Outside Options and Labor Supply: Evidence from the Gig Economy

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Motivation

Firms with market power can mark down wages

- How far depends on where else workers can go
- Better options $\Rightarrow$ more firm-elastic $\Rightarrow$ smaller markdown
- Robinson (1933); Manning (2003)

Linking labor supply elasticities to outside options is hard

A researcher needs:

- Exogenous variation in **wages**
- Quasi-experimental variation in **outside options**

We combine:

- Randomized pay experiments among Houston Uber drivers
- Lyft's temporary exit from the Houston market

"Perfect discrimination is probably rare in buying labor but imperfect discrimination may often be found. For instance there may be two types of workers (for example, men and women or men and boys) whose efficiencies are equal but whose conditions of [labor] supply are different. It may be necessary to pay the same wage within each group, but the wages of the two groups (say of men and of women) may differ."

—Joan Robinson (1933)

This Paper

- 20–50% higher earnings per trip, one week, randomly assigned
- Lyft out of Houston Nov 2016–May 2017, then back
- Same task, same pay algorithm, flexible hours

1. Market-hours elasticity 0.47–0.64
2. One competitor nearly doubles the firm-specific elasticity: 0.47 $\rightarrow$ 0.87
3. Implied markdown 68% $\rightarrow$ 50%
4. Women about twice as elastic to the market, no less elastic to the firm

What We Add

1. Markdowns when hours are flexible
   - Firm elasticity $=$ market-hours $+$ firm-substitution component
2. A direct test of the outside-option mechanism
   - Variation in market structure, not just in wages
3. Experimental firm-specific elasticities, by sex
   - Among the first; speaks to Robinson's account of the gender wage gap

Comparison to Existing Estimates

Conceptual Framework

Setting, Experiments, and Data

Market-Level Labor Supply

Outside Options and Firm-Specific Labor Supply

Conclusion

Textbook Monopsony

$$\max_{w} \; Y(L(w)) - wL(w) \qquad \Longrightarrow \qquad w^* = \frac{Y'(L(w^*))}{1 + 1/\tau(w^*)}$$

- $\tau = d\log L / d\log w$: elasticity of labor supply to the firm
- Higher $\tau \Rightarrow$ less market power
- τ reflects the density of reservation wages at the going wage: $\eta^{\text{firm}}(w) = f(w)w/F(w)$

Flexible Hours Add a Second Margin

Fixed cost $\chi_i \sim G$, hours from $w = v'(h^*(w))$, so $L(w) = N\, G(u(w))\, h^*(w)$:

$$\tau = \underbrace{\frac{d \log N(w)}{d \log w}}_{\eta^{\mathrm{firm}} \text{ participation}} + \underbrace{\frac{d \log h^*(w)}{d \log w}}_{\varepsilon \text{ market hours}}$$

- Fixed hours: only η^{firm} matters
- Flexible hours: the hours response matters too
- Most prior work focuses on participation and ignores hours ↪

Adding an Outside Employer

Outside earnings $S_i(r)$, increasing and strictly concave:

$$\max_{h,r} \; wh + S_i(r) - v_i(h + r)$$

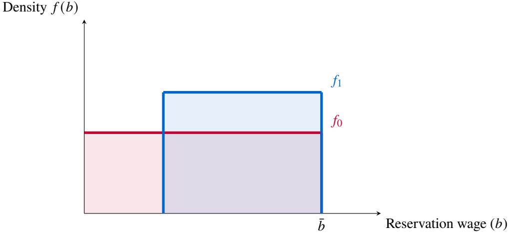
Intuition:

- *Extensive*: reservation wages rise, strictly if the option has value alone
- *Intensive*: a higher inside wage pulls hours back from the outside firm

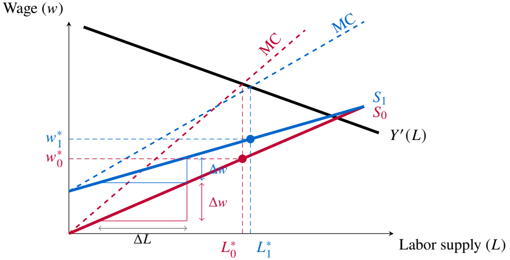
Result 1: Participation

Result 1. *A new outside employer shifts the reservation-wage distribution up in the FOSD sense. Under MLRP, $\eta^{\text{firm}}(w)$ rises at every wage the firm hires at.*

Reservation-wage densities



Labor supply to the firm



Workers with the weakest existing options gain most, compressing the distribution from below and flattening labor supply.

