Empowering Inclusive Work

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November 2025

Motivation

- Workers with disabilities struggle in labor markets around the world
- Little known on "what works" in improving labor outcomes for disabled workers
  - Americans with Disabilities Act: reasonable accommodations & no discrimination
    - *decreases* employment of disabled workers (Acemoglu and Angrist (2001), DeLeire (2000))
  - Quotas: certain share of jobs at large firms filled by disabled workers
    - disabled workers hired for lower-paid jobs (Szerman, 2023; Lalive et al., 2013)
  - These may not address firm "underlying concerns". Can AI?
- Research questions:
  - in same job, how do disabled & non-disabled workers compare in productivity, compensation, & profitability?
  - can AI-based tools improve workplace outcomes for disabled workers?

Our Study and Main Results

- Compare outcomes of new disabled & non-disabled workers on anonymous Platform (2021-2023), one of two main food delivery companies in China
  - like DoorDash, but motor bikes. 10M workers on two platforms
  - everyone hired; no differential hiring thresholds for disabled & non-disabled workers
  - granular, high-frequency data on worker behavior, many dimensions

- Focus on hearing impaired workers, one of most common disabilities
  - highly specific disability, but concrete, easy to define
  - gig economy is growing sector for hearing-impaired workers

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- Focus on hearing impaired workers, one of most common disabilities
  - highly specific disability, but concrete, easy to define
  - gig economy is growing sector for hearing-impaired workers
- Pre-AI, disabled workers slower, esp. for tasks w/ communication. worse ratings
  - but work more, much less likely to quit
- AI tool: Intelligent Outbound Calling, suddenly introduced in April 2022
  - for disabled workers only: realistic text-to-voice, suggested prompts
  - eliminates over half of gaps in productivity & earnings

Related Literature and Contribution

- **Disability** (e.g., Ameri et al., 2018; Baldwin and Johnson, 2006; L'Horty et al., 2022; Bellemare et al., 2023; Acemoglu and Angrist, 2001; DeLeire, 2000; Szerman, 2022; Lalive et al., 2013)
  - first descriptive evidence on productivity differences by disability status in same job
  - largest impact of any intervention we know of on closing disability wage gap & disability productivity gap

- **AI and Productivity** (Brynjolfsson et al., 2025; Cui et al., 2025; Hoffmann et al., 2024; Noy and Zhang, 2023)
  - first analysis of how AI affects productivity gaps.
  - HTEs by productivity are not same as

- **Hiring of Disadvantaged Workers** (Benson et al., 2024; Cullen et al., 2023; Minor et al., 2018)
  - first descriptive evidence on *profit* diffs. by disability status in same job
  - show disabled workers can have unappreciated value to firms, being less likely to quit

Outline

Setting and Data

Modeling Disabled vs. Non-disabled Differences

Pre-AI Differences in Workplace Outcomes

AI Tool: Average Impacts

Heterogeneous Treatment Effects

Conclusion

Food-Delivery Platform

- All over China, especially in big cities. 100Ms of deliveries per month
- $\text{MatchingScore}_{it} = f(\text{tenure, service, acceptance})$
  - Biggest effect: how many orders a driver can carry at once
  - $\text{OrderAllocation}_{it} = g(\text{location, demand, MatchingScore}_{it})$

Work Configuration	**Gig**	**Team**
Share of worker-weeks	43%	57%
Work structure	Work by self	In team with manager
How assigned orders?	Choose from pool	Assigned
Role of OrderAllocation	What's seen	Assignment
Work for other platform at same time?	Penalized by MatchingScore	No

Fieldwork



Workers with a Disability

- Gig economy is essential source of work for disabled workers in China
  - call centers also hire disabled
- Platform's disabled workers predominantly hearing-impaired workers (*wú shēng*)
- Pre-AI, drivers informed that customers were hearing-impaired
  - many customers don't see notifications
  - expectation in China to get call from driver
- Like many platforms (Uber, Lyft, UberEats), Platform integrates features that make job feasible for hearing-impaired

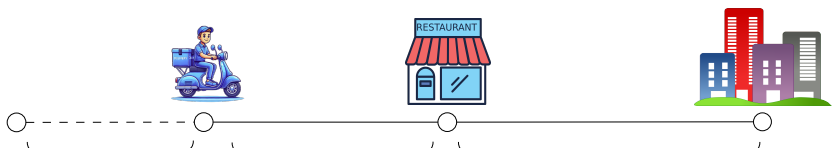
▸ Registration

Proprietary Administrative Data from Platform

- Worker-week panel from 2021-2023. 43,650 workers
  - all 4296 newly-hired hearing-impaired workers
  - randomly selected ≈40k newly-hired non-disabled workers
  - excludes workers with any non-hearing disability
- Attrition is not working for 8 weeks
- Imputed wages accounting for differences between gig & team
  - team drivers: increasing step function in orders
  - accounts for bad ratings
- Profits account for orders, bad ratings, & attrition

Outcome Variables

Total Output (zh)	**Efficiency** (z)	**Labor Supply** (h)
Total Orders Delivered	Order → Worker	Total Hours Online
Total Orders in Peak Hours	Worker → Store	Number of Working Days
Number of Restaurants Served	Store → Delivery	Working Days During Bad Weather
Number of Customers Served	Bad Ratings from Customers	Attrition
	OverTime Rate	



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Modeling Work Time Spent on the Platform

$$U = w \cdot zh + \frac{1}{\theta} r \left(1 - h\right)^{\theta}$$

- $z =$ productivity
- $h =$ share of total work time on Platform
  - w piece rate, zh total output, $A \cdot zh$ profits
- $r =$ value of non-Platform outside option

$$h = 1 - r^{\beta} \left(wz\right)^{-\beta} \rightarrow \frac{\partial h}{\partial r} < 0, \frac{\partial h}{\partial z} > 0$$

Consistent with initial fieldwork, we assume that:

$$z_D < z_N$$
$$r_D < r_N$$

Implications

Implication 1 *Pre-AI, disabled workers have lower efficiency than non-disabled.*

