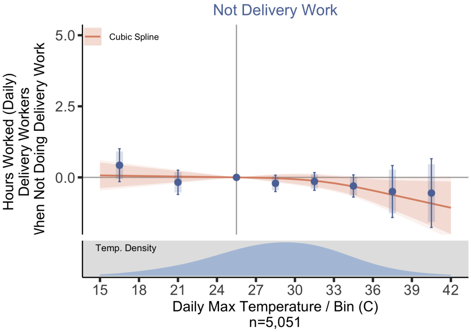
Appendix: ↑ in labor supply limited to platforms

- This response to heat is limited to platforms

- Suggestive evidence that delivery workers are *not* indifferent to working in the heat
  - Consistent with literature (e.g., Graff Zivin and Neidell 2014; Garg et al. 2020; Rode et al. 2022)

  → **disamenity of working in the heat**





▸ back ▸ Self-employed details

Appendix: Role of platforms

- Increase in hours limited to self-employed workers in platformized jobs/industries

self-employed workers
(with no boss, no employees, no health insurance)

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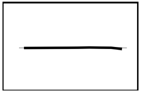
Appendix: Role of platforms

- Increase in hours limited to self-employed workers in platformized jobs/industries

self-employed workers
(with no boss, no employees, no health insurance)



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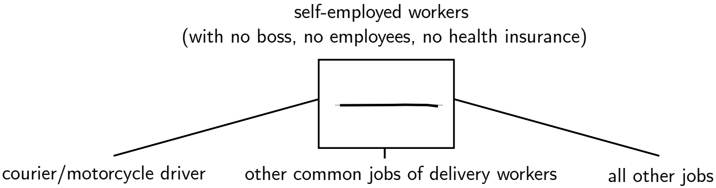
Appendix: Role of platforms

- Increase in hours limited to self-employed workers in platformized jobs/industries



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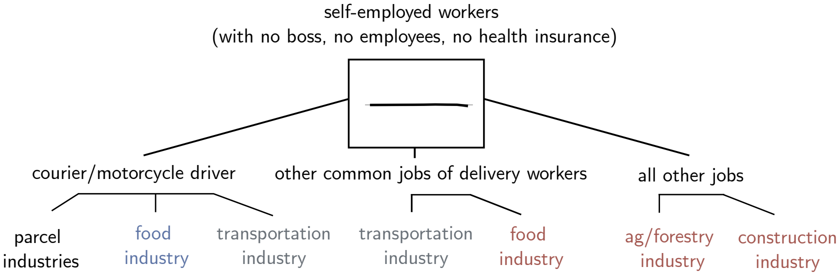
Appendix: Role of platforms

- Increase in hours limited to self-employed workers in platformized jobs/industries



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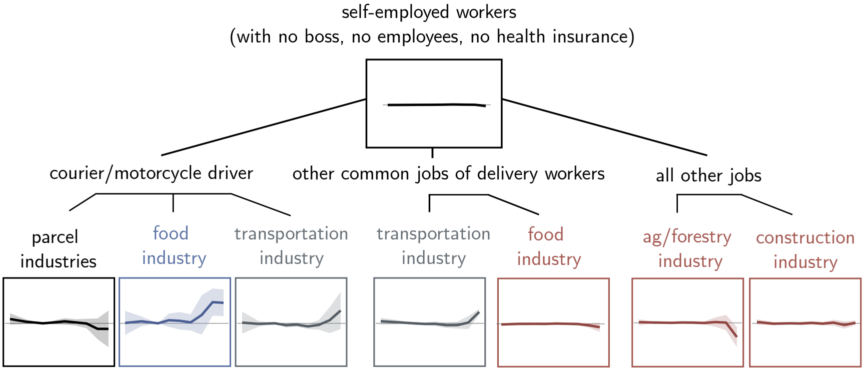
Appendix: Role of platforms

- Increase in hours limited to self-employed workers in platformized jobs/industries