Result 2: Reallocation

With hours at both firms, $w = S_i'(r)$. Let $H = h + r$, $\phi = h/H$:

$$\frac{\partial h}{\partial w}\frac{w}{h} = \frac{1}{\phi}\,\varepsilon - \frac{1-\phi}{\phi}\,\sigma, \qquad \sigma < 0$$

- ε: market hours — unchanged by the entrant, since $w = v_i'(H)$
- σ: elasticity of outside hours to the inside wage
- Amplification grows as ϕ falls

Result 2. *A new outside employer weakly raises the inside-hours elasticity; strictly for anyone with positive outside hours.* ↪

Mapping to the Data

Non-shifters (no Lyft): $S_i \equiv 0$, $\phi = 1$, so $\tau_{\text{non}} = \eta^{\text{firm}} + \varepsilon =: \bar{\varepsilon}$

Shifters (Lyft access): the multi-firm case

$$\tau_{\text{shift}} - \tau_{\text{non}} = \underbrace{\left(\eta^{\text{firm}}_{\text{shift}} - \eta^{\text{firm}}_{\text{non}}\right)}_{\text{Result 1}} + \underbrace{\frac{1-\phi}{\phi}(\varepsilon - \sigma)}_{\text{Result 2}}$$

- Identification: shifter status exogenous to labor supply preferences
- Non-shifters need not lack all options — both groups need only substitute with non-Lyft employers the same way

Vehicle-Age Placebo Balance

Two Sources of Variation

Experimental variation in wages

- Earnings Accelerator: 20–50% more per trip for a week, randomly assigned
- Implemented as a cut to the "Uber fee," visible in-app after every trip

Quasi-experimental variation in outside options

- Lyft out of Houston Nov 2016–May 2017, back that fall
- Elsewhere, Lyft required model year 2004+: vehicle age governs eligibility
- Historical context: no meaningful other ride-share or delivery platforms (Campbell, 2017)

Shifters can also drive for Lyft; non-shifters cannot

Multi-Apping Pay Statement Timeline

Multi-Apping


Anyone drive for both UBER and Lyft at the same time?
Discussion in 'Lyft' started by UberBob2, Sep 9, 2015.
Page 1 of 5 1 2 3 4 5 Next >

UberBob2
Active Member
Location: Miami

I have a hard time even remembering to swipe, start, let alone remembering to turn off one app after getting a ride with the other. Does anyone have a problem doing this?

UberBob2, Sep 9, 2015 #1

elelegido
Well-Known Member
Location: Varies

Don't turn off the other app when you get a ping if the other is surging. Leave it on until the pax is in the car - you may get a better, surge, ride offer while you're driving to the pickup.

elelegido, Sep 9, 2015 #2
Ezridax, SurgeSurferSD, brhlcommish and 2 others like this.

glados
Active Member
Location: -

elelegido said: ↑
Don't turn off the other app when you get a ping if the other is surging. Leave it on until the pax is in the car - you may get a better, surge, ride offer while you're driving to the pickup.

This will hurt your cancellation and acceptance rates and can lead to losing guarantees or even deactivation! It'll also make it harder for zones to surge because you have both apps always open.

glados, Sep 9, 2015 #3
Cynergie, KMANDERSON and Uber_J like this.


News Video Events Crunchbase

Mystro is an app aiming to bring in more bacon for Uber and Lyft drivers
Posted Aug 2, 2017 by Sarah Buhr (@sarahbuhr)

Mystro hopes to put 33 percent more money per year in the pockets of Uber and Lyft drivers through an app.

Roughly two-thirds of drivers drove for both Uber and Lyft (Campbell, 2022). Keeping both apps on and taking the first dispatch cuts idle time; third-party tools that manage the switching sell for $5/week to $100/year.

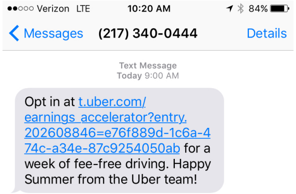
Full Guide
Utilization Evidence

The Earnings Accelerator

- Fixed % more on every trip, one week
- Eligible: $\geq$4 trips/month, 5–40 hours
- Stratified on sex and hours
- Women oversampled; $\approx$2/3 accepted

	Lyft	Drivers	Offer
Houston 1	out	2,020	25/39%
Houston 2	back	2,100	20–50%
Boston	eligibility	1,600	–

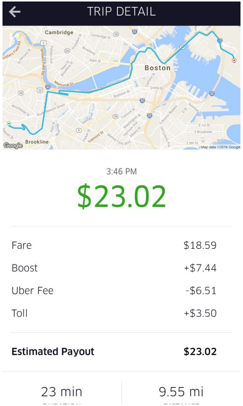
Roughly 2,000 of more than 15,000 active Houston drivers.



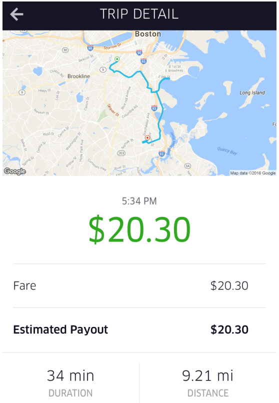
Offer Email Timeline Balance Taxi

Treatment in the App

Control week



Treated week



Implemented as a cut to the “Uber fee,” visible in-app after every trip.

Descriptive Statistics

	Houston 1 (1)	Houston 2 (2)	Boston (3)	IDB (4)
Female	0.52	0.39	0.14	0.18
Age	44.1	–	–	40.3
	(12.2)			(11.7)
Vehicle year	2013.5	2013.6	2010.5	2013.6
	(2.5)	(2.7)	(4.5)	(3.4)
Months on platform	16.0	8.7	11.1	14.6
	(10.2)	(9.4)	(8.7)	(13.1)
Hours per week (pre-period)	19.6	21.5	–	–
	(13.6)	(12.9)		
Vehicle Solutions	0.12	0.08	0.08	0.00
Drivers	2,020	2,100	1,600	58,928

Hours $=$ app on and available for dispatch.