Implication 2 *Pre-AI, differences in working time are ambiguous. Disabled workers will work more if diff in outside options is large relative to diff in efficiency.*

Implication 3 *Pre-AI, differences in total output and profit are ambiguous.*

Implication 4 *Suppose an AI tool increases the efficiency of disabled workers. This will increase their work time, total output, and profits on the Platform.*

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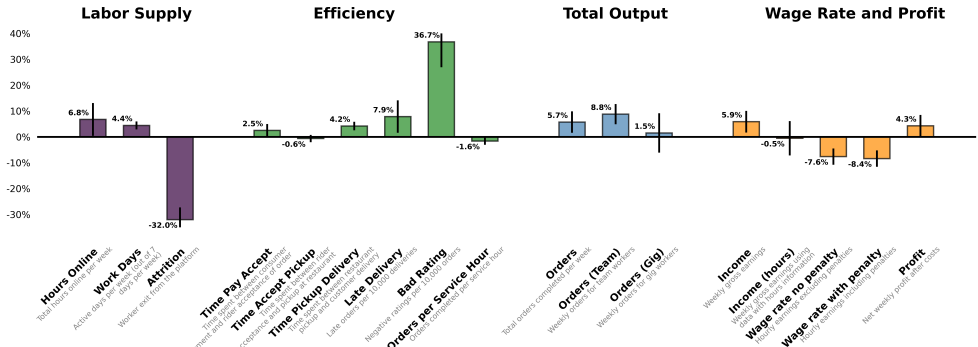
Pre-AI Differences in Workplace Outcomes

We run regressions of the below form:

$$Y_{it} = \alpha + \beta Disabiled_i + X'_{it}\gamma + \mu_t + \epsilon_{it}$$

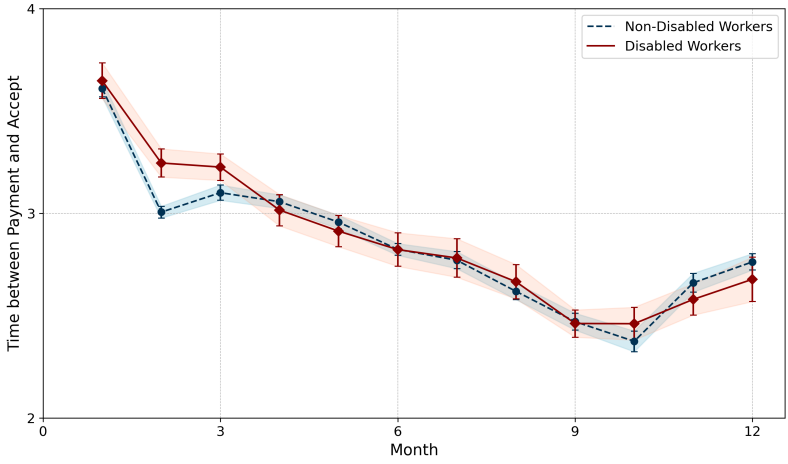
- Y_{it} is outcome of driver i at year-week t
- $Disabled_i$ is dummy for disabled. μ_t is year-week dummy
- X_{it} = controls for city of work, age, gender, registration year
  - no tenure or delivery difficulty controls
- Exclude zero order weeks
- Standard errors clustered by driver

Differences in Workplace Outcomes



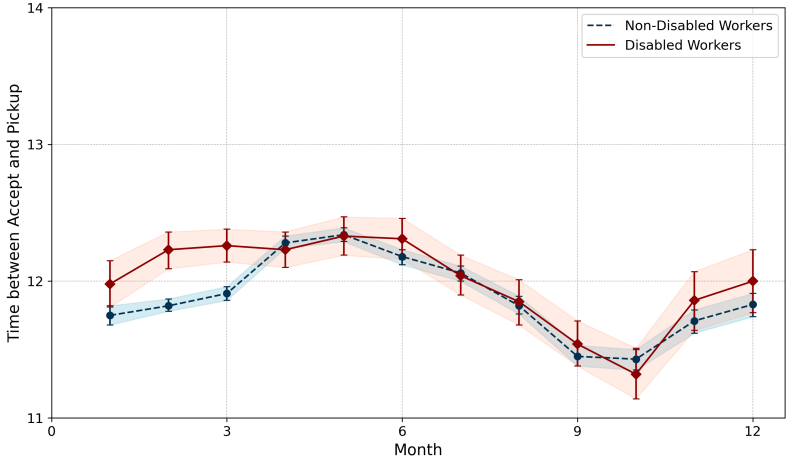
▸ Team Workers ▸ Gig Workers

Time Spent Between Order Initiation and Order Allocation (Per Order)

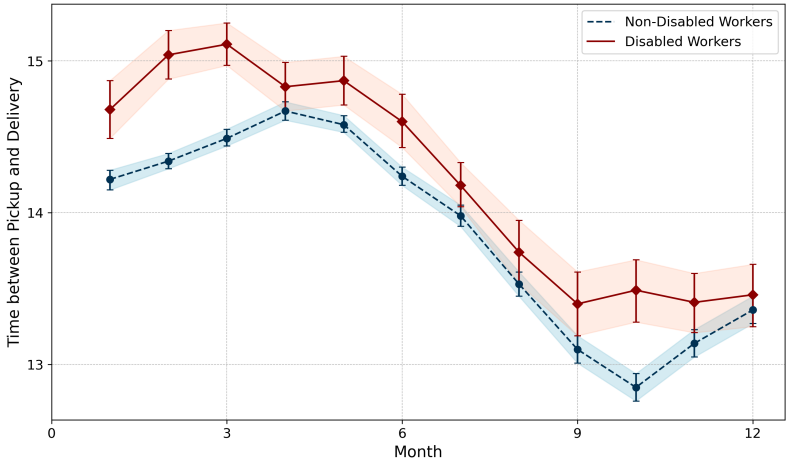


$$y_{it\tau} = \sum \beta_\tau \times 1[Tenure = \tau] + X_{it}\delta + \epsilon_{it\tau}$$

