How Do Gig Workers Respond to Unanticipated Income Shocks?

Evidence from Food Delivery Riders in China

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Gig work is now a defining feature of the Chinese labor market

200M

flexible workers in China

84M

in new employment forms

13M

food delivery riders

Why this matters for labor economics:

- Gig work delivers high-frequency wage variation that traditional labor markets rarely offer
- Algorithmic, task-based pay reshapes how workers form expectations and adjust effort
- Policy relevance: platform incentive design, occupational safety, and labor regulation
- Few empirical studies (concentrated on taxi / ride-hailing in developed economies)

Neoclassical vs. Reference-Dependent Preferences

Neoclassical

Farber (2005, 2008, 2015)

- **Intertemporal utility maximization**
- Substitution effect dominates the income effect
- Prediction: ***positive*** labor-supply elasticity to wages
- cumulative hours, not income, drive the stopping decision

Reference-Dependent

Camerer et al. (1997); Crawford & Meng (2011); Thakral & Tô (2021); Duong et al. (2023).

- **Decisions hinge on a reference point (target income)**
- Loss aversion below target + diminishing marginal utility above
- Reference points may update dynamically
- Prediction: potentially ***negative*** wage elasticity

Anticipated vs. unanticipated shocks are the key test

Kőszegi & Rabin (2006): the two theories diverge sharply only for surprise shocks

Shock type for a wage fluctuation	Neoclassical predicts	Reference-dependent
Anticipated (routine fluctuations)	Workers re-optimize hours given expected wage	Reference point already absorbs the variation → similar response
Unanticipated (surprises)	No response: time disutility & expected income in the future unchanged	Negative shock couldn't have been built into their target → Loss aversion → catch-up effort; Positive shock → quit early

→ the empirical key is to find a setting where you can credibly carve out the unanticipated part of income variation.

Transaction-level administrative data — *Ele me* (*Tao Shan*)

Source & sample

- China's second-largest food delivery platform (4.01M active riders, 33% market share)
- Survey supplement (12,876 valid responses) provides demographics & employment characteristics
- Stratified random sample: 917 riders (322 Fixed, 140 Preferred, 449 Gig) — male:female ≈ 5:1
- Two peak weeks (Jul 15–28, 2024) + two off-peak weeks (Oct 21–Nov 3, 2024)
- 472,045 order records linked to riders, customers, merchants