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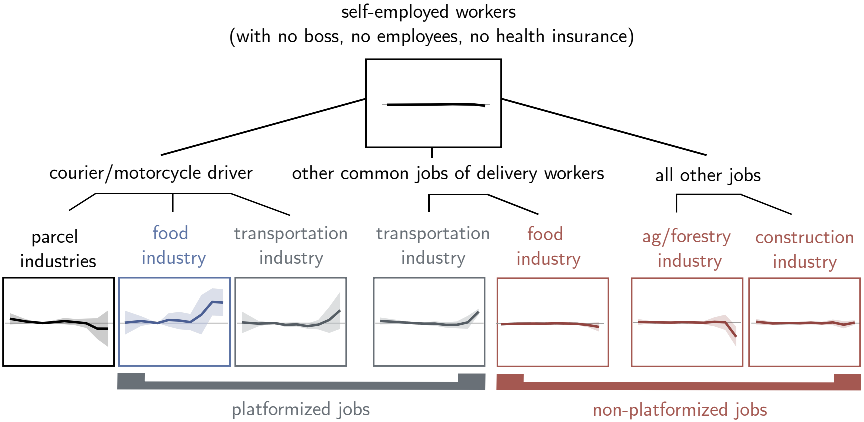
Appendix: Role of platforms

- Increase in hours limited to self-employed workers in platformized jobs/industries



Notes: Dependent variable is hours worked per day; shown on y-axis (standardized across all plots in figure).

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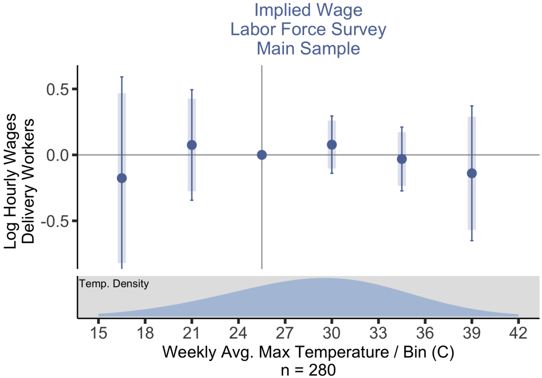
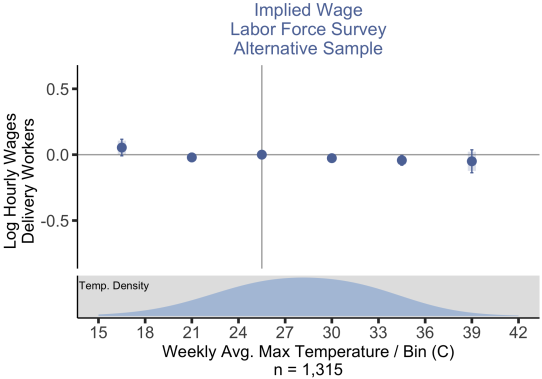
Appendix: Wage results





Notes: Dependent variable is implied log hourly wages. Panels shows implied wages ENOE.

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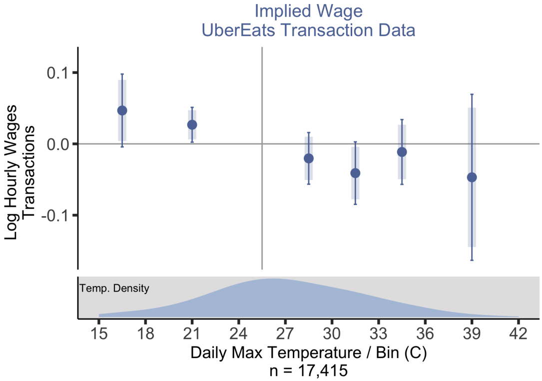
Appendix: Wage results



Notes: Dependent variable is implied log hourly wages. Figure shows implied wages from UberEats transaction data.

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Appendix: COVID-19 wages

Table: 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]
n	1,221	10,792

Notes: Table shows the relationship between local (municipality) COVID-19 deaths and implied hourly wages 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 (* $p<0.1$; ** $p<0.05$; *** $p<0.01$). main text.

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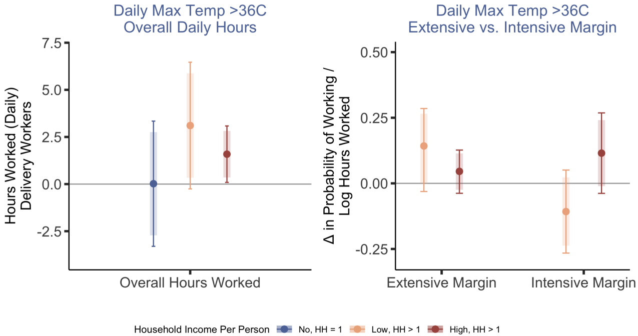
Appendix: Heterogeneity by worker characteristics

- Substantial variation in incomes: according to Tejada et al. (2021), 55% of delivery workers in Mexico City are below the poverty line when considering only their food delivery incomes
- Worker household income includes income of all household members, *excluding* worker



Notes: Dep. variable is binary indicator for any work (left panel, conditional logit model) and log hours worked per day (right panel). SEs clustered by municipality & month (binned) or bootstrapped (spline). Thin (thick) line shows 95% (90%) CI (binned); lighter (darker) shade shows 95% (90%) CI (spline).