Balance IDB Program Uber vs. Taxi

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Outside Options and Firm-Specific Labor Supply

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Specification

$$y_{it} = e \log(1 - \kappa_{it}) + \beta X_{it} + \xi_{it}$$
$$\log(1 - \kappa_{it}) = \gamma Z_{it} + \lambda X_{it} + \nu_{it}$$

- Z_{it}: week $\times$ offer indicators
- X_{it}: strata, months on platform, vehicle solutions, lagged log earnings
- $\log(1-\kappa)$ rather than the wage: observed even for drivers who do not drive
- SEs clustered by driver

$y_{it} =$ log hours (ε), $\mathbf{1}\{\text{drive}\}$ (η^{firm}), or hours via IV-Poisson ($\bar{\varepsilon}$, preferred)

Offers Raised Pay by 0.17–0.20 Log Points

	Offered $\log(1-\kappa)$		$\mathbf{1}\{\text{Accepted}\}$		$\log(1-\kappa)$		$\log(W)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Pooled								
Treated	0.29***	0.29***	0.67***	0.59***	0.20***	0.17***	0.16***	0.17***
	(0.001)	(0.001)	(0.010)	(0.008)	(0.003)	(0.002)	(0.009)	(0.008)
Observations	4,040	6,746	4,040	6,746	4,040	6,746	2,998	5,031
Panel B. By Sex								
Male	0.28***	0.28***	0.61***	0.57***	0.17***	0.16***	0.12***	0.14***
	(0.002)	(0.002)	(0.016)	(0.012)	(0.005)	(0.004)	(0.012)	(0.011)
Female	0.31***	0.31***	0.73***	0.60***	0.22***	0.19***	0.19***	0.20***
	(0.001)	(0.001)	(0.014)	(0.011)	(0.004)	(0.003)	(0.012)	(0.012)
Observations	4,040	6,746	4,040	6,746	4,040	6,746	2,998	5,031
Strata Dummies	✓	✓	✓	✓	✓	✓	✓	✓
Fee-Free Driving Data	✓	✓	✓	✓	✓	✓	✓	✓
Taxi Data		✓		✓		✓		✓

Taxi Balance

A 10% Higher Net-of-Commission Rate Raises Hours 5–6%

	$\mathbf{1}\{\text{Drive}\}$	log(Hours)		Poisson	
	(1)	(2)	(3)	(4)	(5)
Elasticity	0.19***	0.42***	0.69***	0.47***	0.64***
	(0.05)	(0.09)	(0.09)	(0.09)	(0.07)
Observations	3,108	2,766	4,650	3,108	5,154
Fee-Free Driving Data	✓	✓	✓	✓	✓
Taxi Data			✓		✓
Strata Dummies	✓	✓	✓	✓	✓
Baseline Covariates	✓	✓	✓	✓	✓

Robustness Specifications OLS Fares Distributions Compliers

Robustness

- Timing: no effect before or after the treatment week ↪
- Outcome: holds using fares collected ↪
- Specification: just-identified, strata-only ↪
- Distributions: whole complier distribution shifts ↪
- OLS: non-experimental estimates biased down ↪

Women Are Twice as Elastic to the Market

	$\mathbf{1}\{\text{Drive}\}$	log(Hours)		Poisson	
	(1)	(2)	(3)	(4)	(5)
Male	0.11	0.28*	0.43***	0.29**	0.42***
	(0.09)	(0.15)	(0.14)	(0.14)	(0.12)
Female	0.25***	0.53***	0.88***	0.62***	0.81***
	(0.07)	(0.11)	(0.11)	(0.11)	(0.10)
p-value (equal)	[0.217]	[0.171]	[0.013]	[0.061]	[0.012]
First Stage F: Male	759.2	745.8	897.5	–	–
First Stage F: Female	1583.7	1694.4	1669.1	–	–
Observations	3,108	2,766	4,650	3,108	5,154
Fee-Free Driving Data	✓	✓	✓	✓	✓
Taxi Data			✓		✓
Strata Dummies	✓	✓	✓	✓	✓
Baseline Covariates	✓	✓	✓	✓	✓

What Explains It? Heterogeneity Reweighting Distributions

What Explains the Sex Gap?

- Age, tenure: little variation ↪
- Timing: same gap for late-night, weekend, school-pickup ↪
- Usual hours: gap survives among high-hours drivers ↪
- Wealth: no gradient in vehicle year or zip-code income ↪
- Outside options: Lyft absent here; taxi patterns look similar ↪

No observable characteristic accounts for the gap.