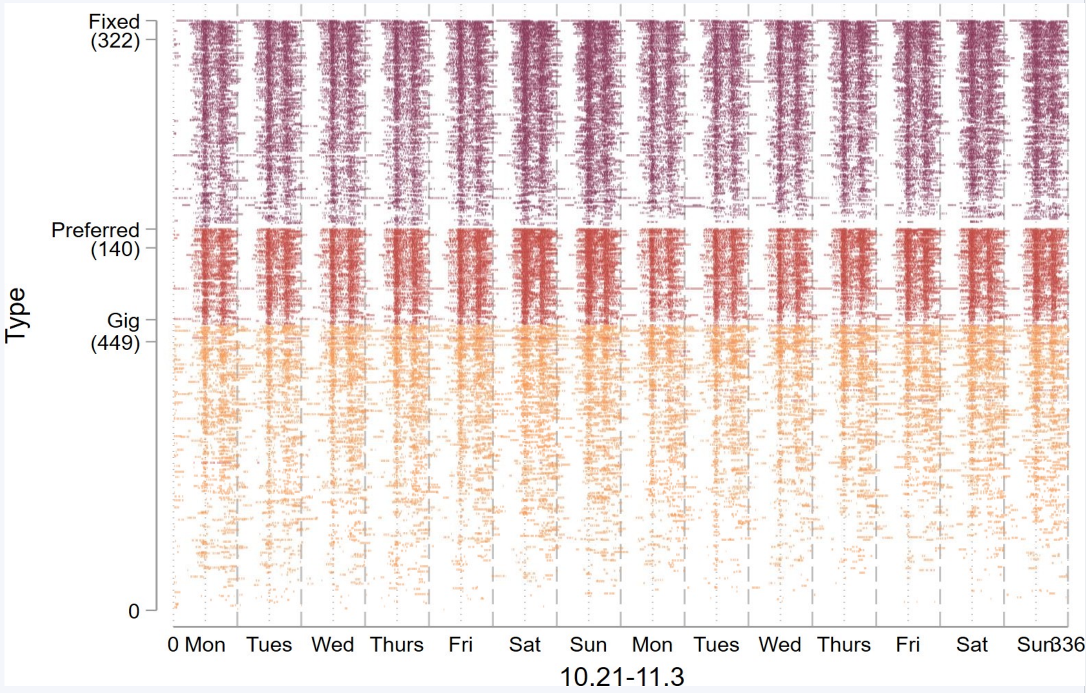
16,112 shifts in panel

29.3 avg. orders / shift

8.5 avg. shift hours

Unit of analysis: the "shift"

- A shift = uninterrupted order sequence separated by gaps > 5-hour



Three rider types — three institutional environments

Fixed (taxi drivers)

30% of riders
50% of orders

- Team-managed; fixed schedules
- Most stable labor supply

Preferred (hybrid)

weekly quotas
performance-based

- Flexible hours, but must meet performance thresholds
- Hybrid: flexibility + commitment
- Higher earnings potential

Ordinary Gig (“Uber”)

highest flexibility
self-scheduling

- No quotas, choose own hours
- May have a second job / caregiving

What counts as an unanticipated income shock?

- ***Unanticipated (8.5%)***
  - ***Badshock:* customer or merchant** issues a low rating, complaint, or rider-caused cancellation
  - Penalty hits AFTER delivery is completed — time/effort already spent is unchanged
  - Income loss only: ¥150–200 (fixed); ¥3–10 (preferred / gig)
  - No persistent algorithmic punishment — no significant change in order value the following hour
- ***Anticipated (91.5%)***
  - self-reported abnormal event by riders (delayed food preparation, wrong address, failure to contact); Traffic, Weather…

Discrete stopping-choice model

$$Y_{it} = \beta_{unp} \cdot badshock_{it} + \beta_p \cdot report_{it}(T-1) + f(h_{it}) + g(y_{it}) + X_{it}\,\gamma + \alpha_i + \varepsilon_{it}$$

Linear probability model — closely follows Duong et al. (2023); i = rider, t = order, T = hour of t

Outcomes — two margins

- **$Quit_{it}$ · extensive margin**
- = 1 if rider ends shift after order t
- **$Rest_{it}(T+1)$ · intensive margin**
- Minutes of rest in the hour after t

Controls absorbing anticipated variation

- f(h) , g(y): 10 dummies each for cumulative hours and cumulative orders
- Hour-of-day (24), day-of-week (7), week-of-year (4)
- Weather severity dummies (5 levels)
- Rider fixed effects α_i — absorb time-invariant preferences & income targets

Baseline: surprise shocks trigger catch-up effort

Type	Full Sample		Fixed		Preferred		Gig	
Variables	$Quit_{it}$ (1)	$Rest_{it(T+1)}$ (2)	$Quit_{it}$ (3)	$Rest_{it(T+1)}$ (4)	$Quit_{it}$ (5)	$Rest_{it(T+1)}$ (6)	$Quit_{it}$ (7)	$Rest_{it(T+1)}$ (8)
Badshock	-0.0112***	-0.0256***	0.0029	-0.0122	-0.0047*	-0.0236***	-0.0204***	-0.0300***
	(0.0021)	(0.0029)	(0.0074)	(0.0084)	(0.0024)	(0.0040)	(0.0034)	(0.0045)
Controls	X	X	X	X	X	X	X	X
Rider FE	X	X	X	X	X	X	X	X
Observations	472,045	455,933	229,986	223,397	144,221	141,171	97,838	91,365
R-squared	0.0777	0.1784	0.0787	0.1708	0.0823	0.1898	0.0645	0.1848