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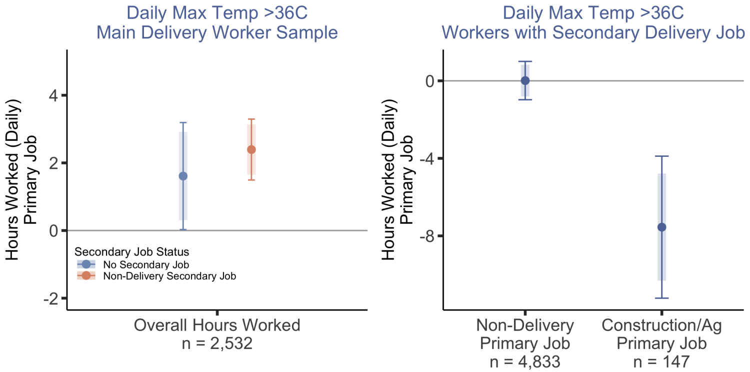
Appendix: Secondary jobs



Notes: Figure shows the relationship between daily maximum temperatures above 36°C and hours worked 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.

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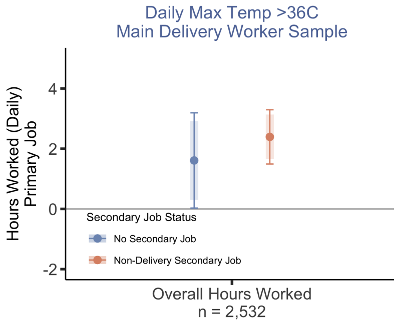
Appendix: Secondary jobs

- Only 7-9% of food delivery workers report having another job at the time of the survey



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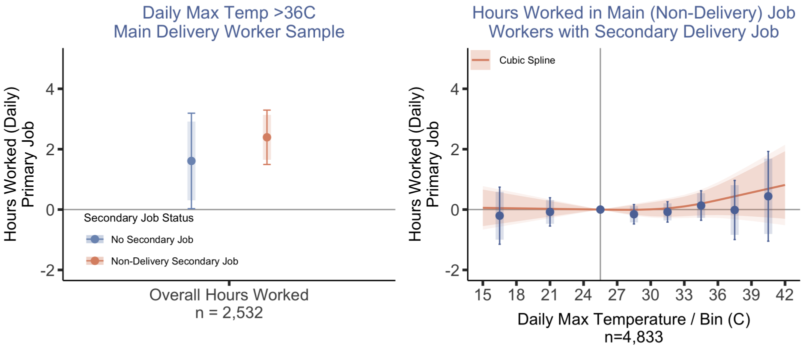
Appendix: Secondary jobs

- Only 7-9% of food delivery workers report having another job at the time of the survey
- Increase in hours **not** replacing lost hours from other, non-food-delivery jobs
    - Those with secondary delivery jobs do not work less in their main (non-delivery) job



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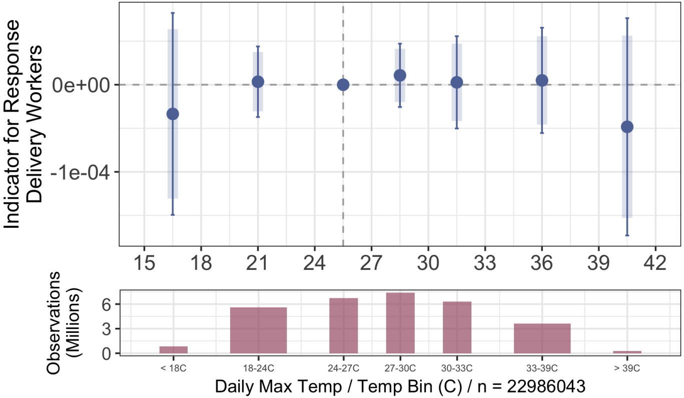
Appendix: Delivery worker survey answers

- No change in the probability of delivery workers being included in the sample



Notes: Dep. variable is dummy variable if there is an answer from a delivery worker. SEs clustered by municipality & month. Thin (thick) line shows 95% (90%) CI.