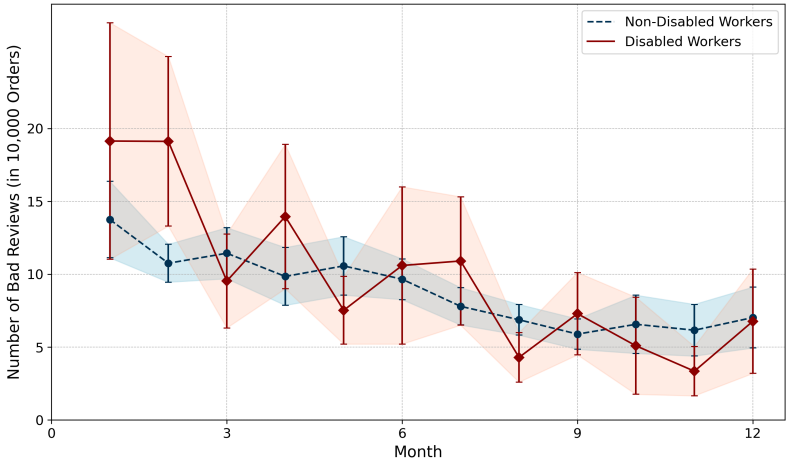
Time Spent Between Order Allocation and Pickup (Per Order)



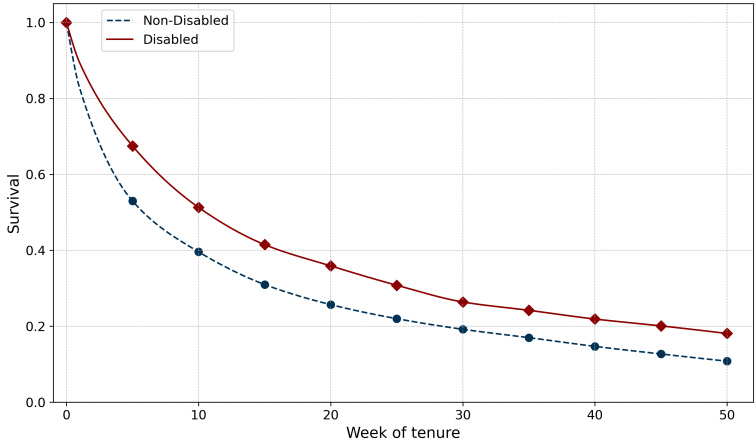
Time Spent Between Pickup and Delivery (Per Order)



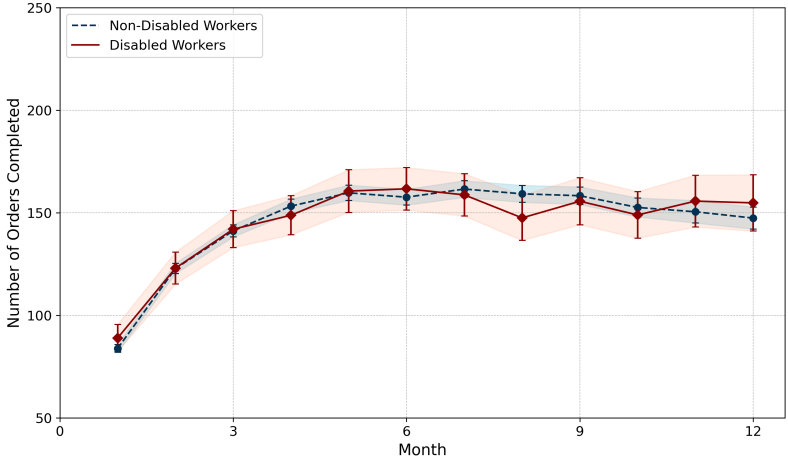
Number of Bad Reviews (Per 10,000 Order)



Survival Curve



Number of Orders Completed (Weekly)



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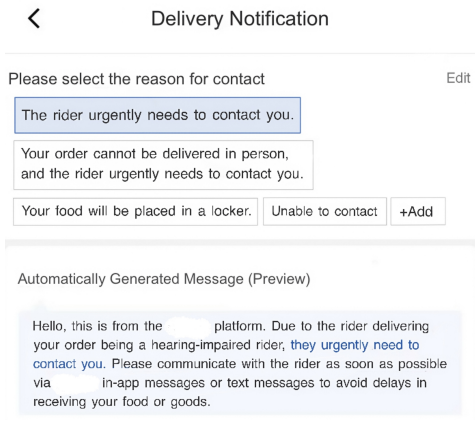
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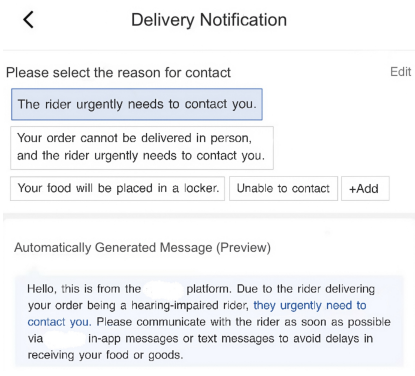
Intelligent Outbound Call

- Pre-AI tool, disabled workers, particularly those unable to speak, were limited to communicating with customers through in-app messaging
  - in China, customers generally expect phone call when food delivered
- Late April 2022: Platform introduces "Intelligent Outbound Call" feature to help disabled workers
  - call customers using pre-set & customized messages
  - phone calls use AI to sound more natural
- Part of Platform's of CSR Innovation Policy, "Technology for Good"
  - built by 3 developers in free time over several months