Full sample

–1.12 ppt

Quit probability

–1.50 min

Rest in next hour

Ordinary Gig

–2.04 ppt

Quit probability

–1.80 min

Rest in next hour

Preferred

–0.47 ppt

Quit probability

–1.40 min

Rest in next hour

Equivalent-hours benchmark

Following Duong et al. (2023), benchmark Δquit / Δhour using a flexible (cubic) specification:

≈ 1.02

extra hours of work

for ordinary gig riders, induced by a single negative shock

(Δbadshock / Δextra hour = −2.06 pp / +2.02 pp)

- Duong et al. (2023), Singapore ride-hailing — 1.21 equiv. hours after no-shows/cancellations
- Our China food delivery estimate — 1.02 equiv. hours after low ratings / complaints / cancellations
- → small platform penalties can shift same-day labor supply by a meaningful amount

Reference points update dynamically

Type	Full Sample		Fixed		Preferred		Gig	
Variables	$Quit_{it}$ (1)	$Rest_{it(T+1)}$ (2)	$Quit_{it}$ (3)	$Rest_{it(T+1)}$ (4)	$Quit_{it}$ (5)	$Rest_{it(T+1)}$ (6)	$Quit_{it}$ (7)	$Rest_{it(T+1)}$ (8)
Last 0-20 mins	-0.0041***	-0.0472***	0.0012	-0.0459***	0.0003	-0.0395***	-0.0107***	-0.0540***
	(0.0016)	(0.0026)	(0.0049)	(0.0068)	(0.0017)	(0.0033)	(0.0028)	(0.0044)
Last 20-40 mins	-0.0003	-0.0396***	-0.0112**	-0.0338***	-0.0029	-0.0331***	0.0069	-0.0510***
	(0.0022)	(0.0026)	(0.0051)	(0.0070)	(0.0024)	(0.0031)	(0.0049)	(0.0051)
Last 40-60 mins	-0.0041**	-0.0254***	-0.0104**	-0.0093	-0.0063***	-0.0240***	0.0011	-0.0346***
	(0.0021)	(0.0027)	(0.0042)	(0.0079)	(0.0023)	(0.0033)	(0.0045)	(0.0048)
Last 60-80 mins	-0.0002	-0.0094***	-0.0053	-0.0130	0.0019	-0.0137***	-0.0026	-0.0057
	(0.0023)	(0.0029)	(0.0049)	(0.0092)	(0.0029)	(0.0032)	(0.0044)	(0.0057)
Last 80-100 mins	-0.0003	0.0004	-0.0150***	0.0073	0.0009	-0.0044	0.0031	0.0000
	(0.0023)	(0.0034)	(0.0049)	(0.0086)	(0.0027)	(0.0045)	(0.0048)	(0.0066)
Last 100-120 mins	0.0027	0.0026	0.0058	-0.0084	0.0000	-0.0071	0.0063	0.0155*
	(0.0028)	(0.0040)	(0.0072)	(0.0102)	(0.0029)	(0.0046)	(0.0058)	(0.0084)
Controls	X	X	X	X	X	X	X	X
Rider FE	X	X	X	X	X	X	X	X
Observations	472,045	455,933	229,986	223,397	144,221	141,171	97,838	91,365
R-squared	0.0715	0.1558	0.0711	0.1531	0.0748	0.1798	0.0610	0.1317

- **Extensive Margin:**
- Only shocks in the last 20 mins matter for gig riders

- **Intensive Margin:**
- Coefficients decay gradually
- Most types are insignificant beyond ≈ 60 min