Drivers with Access to Lyft Are Twice as Elastic

	$\mathbf{1}\{\text{Drive}\}$		Log(Hours)		Poisson Model	
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Shifter	0.19***	0.19***	0.42***	0.42***	0.47***	0.48***
	(0.06)	(0.05)	(0.09)	(0.09)	(0.09)	(0.09)
Shifter	0.37***	0.26***	0.81***	1.10***	0.87***	1.01***
	(0.13)	(0.06)	(0.21)	(0.11)	(0.18)	(0.12)
p-value (equal)	[0.202]	[0.408]	[0.091]	[0.000]	[0.051]	[0.000]
Observations	4,700	7,172	4,155	6,369	4,700	7,172
Houston EA	✓	✓	✓	✓	✓	✓
Boston EA		✓		✓		✓

Robustness Balance Adjusted Gaps Permutation IDB Utilization

Is It Really Lyft Access?

- Balance: groups differ on sex, tenure, baseline hours ↪ ↪
- Entropy balancing: gap 0.35/0.50, positive in every quartile ↪
- Covariates held fixed: little changed ↪
- Permutation: 1,000 reassignments, one-sided $p < 0.001$ ↪
- Complier means (Abadie, 2002): similar gap ↪
- Specification: just-identified, strata-only, and by sex ↪
- Different city, different design: the IDB gives the same pattern ↪
- Not wealth: vehicle age does not predict elasticities when Lyft is absent ↪

Shifters Have Higher Utilization

	All (1)	Male (2)	Female (3)	Placebo (4)
Non-Shifter	0.586 [0.147]	0.583 [0.137]	0.590 [0.156]	0.591 [0.141]
Shifter	0.615 [0.190]	0.617 [0.186]	0.611 [0.196]	0.584 [0.151]
p-value (equal)	$<.001$	$<.001$	0.018	0.317
Observations	1,776 / 1,850	851 / 1,164	925 / 686	721 / 1,055

Utilization = share of online time en route or on a trip.

Elasticities Robustness

A Competitor Cuts the Implied Markdown from 68% to ≈50%

	Earnings Accelerator	
	Houston (1)	+ Boston (2)
Non-Shifter (τ_{non})	0.47***	0.48***
	(0.09)	(0.09)
Shifter (τ)	0.87***	1.01***
	(0.18)	(0.12)
Markdown $1/(1+\tau)$, Non-Shifter	67.8%	67.8%
	(4.0%)	(4.0%)
Shifter	53.5%	49.7%
	(5.2%)	(2.9%)
Implied $\|\sigma\|$ by market share ϕ, from intensive-margin elasticities (SE in parentheses):		
$\phi = 0.67$ (symmetric tastes)	0.37	0.94
	(0.51)	(0.35)
$\phi = 0.72$ (Uber market share)	0.58	1.31
	(0.63)	(0.43)
$\phi = 0.83$ (Aucejo et al.)	1.48	2.86
	(1.16)	(0.76)
$\phi = 0.93$ (Koustas)	4.75	8.52
	(3.10)	(1.95)
Houston EA	✓	✓
Boston EA		✓

ϕ Sensitivity Markdown Sensitivity vs. MTurk

Markdowns vs. Substitution Elasticities

Markdowns need no market-share assumption

- $1/(1+\tau)$: 68% $\rightarrow$ 50%–54%
- In levels: $\approx$1/3 of marginal revenue product $\rightarrow$ $\approx$1/2
- A 45–60% pay increase; about a quarter of the gap to the competitive wage

Recovering $|\sigma|$ requires one

- $\phi = 0.67$ symmetric tastes: 0.37–0.94
- $\phi = 0.72$ Uber market share: 0.58–1.31
- $\phi = 0.83$ (Aucejo, Perry, and Zafar, 2024), preferred: 1.48–2.86
- $\phi = 0.93$ (Koustas, 2018): 4.75–8.52

ϕ Sensitivity Sensitivity

If Workers Held One Job at a Time

These calculations assume drivers freely choose both their total hours and their allocation across platforms. Where workers hold one job at a time, substitution means quitting:

Markdown: 84% $\rightarrow$ 73%

- From participation elasticities alone: 0.19 $\rightarrow$ 0.37
- Still falls, but by 11 pp rather than 15–18 pp
- Shifting hours freely between employers further constrains wage-setting

Decomposition Sensitivity

Women Are No Less Elastic to the Firm

	Male		Female	
	$\mathbf{1}\{\text{Drive}\}$	Poisson	$\mathbf{1}\{\text{Drive}\}$	Poisson
	(1)	(2)	(3)	(4)
Non-Shifter (τ_{non})	0.11	0.30**	0.26***	0.62***
	(0.09)	(0.14)	(0.07)	(0.11)
Shifter (τ_{shift})	0.18***	1.00**	0.52***	1.10***
	(0.07)	(0.44)	(0.15)	(0.27)
Implied $\lvert\sigma\rvert$ by market share ϕ, from total-response (Poisson) elasticities:				
$\phi = 0.67$ (symmetric tastes)	1.14		0.35	
$\phi = 0.72$ (Uber market share)	1.52		0.61	
$\phi = 0.83$ (Aucejo et al.)	3.16		1.72	
$\phi = 0.93$ (Koustas)	9.10		5.74	

Market vs. Firm By Sex Heterogeneity

Women: More Market-Elastic, No Less Firm-Elastic

	Male	Female
Market hours $\bar{\varepsilon}$	0.42	0.81
Firm, no Lyft τ_{non}	0.30	0.62
Firm, Lyft τ_{shift}	1.00	1.10
Implied markdown $1/(1+\tau_{\text{shift}})$	50%	48%
Substitution $\lvert\sigma\rvert$ at $\phi = 0.83$	3.16	1.72
Participation gap, shifter $-$ non	0.07	0.26

A larger participation response offsets less cross-platform reallocation.