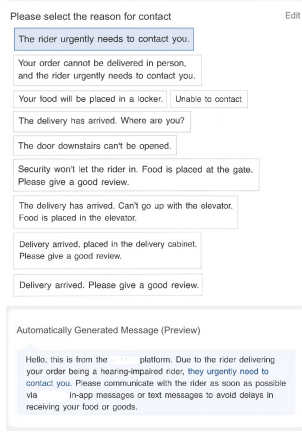
Intelligent Outbound Call



Intelligent Outbound Call



(a) Default



(b) Customized

Aside on Non-generative AI Tools for Disabled Workers

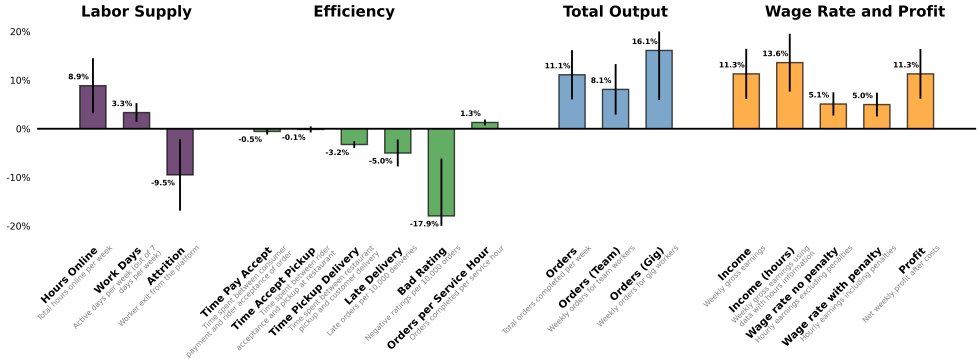
- Generative AI uses generative models to create new content
- Non-generative AI analyzes, classifies, or predicts based on input data.
  - non-generative AI underlies automation, optimization, perception tasks
    - routing, forecasting, quality control, voice recognition
- Visual impairment
  - image recognition & object detection: helps avoid obstacles
  - text to speech from on-screen or printed materials
- Mobility impairment
  - smart routing

Diff-in-Diff Specification

$$y_{it} = \gamma Disabled_i \times Post_t + \lambda_i + \xi_t + e_{it},$$

- y_{it} is outcome worker i in year-week t
- $Post_t$ is a dummy variable for April 2022 and after
- Worker fixed effects λ_i and year-week fixed effects ξ_t
- No order distance or delivery difficulty controls

Treatment Effects

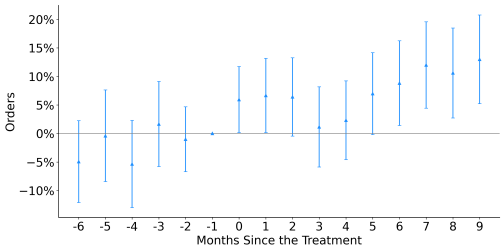


▸ Team Workers ▸ Gig Workers

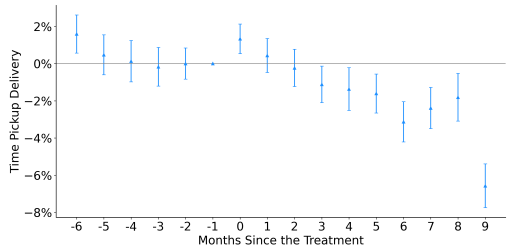
▸ Restrict to Workers Present Pre- & Post-AI ▸ Restrict to Obs with Hours

▸ Exclude Early Months ▸ Control for Distance ▸ Raw Means

Parallel Trend Test (Productivity)

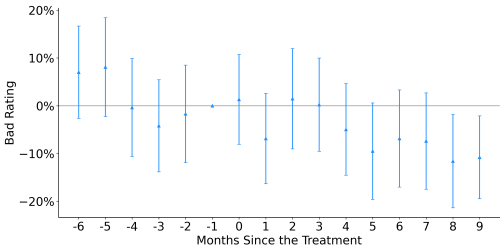


(a) Number of Orders Completed

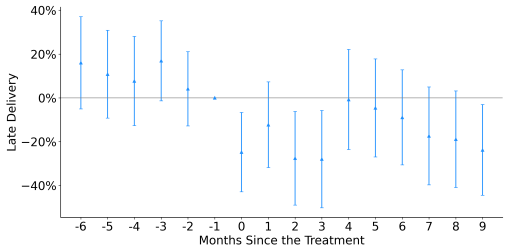


(b) Time Spent Between Store → Delivery

Parallel Trend Test (Productivity)



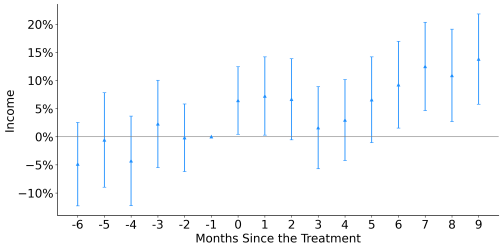
(c) Bad Ratings



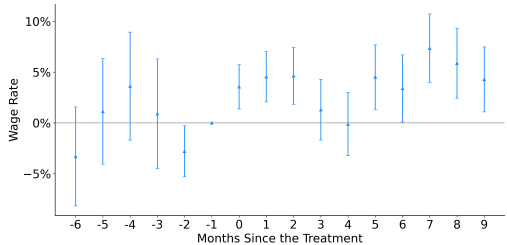
(d) Number of Delayed Orders

Parallel Trend Test (Wage and Profits)