- Consistent with dynamically adapting reference points

Heterogeneity analysis: based on cumulative hours

Type	Full Sample		Fixed		Preferred		Gig	
Variables	$Quit_{it}$ (1)	$Rest_{it(T+1)}$ (2)	$Quit_{it}$ (3)	$Rest_{it(T+1)}$ (4)	$Quit_{it}$ (5)	$Rest_{it(T+1)}$ (6)	$Quit_{it}$ (7)	$Rest_{it(T+1)}$ (8)
Badshock	-0.0012	-0.0233***	0.0248**	-0.0105	0.0083**	-0.0073	-0.0104**	-0.0217***
	(0.0032)	(0.0042)	(0.0114)	(0.0132)	(0.0035)	(0.0050)	(0.0047)	(0.0061)
H_{it}	0.0089***	0.0319***	0.0083***	0.0309***	0.0076***	0.0237***	0.0092***	0.0446***
	(0.0005)	(0.0008)	(0.0010)	(0.0011)	(0.0012)	(0.0015)	(0.0008)	(0.0015)
Badshock	-0.0019***	-0.0006	-0.0036*	-0.0002	-0.0021***	-0.0028***	-0.0024**	-0.0021*
$\times H_{it}$	(0.0006)	(0.0007)	(0.0020)	(0.0018)	(0.0008)	(0.0008)	(0.0011)	(0.0013)
Controls	X	X	X	X	X	X	X	X
Rider FE	X	X	X	X	X	X	X	X
Observations	472,045	455,933	229,986	223,397	144,221	141,171	97,838	91,365
R-squared	0.0758	0.1823	0.0745	0.1745	0.0775	0.1891	0.0651	0.1965

- **Reference points are dynamic AND target-seeking.** The interaction *Badshock × Hours* is significantly negative — riders later in the shift, closer to their daily target, fight harder to recover.

Shift length also matters

- **Short shifts (2–5h)**
- Bad shock → quit prob.↓ 1.5–2 pp (25–35% rel.)
- **Long shifts (11–13h)**
- Effect ≈ 0 — fatigue dominates

Who responds most? Full-time, less experienced

Gig	Scheme		Experience		Gender	
Variables	$Quit_{it}$ (1)	$Rest_{it(T+1)}$ (2)	$Quit_{it}$ (3)	$Rest_{it(T+1)}$ (4)	$Quit_{it}$ (5)	$Rest_{it(T+1)}$ (6)
Badshock (dummy)	-0.0156***	-0.0251***	-0.0299***	-0.0406***	-0.0187***	-0.0313***
	(0.0038)	(0.0052)	(0.0050)	(0.0076)	(0.0036)	(0.0049)
Badshock×Fulltime	-0.0166**	-0.0170*				
	(0.0072)	(0.0100)				
Badshock×Experienced			0.0152**	0.0169*		
			(0.0066)	(0.0095)		
Badshock×Female					-0.0115	0.0086
					(0.0094)	(0.0125)
Controls	X	X	X	X	X	X
Rider Fixed Effect	X	X	X	X	X	X
Observations	97,838	91,365	97,838	91,365	97,838	91,365
R-squared	0.0645	0.1848	0.0645	0.1848	0.0645	0.1848

Ordinary gig riders: scheme, experience, gender interactions (Table 8b)

Full-time gig riders

Stronger response: Badshock × Fulltime = −0.017 (extensive) / −0.017 (intensive). Outside options matter.

Experienced riders

Significantly muted response on both margins — learning toward neoclassical optimization.

Gender

No robust heterogeneity among gig riders. Among fixed riders, women quit more on extensive but compensate via intensive — likely care constraints.