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Appendix: Role of platforms

- Compare two jobs that involve driving passengers
  - Transportation platform workers (e.g., Uber, Ola, Didi in Mexico)
  - Private chauffeurs (non-platform-based employment model)

Table: 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 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. Standard errors (clustered by municipality and month) are shown in parentheses; p-values shown in brackets (* $p<0.1$; ** $p<0.05$; *** $p<0.01$).

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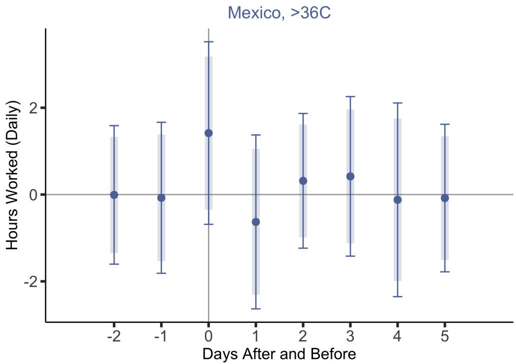
Appendix: Intertemporal substitution

- As temperatures highly correlated, results are less precise



Notes: Figure shows the relationship between daily maximum temperature above 36°C and hours worked 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).

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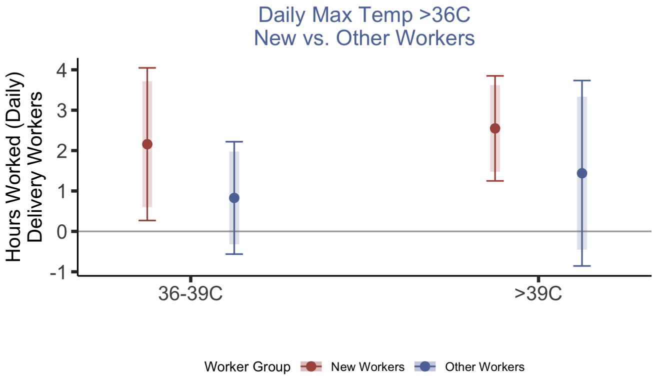
Appendix: Algorithmic management

- Increase in hours worked on hot days is concentrated among workers **new** to platforms
  - Marginal impact of each hour of work or order on their overall statistics is higher



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Appendix: Algorithmic management

Table: 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 for transportation (ride-share) platform workers. 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. 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).

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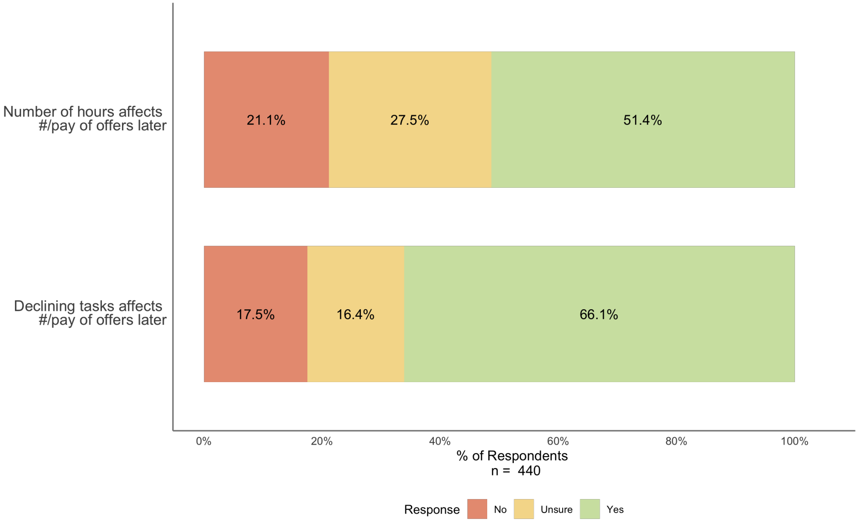
Appendix: Additional survey results