Figure: Event Study Analysis: Wage and Profits

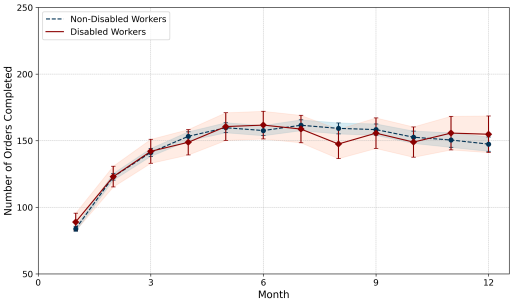


(a) Income

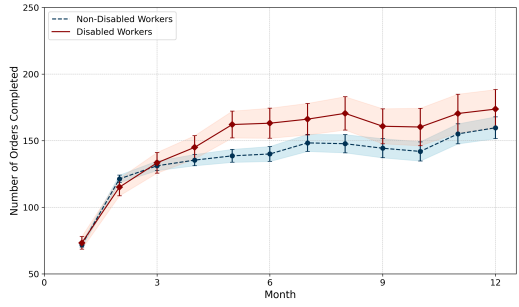


(b) Wage

Tenure Curves: Number of Orders Completed

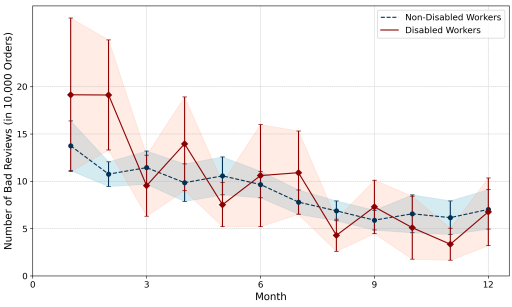


(a) Pre-Periods

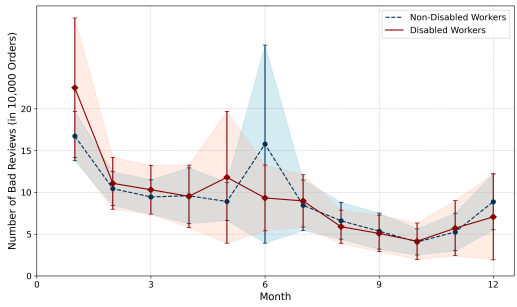


(b) Post-Periods

Tenure Curves: Bad Reviews (in 10,000 Orders)

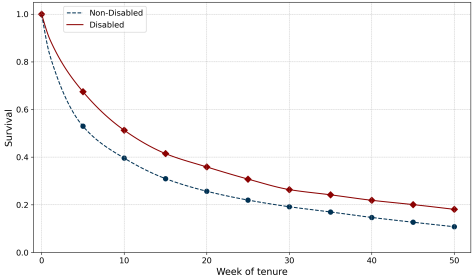


(a) Pre-Periods

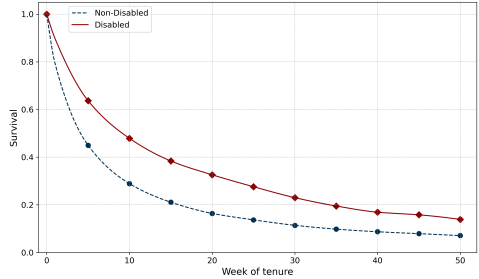


(b) Post-Periods

Survival Curves



(a) Pre-Periods



(b) Post-Periods

Magnitudes

- Weeks with bad ratings go down by 18%
  - closes half of 36% gap with non-disabled
  - AI tool is like moving someone 3m down tenure curve
- Time between pickup and delivery goes down by 3.2%
  - closes 3/4 of 4.2% gap with non-disabled
  - AI tool is like moving someone 6m down tenure curve
- Brynjolfsson et al. (2025): gen AI tool worth about 4m of tenure

Benefits and Costs of the AI Tool

- Benefit is 11% increase in variable profit
  - with profit of 7 RMB per order ($1), benefit is $19k per month
- Cost is free time of 3 engineers for several months.
  - if 10 hrs/wk for 3m, that's 390 hours, less than 0.2 FTE
  - no more than about $20k USD in time
- Pays back cost in one month

What does AI not do? Coauthor field notes

The intelligent outbound call tool is frequently used when workers request customers to open doors, and it is generally very effective. However, there was one exception during our deliveries. In this case, when we arrived at the destination, the worker followed the customer's instructions to contact the apartment complex management via the intercom. After the system connected, no one spoke on the other side. Although I heard the door unlocking sound, the door did not automatically pop open, and there was no visible indication that it had unlocked. The worker continued waiting by the intercom until I eventually walked over and pulled the door open.

What does AI not do? Coauthor field notes

One order was delivered to an urban village, but the address was inaccurate. Upon arriving, the worker used the intelligent outbound call to contact the customer, who said, "I'm upstairs." However, it was unclear what the customer meant by 'upstairs.' I then heard the customer shouting from inside a factory behind us, but by that time, the worker had already started riding in the opposite direction. I stopped the worker, informing him that the customer was inside the factory, and we managed to find the customer. In such situations, a worker with a hearing disability could waste significant time locating the exact address. Later that afternoon, we encountered a similar issue with an order delivered to a construction site.

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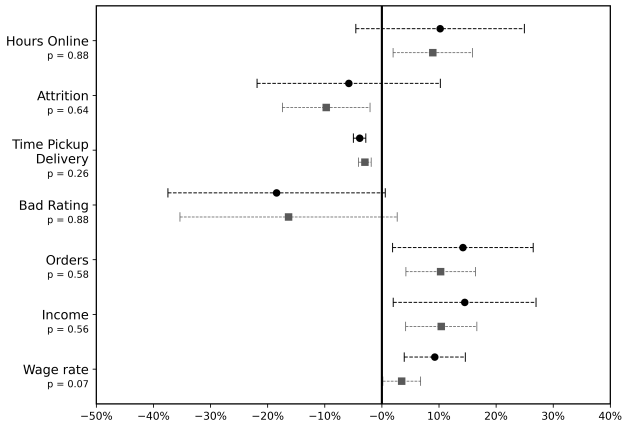
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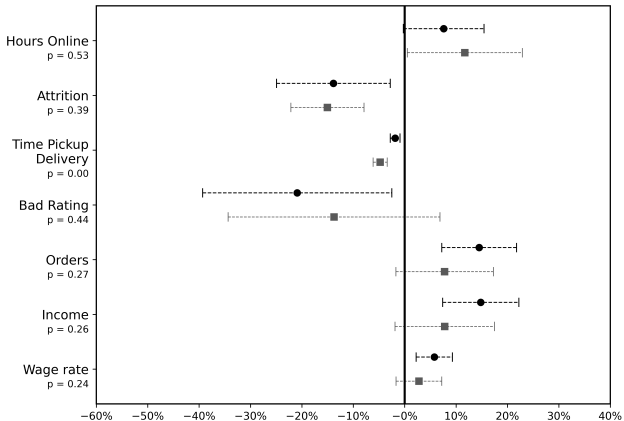
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No Clear Heterogeneity by Pre-AI Productivity