Anticipated variation: workers behave neoclassically

Type	Full Sample		Fixed		Preferred		Gig	
Variables	$Quit_{it}$	$Rest_{it(T+1)}$	$Quit_{it}$	$Rest_{it(T+1)}$	$Quit_{it}$	$Rest_{it(T+1)}$	$Quit_{it}$	$Rest_{it(T+1)}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Report_{it(T-1)}$	0.0034***	-0.0374***	0.0008	-0.0442***	0.0018*	-0.0300***	0.0087***	-0.0366***
	(0.0009)	(0.0017)	(0.0013)	(0.0030)	(0.0011)	(0.0023)	(0.0021)	(0.0033)
Weather (Base: Normal Conditions)								
Level 1 Bad Weather	-0.0001	-0.0241***	0.0008	-0.0274***	0.0010	-0.0232***	-0.0065**	-0.0177***
	(0.0008)	(0.0021)	(0.0011)	(0.0029)	(0.0011)	(0.0039)	(0.0025)	(0.0046)
Level 2 Bad Weather	-0.0053***	-0.0592***	-0.0038	-0.0636***	-0.0014	-0.0576***	-0.0204***	-0.0527***
	(0.0017)	(0.0040)	(0.0024)	(0.0058)	(0.0020)	(0.0066)	(0.0064)	(0.0095)
Level 3 Bad Weather	-0.0069***	-0.0584***	-0.0058*	-0.0635***	-0.0024	-0.0494***	-0.0226***	-0.0604***
	(0.0023)	(0.0049)	(0.0032)	(0.0081)	(0.0024)	(0.0079)	(0.0082)	(0.0090)
Level 4 Bad Weather	-0.0012	-0.0854***	0.0026	-0.0981***	-0.0040	-0.0607***	-0.0105	-0.0868***
	(0.0048)	(0.0087)	(0.0061)	(0.0137)	(0.0074)	(0.0113)	(0.0122)	(0.0186)
Day of Week (Base: Monday)								
Tuesday	-0.0001	0.0019	-0.0004	-0.0022	0.0015	0.0045	-0.0024	0.0050
	(0.0007)	(0.0019)	(0.0008)	(0.0028)	(0.0010)	(0.0030)	(0.0025)	(0.0044)
Wednesday	-0.0005	0.0019	-0.0017*	-0.0001	0.0008	0.0039	-0.0005	0.0016
	(0.0007)	(0.0019)	(0.0008)	(0.0028)	(0.0010)	(0.0030)	(0.0028)	(0.0044)
Thursday	-0.0018**	-0.0026	-0.0021**	-0.0055*	0.0001	-0.0005	-0.0044	0.0000
	(0.0008)	(0.0020)	(0.0010)	(0.0030)	(0.0010)	(0.0031)	(0.0027)	(0.0042)
Friday	-0.0054***	-0.0125***	-0.0063***	-0.0122***	-0.0026**	-0.0163***	-0.0084***	-0.0098**
	(0.0008)	(0.0019)	(0.0010)	(0.0029)	(0.0010)	(0.0032)	(0.0028)	(0.0044)
Saturday	-0.0068***	-0.0226***	-0.0062***	-0.0224***	-0.0041***	-0.0305***	-0.0157***	-0.0151***
	(0.0008)	(0.0021)	(0.0010)	(0.0031)	(0.0011)	(0.0033)	(0.0028)	(0.0042)
Sunday	-0.0030***	-0.0276***	-0.0032***	-0.0293***	-0.0006	-0.0340***	-0.0089***	-0.0170***
	(0.0008)	(0.0022)	(0.0010)	(0.0032)	(0.0010)	(0.0036)	(0.0029)	(0.0045)
Controls	X	X	X	X	X	X	X	X
Rider Fixed Effect	X	X	X	X	X	X	X	X
Observations	472,045	455,933	229,986	223,397	144,221	141,171	97,838	91,365
R-squared	0.0777	0.1784	0.0787	0.1708	0.0823	0.1898	0.0645	0.1848

- **Expected earnings are significantly positively correlated with labor supply**
- **Consistent with the neoclassical model**

Takeaways and policy implications

What we learn

1 **Dichotomy in worker response**
Anticipated variation → neoclassical; surprise shocks → reference-dependent loss aversion.

2 **Dynamic reference points**
Short memory (~60 min) + target proximity

3 **Institutions & experience matter**
Flexible contracts and inexperience amplify loss aversion; experience pushes workers toward neo-classical behavior.

Policy & platform design

- **Worker-welfare risk:**
- Catch-up effort means skipped breaks and longer shifts → fatigue, road-safety risk
- **Redesign penalty structures:**
- Roll daily fines into longer windows
- **Smart dispatch:**
- After a penalty, route easier orders with generous time windows
- **Regulation:**
- Cap maximum daily financial penalties; integrate fatigue-monitoring protocols

Thank you!