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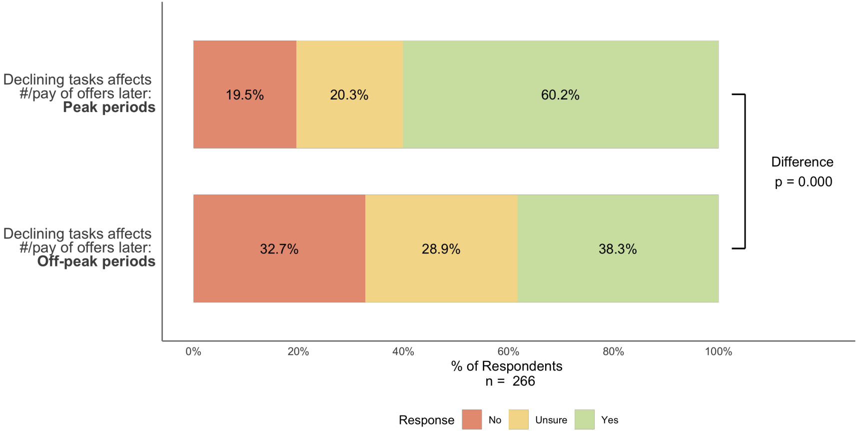
Appendix: Additional survey results

- US results only



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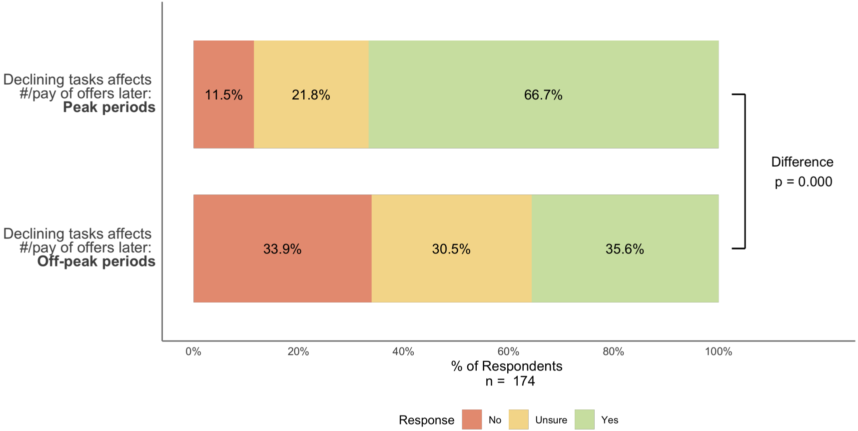
Appendix: Additional survey results

- Mexico results only



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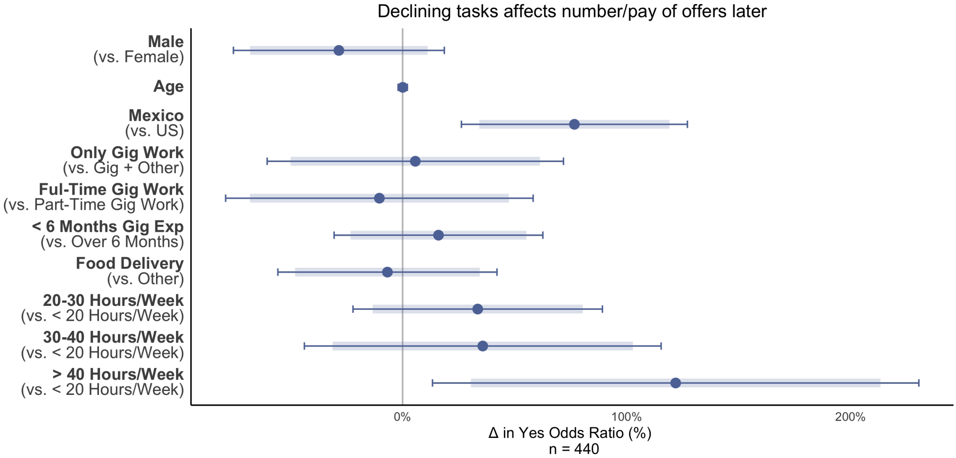
Appendix: Additional survey results



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Appendix: Additional survey results

How do you think the number of hours you spend working on the app or saying no to jobs today affects the number or pay of jobs the app offers you later?