Estimates

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Setting, Experiments, and Data

Market-Level Labor Supply

Outside Options and Firm-Specific Labor Supply

Conclusion

Summary

- Framework. With flexible hours the firm elasticity combines market-hours and firm-substitution components; a new employer raises both
- Market level. Market-hours elasticity of 0.47–0.64
- Outside options. One competitor nearly doubles the firm elasticity (0.47 $\rightarrow$ 0.87), cutting the markdown from 68% to $\approx$50%; $|\sigma| = 1.48$–2.86
- Sex. Twice as market-elastic, no less firm-elastic

vs. MTurk

Additional Material

References I

Abadie, Alberto (2002). "Bootstrap Tests for Distributional Treatment Effects in Instrumental Variable Models". In: *Journal of the American Statistical Association* 97.457, pp. 284–292.

Aucejo, Esteban M., A. Spencer Perry, and Basit Zafar (2024). *Assessing the Costs of Balancing College and Work Activities: The Gig Economy Meets Online Education*. Working Paper 32357. National Bureau of Economic Research.

Campbell, Harry (2017). *2017 Rider Survey*. Tech. rep. The Rideshare Guy. URL: https://docs.google.com/document/d/1QSUFSqasfjM9b9UsqBwZlpa8EgqNj6EBfWybFBSHj3o/edit.

— (2022). *How Many Uber Drivers Are There?* Tech. rep. The Rideshare Guy. URL: https://therideshareguy.com/how-many-uber-drivers-are-there/.

Dube, Arindrajit et al. (2020). "Monopsony in Online Labor Markets". In: *American Economic Review: Insights* 2.1, pp. 33–46. DOI: 10.1257/aeri.20180150.

Koustas, Dmitri (2018). *Consumption Insurance and Multiple Jobs: Evidence from Rideshare Drivers*. Working Paper. University of Chicago.

Manning, Alan (2003). *Monopsony in Motion: Imperfect Competition in Labor Markets*. Princeton University Press.

Robinson, Joan (1933). *The Economics of Imperfect Competition*. Palgrave Macmillan.

Elasticity Decomposition Back

Single firm:

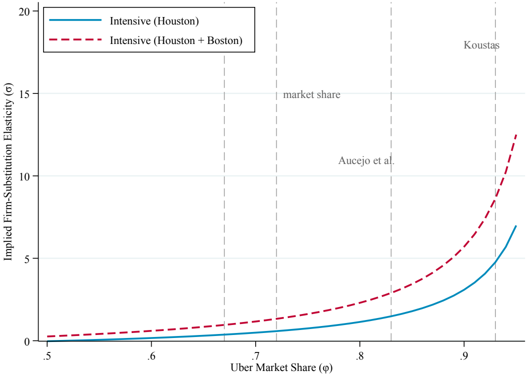
$$\tau = \eta^{\text{firm}} + \varepsilon$$

Two firms, hours freely chosen at each:

$$\tau = \eta^{\text{firm}} + \frac{1}{\phi}\varepsilon - \frac{1-\phi}{\phi}\sigma$$

- Holds exactly per worker, with worker-specific ϕ_i, σ_i
- Common η^{firm}, $\varepsilon \Rightarrow$ the difference isolates $\frac{1-\phi}{\phi}(\varepsilon - \sigma)$
- Result 2 needs MLRP and a common ε for total τ to rise everywhere

Sensitivity of $|\sigma|$ to ϕ Back



Firm-Specific Elasticities and Substitutability Back

Ride-share should be an easy case: co-located competitors, near-identical work, real-time multi-apping, salient pay

- Dube et al. (2020): substantial monopsony power on MTurk, many requesters
- There the alternative is a *differentiated task*; here it is the *same job at a near-identical firm*
- Adjustment still costly — hence a market for paid switching tools

Same mechanism: firm-specific labor supply rises in the substitutability of outside options.

Earnings Accelerator Offer Back

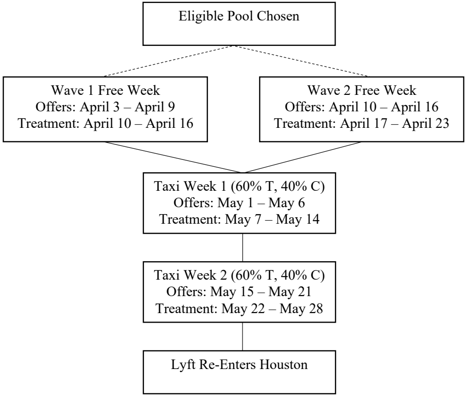
Celebrate spring with no Uber Fee

To celebrate spring, we're offering a new earnings opportunity: the ***Earnings Accelerator***. Opt in by clicking the button below by Saturday, April 8 at 11:59pm, and you'll keep the Uber Fee on ***every*** trip between Monday, April 10 and Sunday, April 16. (That's a 39% higher payout!)