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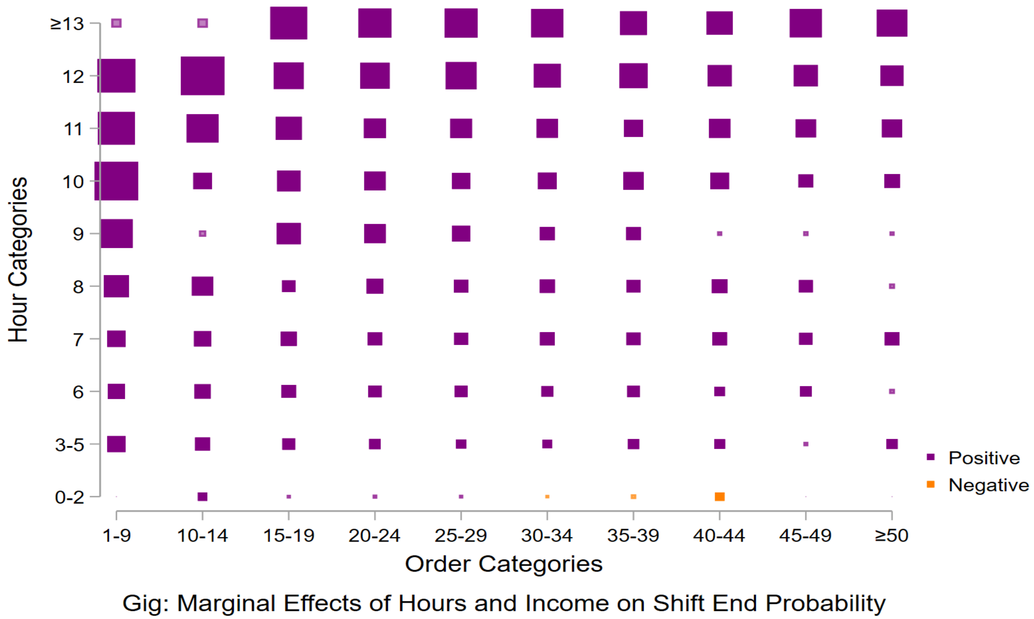
Anticipated variation: workers behave neoclassically

Cumulative hours drive stopping; cumulative orders do not — ***consistent with Farber (2015)***