▸ Gap Pre-AI

No Clear Heterogeneity by Pre-AI Tenure



▸ Gap Pre-AI

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- Workers with disabilities sometimes thought of as imposing "costs" on firms, but what firms gain from employing workers with disabilities not well-understood
- Pre-AI technology, disabled workers are less efficient & worse reviews
  - but work many more hours, higher output, higher profit
- Simple AI tool eliminates half of gaps & boosts profits
- Big data shows subtle ways disabled workers do or don't benefit firms
- Hearing loss very common. Firm private benefit of AI outweighs cost
  - AI may help reduce disability gaps w/o govt interventions
  - less common disabilities, government tech subsidies could be useful

Relation to Discussion on AI

- Lot of focus on AI for decisions
  - serious concerns it will uproot jobs
- David Autor lectures: how can AI augment workers?
- For workers with disabilities, AI can assist for faculties / areas with impairments
  - many aspects of human sensation are prediction problems

Thank you

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Outline

Back-up Slides

Registration Requirement

Setting and Data





New Drivers in Platform Over Data

Table: Number of Newly Registered Workers in the Data Sample

	Number of Newly Registered Workers	
Year	Non-Disabled Workers	Disabled Workers
2021	13318	1233
2022	11629	1410
2023	14407	1653

Descriptive Statistics

	Mean	Median	Std. Error
A. Total Output			
Orders	128.75	89	141.30
Peak Hour Orders	76.82	52	87.69
Orders (Team)	198.46	194	150.75
Orders (Gig)	55.01	21	80.40
Restaurants	55.79	47	51.28
Customers	116.15	75	127.22
B. Efficiency			
Order $\rightarrow$ Worker	3.35	2.41	12.35
Worker $\rightarrow$ Store	11.59	11.35	7.07
Store $\rightarrow$ Delivery	13.82	13.34	5.59
Overtime Rate (in 10,000 orders)	81.29	51.15	96.75
Bad Rating (in 10,000 orders)	9.62	0.00	94.14
C. Work Time on the Platform			
Online Duration	1519.69	592.51	1807.71
Work Days	4.49	6.00	2.74
Bad Weather Work Days	0.63	0.00	1.10
Number of Weeks Worked	11.00	3.00	20.00

Profit Calculation

Profit difference between disabled (D) and non-disabled (N) workers can be formally expressed as:

$$\Delta\pi = A \cdot E(Y^D - Y^N) - c \cdot \Delta Pr(\text{hired} = 1) - k\Delta Pr(\text{Bad Rating}), \quad (1)$$

where Y^D and Y^N represent the number of orders completed by disabled and non-disabled workers, respectively; A denotes the piece rate the firm receives per order; c represents the onboarding cost; $Pr(\text{hired} = 1)$ captures the differential probability of worker retention (i.e., survival probability); and Pr(Bad Rating) captures probability of bad rating.

Profit Calculation Before Technology

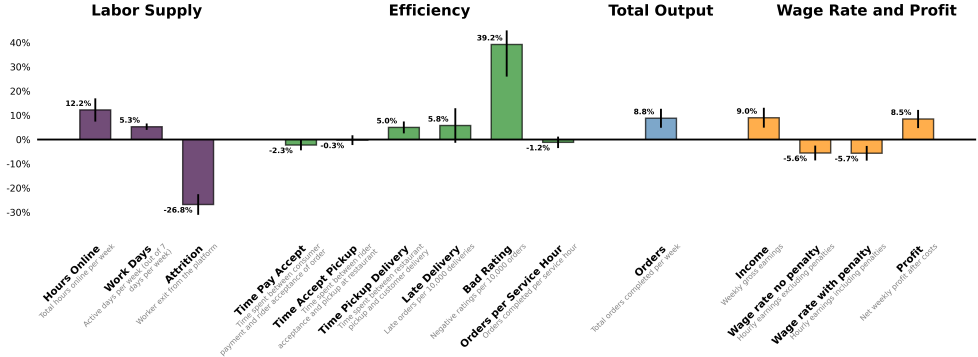
- Disabled workers do 2.3 more orders per week (regression-adjusted). Platform earns profit of about 8-10 CNY per order. Platform earns $\approx$ 20 CNY ($3 USD) per worker-week from disabled workers doing more orders.
- Disabled workers have lower attrition of 6.2pp per month. Using relatively conservative hiring cost of 500 CNY, Platform saves about 7 CNY ($1 USD) per worker-week) from disabled workers having lower attrition.
- Disabled workers receive about 2 more bad ratings per 10,000 orders per week. This is about 0.02 more bad ratings per week. Even if cost of bad rating is entire cost of the order, this is only cost of 1 CNY per worker-week.
  - for disabled workers to lose profitability advantage from more output and lower turnover, bad ratings must produce cost 40-50 times total revenue for the order

Performance Difference

	Estimate	Std. Error	Observations	R-squared
A. Total Output				
Orders	2.336***	(0.761)	206,966	0.341
Peak Hour Orders	1.909***	(0.472)	206,966	0.332
Orders (Team)	9.786***	(1.225)	116,370	0.108
Orders (Gig)	-4.810***	(0.816)	905,96	0.043
Restaurants	4.320***	(0.303)	206,966	0.243
Customers	6.484***	(0.730)	206,966	0.304
B. Efficiency				
Order → Worker	0.155***	(0.0232)	181,539	0.197
Worker → Store	0.205***	(0.0319)	181,539	0.093
Store → Delivery	0.820***	(0.0360)	181,539	0.326
Overtime Rate	34.24***	(5.87)	181,539	0.034
Bad Rating	5.183***	(0.684)	181,539	0.006
C. Hours				
Online Duration	24.62***	(7.070)	206,966	0.306
Work Days	0.235***	(0.0165)	206,966	0.253
Bad Weather Work Days	0.0432***	(0.00753)	206,966	0.168
Survival	0.0628***	(0.0130)	15,710	0.108