CLAIM YOUR OFFER →

Experiment Timeline

Back



Randomization Balance Back

	Boston		Houston Experiments			
			Experiment 1		Experiment 2	
	Sample Mean (1)	Week 1-2 Balance (2)	Wave 1- Wave 2 (3)	Taxi Treated-Control (4)	Sample Mean (5)	Treatment-Control (6)
Female	0.14	-0.02	0.02	0.01	0.39	0.01
		(0.019)	(0.020)	(0.017)		(0.020)
Months on Platform	11.14	-0.01	0.30	0.06	8.75	-0.19
		(0.250)	(0.212)	(0.184)		(0.250)
Vehicle Solutions	0.08	-0.00	0.01	-0.01	0.08	0.01
		(0.016)	(0.014)	(0.013)		(0.012)
Vehicle Year	2009.27	0.13	0.03	-0.10	2013.63	0.07
		(0.192)	(0.111)	(0.096)		(0.119)
Prior Week Hours	13.87	-0.01	-0.37	-0.52	14.82	0.71
		(0.690)	(0.565)	(0.619)		(0.619)
Prior Week Earnings	242.90	-2.92	-6.88	-9.69	205.76	3.75
		(12.325)	(8.973)	(8.942)		(8.444)
F-statistic		0.48	0.70	0.48		0.82
p-value from F-test		0.82	0.65	0.83		0.55
Observations		1,600	2,020	2,710		2,100

Taxi Treatments and Opt-In

Back

	20% Fee Class			28% Fee Class		
Bandwidth (1)	Lease (2)	Treatment Fraction (3)	Opt-In Rate (4)	Lease (5)	Treatment Fraction (6)	Opt-In Rate (7)
Week 1						
Very High	\$100	60%	36%	\$120	60%	36%
High	\$40	60%	47%	\$50	60%	46%
Low	\$15	60%	47%	\$15	60%	52%
Week 2						
Very High	\$65	60%	47%	\$90	60%	39%
High	\$35	60%	45%	\$35	60%	46%
Low	\$10	60%	57%	\$10	60%	52%

Extra weeks of higher pay for an up-front payment, like a taxi lease.

Pay Statement

Back

Weekly Earnings

Trip Earnings	**$19.34**
Fare	$24.12
Uber Fee	- $6.03
Toll	+ $1.25
Estimated Payout	**$19.34**

Timing Back

	Before Wave 1		Treatment Weeks		After Wave 2	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. $\mathbf{1}\{\text{Drive}\}$					
Treated	-0.014	-0.015	0.033***	0.033***	0.012	0.012
	(0.018)	(0.018)	(0.008)	(0.008)	(0.022)	(0.022)
Observations	2,020	2,020	4,040	4,040	1,355	1,355
	Panel B. $\log(\text{Hours})$					
Treated	-0.040	-0.037	0.087***	0.089***	0.032	0.032
	(0.037)	(0.037)	(0.022)	(0.022)	(0.044)	(0.044)
Observations	1,554	1,554	2,998	2,998	1,066	1,066
Strata Dummies	✓	✓	✓	✓	✓	✓
Baseline Covariates		✓		✓		✓

Fares as the Dependent Variable Back

	$\mathbf{1}\{\text{Earn}\}$	Log(Fares)		Poisson Model	
	(1)	(2)	(3)	(4)	(5)
Panel A. Just-Identified Model					
Male	0.11	0.25	0.45***	0.26*	0.43***
	(0.09)	(0.16)	(0.15)	(0.15)	(0.12)
Female	0.24***	0.61***	1.01***	0.68***	0.91***
	(0.07)	(0.13)	(0.12)	(0.11)	(0.10)
p-value (equal)	[0.290]	[0.080]	[0.005]	[0.022]	[0.002]
Observations	3,108	2,715	4,581	3,108	5,154
Panel B. Over-Identified Model					
Male	0.14	0.25	0.43***	0.32	0.36*
	(0.09)	(0.17)	(0.16)	(0.22)	(0.20)
Female	0.31***	0.52***	0.90***	0.71***	0.84***
	(0.07)	(0.13)	(0.13)	(0.16)	(0.15)
p-value (equal)	[0.164]	[0.218]	[0.025]	[0.159]	[0.047]
First Stage F: Male	212	213	80	–	–
First Stage F: Female	417	533	177	–	–
Observations	4,040	2,944	4,954	4,040	6,750
Fee-Free Driving Data	✓	✓	✓	✓	✓
Taxi Data			✓		✓
Strata Dummies	✓	✓	✓	✓	✓
Baseline Covariates (Panel A)	✓	✓	✓	✓	✓