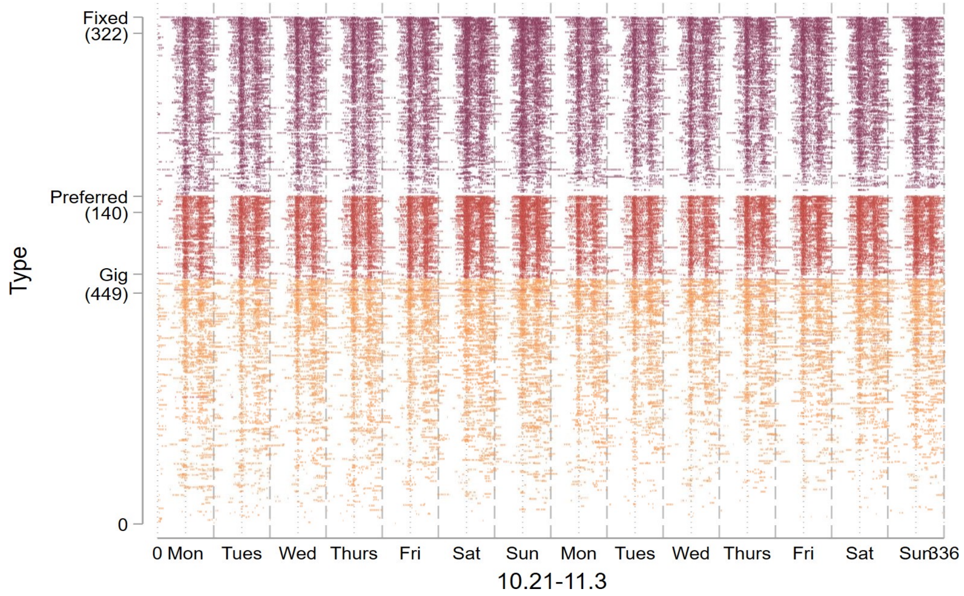
Gig riders

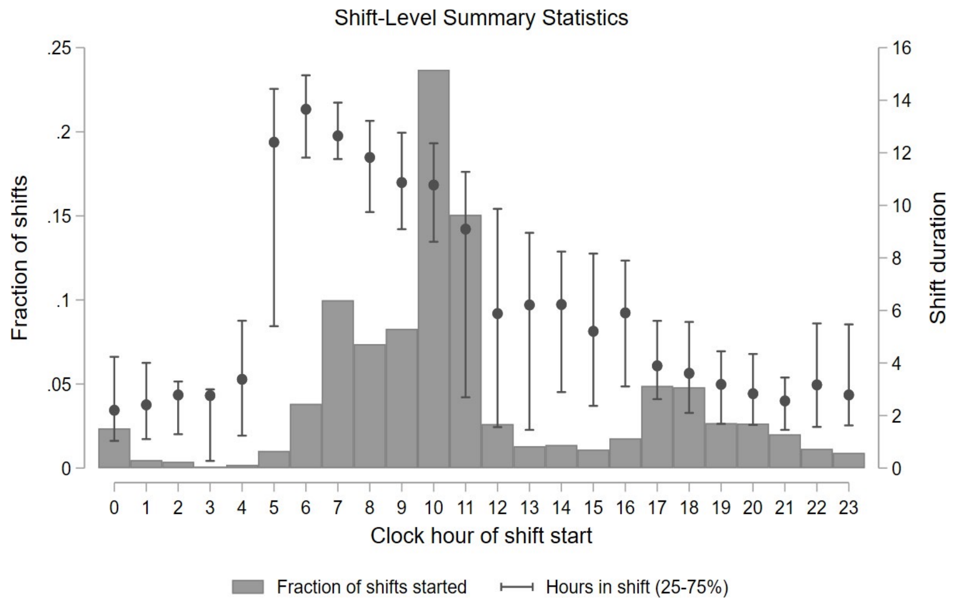
Fixed riders

The dichotomy is real: for predictable factors (hours, weather, day-of-week), labor supply aligns with the neoclassical model; **for surprises, riders behave reference-dependently.**

Descriptive Statistics

Statistic	Observations	Mean	SD
Panel A: Rider-Level Summary Statistics			
Female	911	0.166	0.372
Local	911	0.491	0.500
Urban	911	0.318	0.466
Age	911	35.138	8.745
Years of Education	911	7.921	3.841
Fulltime	911	0.434	0.496
Number of Months Worked	911	19.418	13.787
Panel B: Order-Level Summary Statistics			
Statistic	Observations	Mean	SD
Order Duration (min)	472045	26.080	12.687
Distance (m)	471861	2.141	1.390
Abnormal Report	472045	0.041	0.199
Bad shocks	472045	0.022	0.146
Low ratings	472045	0.001	0.028
Complaints	472045	0.021	0.142
Rider-Caused Cancelations	472045	0.001	0.025
Panel C: Shift-Level Summary Statistics			
Statistic	Observations	Mean	SD
Number of Orders	16112	29.298	20.505
Number of Total Hours	16112	8.450	4.711
Number of Working Hours	16112	5.289	3.092
Number of Bad shocks	16112	1.205	1.792
Number of Abnormal Events	16112	0.638	1.493





Addressing residual endogeneity — IV & two exogeneity tests

Instrumental Variables

Concern: time-varying rider shocks (illness, family events) may jointly move targets & shock risk

- **CustRisk_{it} — total low ratings / complaints issued by this customer to any rider in the past year**
- **ShopRisk_{it} — same metric at the merchant level**
- Exogenous, order-specific risk that's orthogonal to unobserved rider shocks
- First-stage F passes for Full / Fixed / Gig samples (Preferred under-powered)

1. Cross-rider balance test

- Regress badshock on demographics (gender, age, hukou, education, tenure)
- All coefficients indistinguishable from zero; joint F = 1.63, p = 0.07
- Only contract-type loads → motivates separate subsamples

2. Within-rider placebo

- Hold total shocks within rider × shift constant; randomly reassign their timing
- Re-estimate baseline with “pseudo shocks” — effect vanishes (Appendix A2)
- Confirms timing of shocks is unpredictable conditional on FE