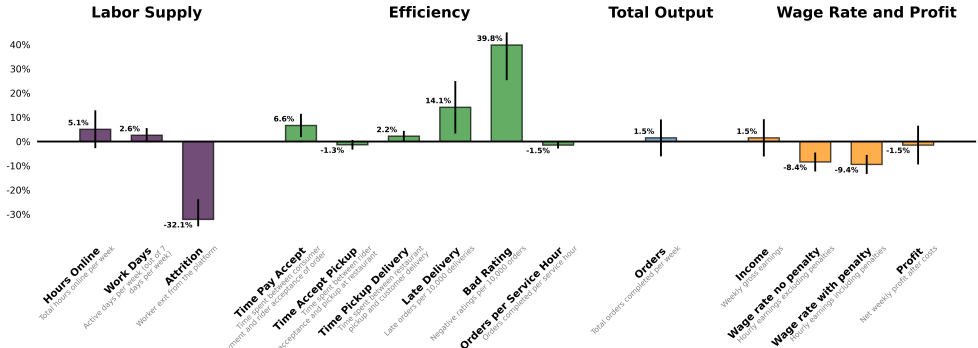
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Performance Difference for Team Workers



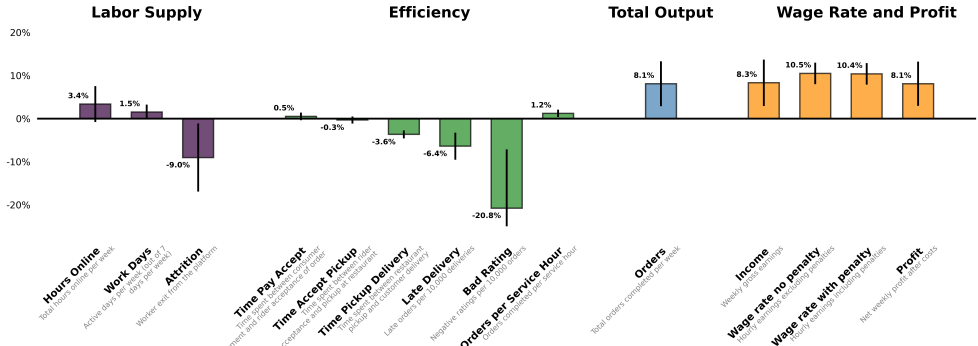
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Performance Difference for Gig Workers



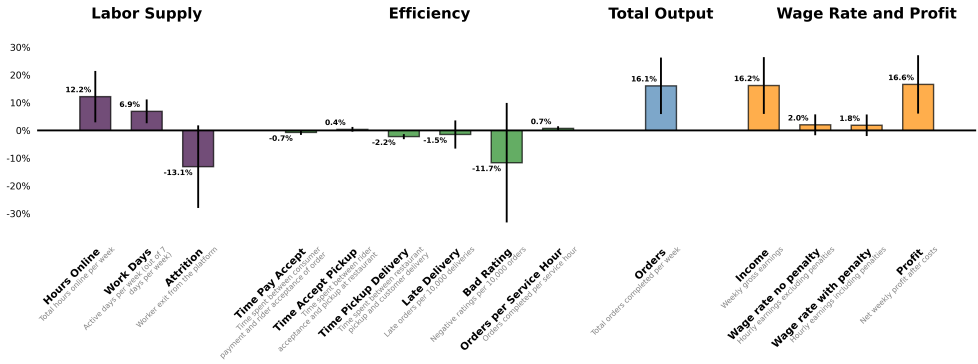
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Treatment Effects for Team Workers



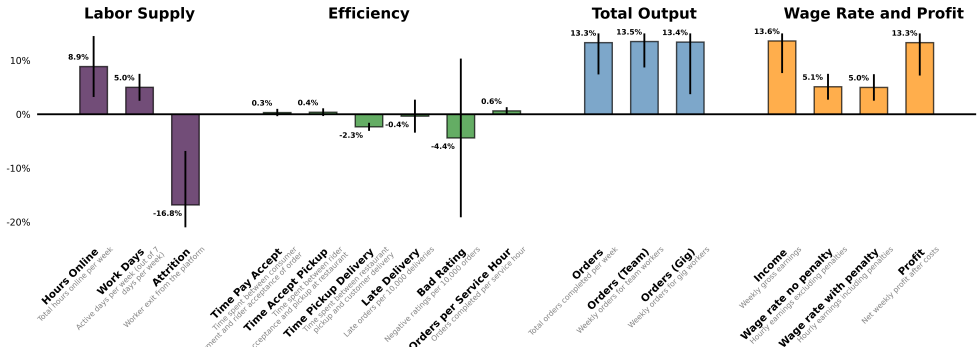
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Treatment Effects for Gig Workers



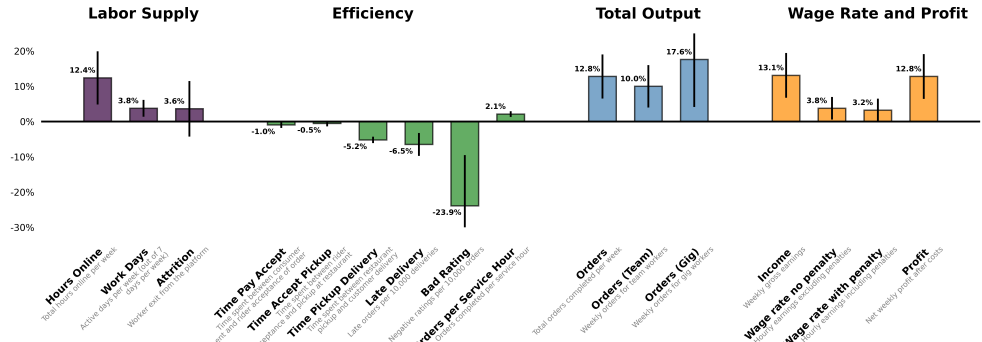
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Treatment Effects Using Observations with Observed Online Duration