- **Algorithm-Based Punishment/Reward** (89): Platforms actively track and respond to behavior
  "The algorithm punishes you"
- **Reliability and Trust Building** (52): Consistent acceptance builds platform trust
  "You have to show a strong willingness to work so that the perception of you is that you will always step up"
- **Profile/Rating Impact** (35): Actions affect cumulative standing and opportunities
  "The more jobs the more visibility through reviews"
- **Queue Position Theory** (43): Workers move up/down priority list based on choices
  "It puts you at the bottom of the list to get rides"
- **Simple Supply and Demand** (28): Market forces matter more than individual behavior
  "It's all offer and demand. What people go to, that's where the money follows"
- **Uncertainty/Skepticism** (21): Relationship between actions and consequences unclear
  "Not sure if there is a correlation"

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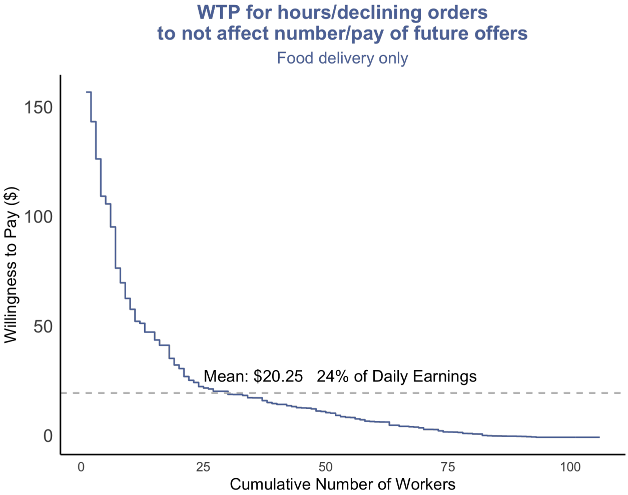
Appendix: Additional survey results



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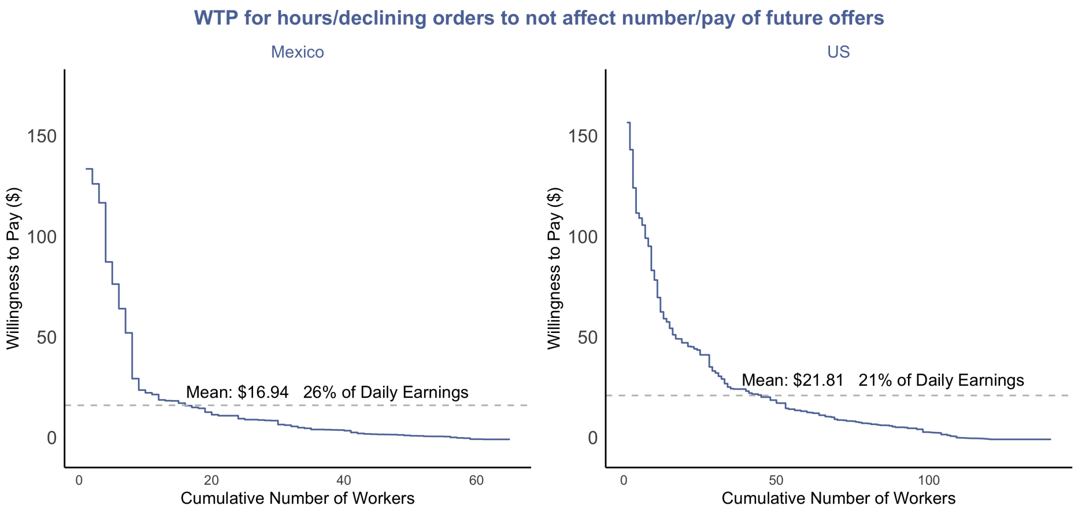
Appendix: Additional survey results



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Outline

Appendix: Derivation of change in wages

- A is constant, $Q_d = Q_d(T)$, and $H_s = H_s(\phi(Q_d), T, E[w_{t+1}])$ given evidence that all other factors do not vary with temperatures

$$\ln(w_t) = \ln(A) + \ln(Q_d) - \ln(H_s)$$

- Taking the total derivative with respect to $\ln(T)$

$$\frac{d\ln(w_t)}{d\ln(T)} = \frac{d\ln(A)}{d\ln(T)} + \frac{d\ln(Q_d)}{d\ln(T)} - \frac{d\ln(H_s)}{d\ln(T)}$$

$$= 0 + \frac{\partial\ln(Q_d)}{\partial\ln(T)} - \frac{d\ln(H_s)}{d\ln(T)}$$

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Appendix: Derivation of change in wages

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

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

- Substituting this back:

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

- Defining and plugging in elasticities and $m = \frac{d\phi}{d\ln(Q_d)} \cdot \frac{\partial\ln(Q_d)}{\partial\phi}$

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

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Appendix: Revisiting Simple Framework