Alternative Specifications Back

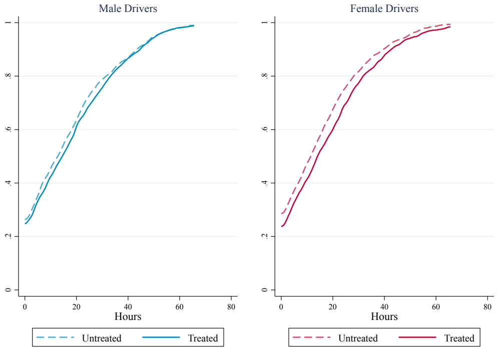
	$\mathbf{1}\{\text{Drive}\}$	log(Hours)				Poisson Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Just-Identified Model							
Male	0.13	0.47*	0.30*	0.61***	0.47***	0.39*	0.55***
	(0.09)	(0.24)	(0.16)	(0.19)	(0.15)	(0.21)	(0.18)
Female	0.29***	0.62***	0.46***	0.95***	0.86***	0.66***	0.90***
	(0.07)	(0.16)	(0.12)	(0.14)	(0.13)	(0.15)	(0.15)
p-value (equal)	[0.179]	[0.600]	[0.417]	[0.148]	[0.048]	[0.307]	[0.140]
Observations	4,040	2,998	2,998	5,031	5,031	4,040	6,746
Panel B. Strata Only							
Male	0.12	0.40*	0.28*	0.55***	0.41***	0.37*	0.39**
	(0.09)	(0.23)	(0.16)	(0.19)	(0.15)	(0.21)	(0.19)
Female	0.31***	0.57***	0.45***	0.93***	0.80***	0.65***	0.75***
	(0.07)	(0.16)	(0.12)	(0.14)	(0.12)	(0.15)	(0.15)
p-value (equal)	[0.115]	[0.544]	[0.413]	[0.091]	[0.043]	[0.285]	[0.118]
Observations	4,040	2,998	2,998	5,031	5,031	4,040	6,750
Endogenous Variable	$\log(1-\kappa)$	$\log(W)$	$\log(1-\kappa)$	$\log(W)$	$\log(1-\kappa)$	$\log(1-\kappa)$	$\log(1-\kappa)$
Fee-Free Driving Data	✓	✓	✓	✓	✓	✓	✓
Taxi Data				✓	✓		✓
Strata Dummies	✓	✓	✓	✓	✓	✓	✓

Non-Experimental (OLS) Estimates Back

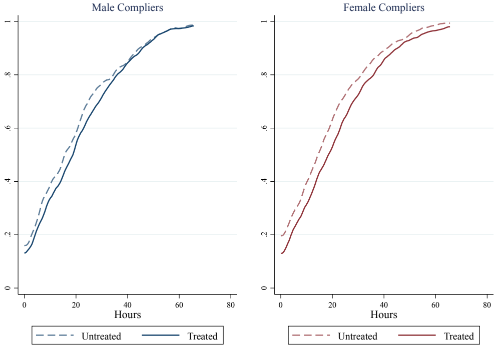
	Non-Experimental Weeks			Experimental Weeks		
	(1)	(2)	(3)	(4)	(5)	(6)
	A. OLS					
Log(W)	0.13**	0.11*	0.16***	0.20***	0.20***	0.23***
	(0.06)	(0.06)	(0.04)	(0.07)	(0.07)	(0.05)
Observations	9,870	9,870	7,651	5,031	5,031	4,648
	B. 2SLS (Leave-One-Out Log W)					
Log(W)	-0.07	-0.07	0.08	1.90***	1.90***	2.28***
	(0.08)	(0.08)	(0.07)	(0.39)	(0.39)	(0.41)
Observations	9,870	9,870	7,651	5,031	5,031	4,648
Months on Uber		✓	✓		✓	✓
Lag of Log(Hours)			✓			✓

Treatment Shifts the Hours Distribution Back

Treated vs. control



Compliers (Abadie, 2002)

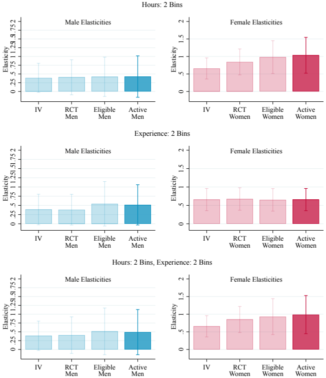


Heterogeneity in Market-Level Elasticities

Back

	By Months on Platform		By Age		Time of Day			By Hours Strata			
	Top 1/2	Bottom 1/2	$\leq$35	$>$35	Late Night	Weekend	School Pick-Up	Low	High	Very High	"Full Time"
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A. $\mathbf{1}\{\text{Drive}\}$ (2SLS Model)											
Male	0.09	0.17	0.06	0.11	0.02	-0.15	0.13	0.10	0.25	0.02	0.01
	(0.10)	(0.17)	(0.17)	(0.10)	(0.20)	(0.25)	(0.10)	(0.22)	(0.17)	(0.08)	(0.10)
Female	0.24*	0.27***	0.35*	0.23***	0.53***	0.92***	0.24***	0.49**	0.41***	0.04	-0.01
	(0.13)	(0.08)	(0.20)	(0.07)	(0.18)	(0.30)	(0.08)	(0.23)	(0.12)	(0.07)	(0.07)
Observations	1,620	1,488	834	2,270	484	426	1,698	818	1,072	1,218	828
Panel B. Poisson Model											
Male	0.55***	0.49**	0.22	0.38***	0.61*	0.83*	0.36**	0.52*	0.63***	0.16	0.12
	(0.18)	(0.21)	(0.23)	(0.14)	(0.35)	(0.47)	(0.14)	(0.31)	(0.24)	(0.15)	(0.17)
Female	1.01***	0.61***	0.69***	0.70***	1.06***	1.23***	0.51***	1.16***	0.90***	0.46***	0.32**
	(0.21)	(0.11)	(0.22)	(0.11)	(0.25)	(0.34)	(0.13)	(0.25)	(0.17)	(0.13)	(0.15)
Observations	2,653	2,501	1,344	3,800	811	707	2,812	1,341	1,765	2,048	1,409