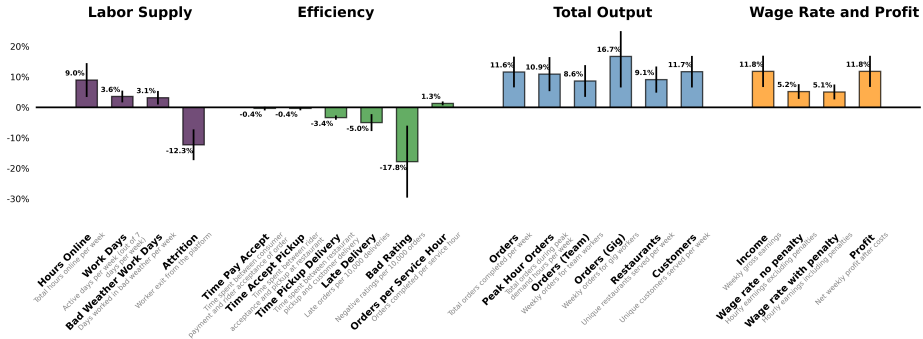
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Treatment Effects Excluding the First Four Months of Orders



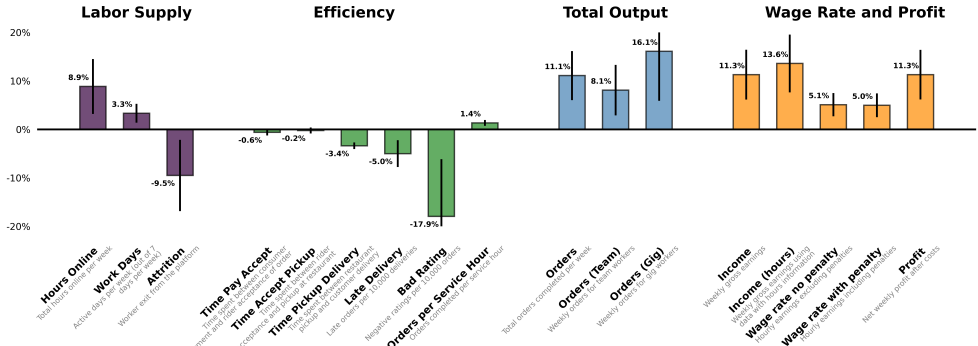
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Treatment Effects Restricting to Drivers Present Pre- and Post-AI



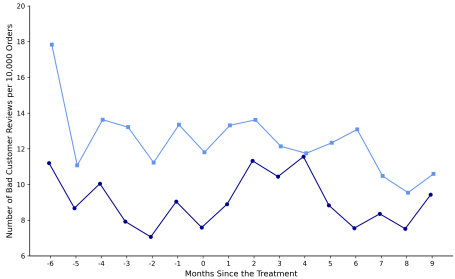
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Treatment Effects with Distance Control

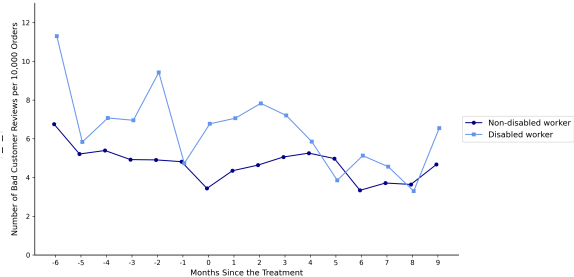


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Comparison of Raw Averages



(a) Bad Rating (All Sample)



(b) Bad Rating (among workers who remained continuously active)

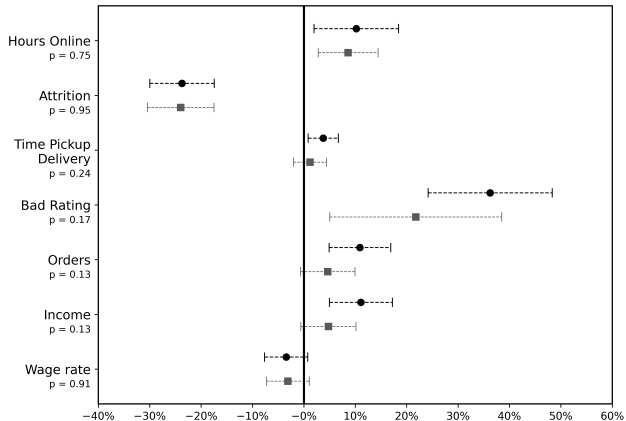
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Treatment Effects

	Estimate	Std. Error	Observations	R-squared
A. Total Output				
Orders	5.800***	(1.545)	559,888	0.638
Peak Hour Orders	2.500***	(0.780)	559,888	0.634
Orders (Team)	2.735*	(1.221)	289,786	0.502
Orders (Gig)	9.216***	(1.221)	270,102	0.568
Restaurants	3.771***	(0.429)	559,888	0.675
Customers	6.108***	(1.085)	559,888	0.663
B. Efficiency				
Order → Worker	0.0551	(0.112)	480,070	0.007
Worker → Store	0.0331	(0.0576)	480,070	0.000
Store → Delivery	-0.291***	(0.0565)	480,070	0.001
Overtime Rate	-10.13***	(3.584)	480,070	0.502
Bad Rating	-2.128***	(0.569)	480,070	0.251
C. Hours				
Online Duration	-73.22	(101.3)	559,888	0.678
Work Days	0.138*	(0.0704)	559,888	0.530
Bad Weather Work Days	0.0489***	(0.0137)	559,888	0.294
Survival	0.062***	(0.00986)	43,650	0.109

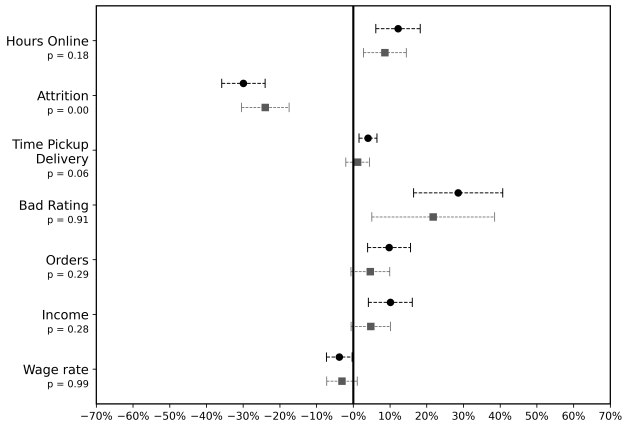
◂ Treatment Effects

Pre-AI Differences by Productivity



HTE Results

Pre-AI Differences by Tenure



◂ HTE Results