- **Consumer demand** (number of orders):

$$Q_d = q_d\Big(\text{price, fees, } \mathbb{E}[\text{delivery times}]\text{, temperatures}\Big)$$

- **Labor supply of workers** (hours active on platform):

$$H_s = h_s\Big(\phi(\text{demand}),\ \gamma(\text{fees}),\ \mathbb{E}[\text{future opportunities}],\ \text{temperatures}\Big)$$

- Realized (ex-post) **hourly wages**:

$$w = \frac{\text{total revenues}}{\text{total hours worked}} = \frac{\text{amount per order} \times Q_d}{H_s}$$

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Appendix: Revisiting Simple Framework : Evidence so far

- **Consumer demand** (number of orders):

$$Q_d = q_d\Big(\underbrace{\text{price, fees, } \mathbb{E}[\text{delivery times}]}_{\text{do not change with T}}, \text{temperatures}\Big)$$

- **Labor supply of workers** (hours active on platform):

$$H_s = h_s\Big(\phi(\text{demand}), \underbrace{\gamma(\text{fees})}_{\text{do not change with T}}, \mathbb{E}[\text{future opportunities}], \text{ temperatures}\Big)$$

- Realized (ex-post) **hourly wages**:

$$w = \frac{\text{total revenues}}{\text{total hours worked}} = \frac{\overbrace{\text{amount per order}}^{\text{does not change with T}} \times Q_d}{H_s}$$

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Appendix: Revisiting Simple Framework: Deviation from optimal temperatures

- A deviation from optimal temperatures:

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

back Derivation

Appendix: Revisiting Simple Framework: Deviation from optimal temperatures

- A deviation from optimal temperatures:

$$\underbrace{\varepsilon_{w,T}}_{\sim 0} = \underbrace{\varepsilon_{D,T}\left(1 - m \cdot \varepsilon_{S,D}\right)}_{\text{demand effects: } +} \underbrace{- \, \varepsilon_{S,T}}_{\text{direct supply effect: } +} \underbrace{- \left(\varepsilon_{S,E} \cdot \varepsilon_{E,T}\right)}_{\text{indirect supply (future earnings) effect}}$$

  - Demand increases with temperatures: $\varepsilon_{D,T} > 0$
  - Workers dislike working in the heat: $\varepsilon_{S,T} < 0$
  - Wages do not change with temperatures: $\varepsilon_{w,T} \sim 0$

▸ back ▸ Derivation

Appendix: Revisiting Simple Framework: Deviation from optimal temperatures

- A deviation from optimal temperatures:

$$\underbrace{\varepsilon_{w,T}}_{\sim 0} = \underbrace{\varepsilon_{D,T}\left(1 - m \cdot \varepsilon_{S,D}\right)}_{\text{demand effects: } +} \underbrace{- \varepsilon_{S,T}}_{\text{direct supply effect: } +} \boxed{\underbrace{- \left(\varepsilon_{S,E} \cdot \varepsilon_{E,T}\right)}_{\text{indirect supply (future earnings) effect}}}$$

  - Demand increases with temperatures: $\varepsilon_{D,T} > 0$
  - Workers dislike working in the heat: $\varepsilon_{S,T} < 0$
  - Wages do not change with temperatures: $\varepsilon_{w,T} \sim 0$
  - Increase in labor supply through future earnings mechanism?

back Derivation

Appendix: Revisiting Simple Framework: Deviation from optimal temperatures

- A deviation from optimal temperatures:

$$\underbrace{\varepsilon_{w,T}}_{\sim 0} = \underbrace{\varepsilon_{D,T}\left(1 - m \cdot \varepsilon_{S,D}\right)}_{\text{demand effects: } +} \quad \underbrace{-\,\varepsilon_{S,T}}_{\text{direct supply effect: } +} \quad \boxed{\underbrace{-\left(\varepsilon_{S,E} \cdot \varepsilon_{E,T}\right)}_{\text{indirect supply (future earnings) effect}}}$$

  - Demand increases with temperatures: $\varepsilon_{D,T} > 0$
  - Workers dislike working in the heat: $\varepsilon_{S,T} < 0$
  - Wages do not change with temperatures: $\varepsilon_{w,T} \sim 0$

  - Increase in labor supply through future earnings mechanism?
    - Platform workers are independent contractors with no set schedules or earnings
    - No evidence of intertemporal substitution
    - Worker survey to further investigate mechanisms

back | Derivation | Intertemporal substitution | Market power