Reweighting to the Driver Population Widens the Gap Back



Female 0.85 $\rightarrow$ 0.99, male 0.41 $\rightarrow$ 0.49; gap 0.44 $\rightarrow$ 0.50.

Complier Characteristics Back

	Male Drivers		Female Drivers		
	$E[X]$	$\frac{E[X \mid D_{i1} > D_{i0}]}{E[X]}$	$E[X]$	$\frac{E[X \mid D_{i1} > D_{i0}]}{E[X]}$	p-value
	(1)	(2)	(3)	(4)	(5)
Age	43.84	1.00	44.27	1.02	0.44
Months Since Signup	20.09	0.99	12.22	1.02	$<.01$
Vehicle Solutions	0.09	1.06	0.15	1.12	$<.01$
Commission	24.17	1.00	26.53	1.00	$<.01$
Usual Hours Worked (Pre-Selection)					
Mean	20.67	1.03	18.62	1.05	$<.01$
Between 0 and 5	0.11	0.70	0.11	0.76	0.75
Between 5 and 15	0.31	1.05	0.35	0.96	0.05
Between 15 and 25	0.28	1.02	0.26	1.04	0.53
Between 25 and 35	0.12	1.11	0.17	1.10	$<.01$
Between 35 and 45	0.10	0.99	0.07	1.11	$<.01$
Over 45	0.08	1.03	0.04	1.08	$<.01$

Houston Uber vs. Houston Taxi Drivers Back

	Houston Uber Drivers		Houston Drivers (ACS)		Houston Taxi (ACS)	
	Male (1)	Female (2)	Male (3)	Female (4)	Male (5)	Female (6)
Age	44.0	44.3	45.0	44.1	43.6	42.5
Vehicle Year	2013.0	2013.4	–	–	–	–
Months on Platform	12.7	9.8	–	–	–	–
Usual Hours Worked						
Mean	18.9	10.3	45.3	36.7	42.1	34.8
Between 0 and 5	0.30	0.44	0.00	0.01	0.00	0.01
Between 5 and 15	0.28	0.33	0.03	0.05	0.08	0.14
Between 15 and 25	0.15	0.13	0.05	0.12	0.06	0.22
Between 25 and 35	0.10	0.06	0.07	0.22	0.11	0.08
Between 35 and 45	0.07	0.03	0.46	0.42	0.44	0.31
Over 45	0.10	0.02	0.40	0.17	0.30	0.24

Shifters vs. Non-Shifters: Balance Back

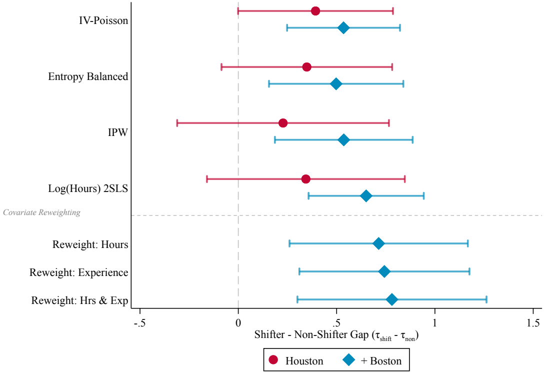
	All Experiments				Houston Only		
	Non-Shifter Mean (1)	Shifter Mean (2)	Raw Difference (3)	Adjusted Difference (4)	Houston 1 Mean (5)	Houston 2 Mean (6)	Difference (7)
Female	0.48	0.30	-0.18***	0.00	0.52	0.41	-0.11***
			(0.013)	(0.027)			(0.016)
Months on Platform	15.48	9.54	-5.94***	1.33**	16.02	8.31	-7.72***
			(0.268)	(0.574)			(0.307)
Vehicle Solutions	0.11	0.08	-0.03***	0.09***	0.12	0.07	-0.05***
			(0.008)	(0.008)			(0.009)
Vehicle Year	2012.55	2012.81	0.26**	—†	2013.55	2013.61	0.06
			(0.102)				(0.083)
Prior Week Hours	17.86	14.34	-3.52***	0.97	18.33	14.58	-3.75***
			(0.453)	(0.962)			(0.536)
Prior Week Earnings	239.69	220.11	-19.59***	17.63	240.90	202.62	-38.28***
			(6.433)	(17.897)			(7.247)
Joint F-statistic			167.50				145.85
p-value			0.000				0.000
Drivers	2,171	3,409			1,976	2,004	

Shifter First Stage

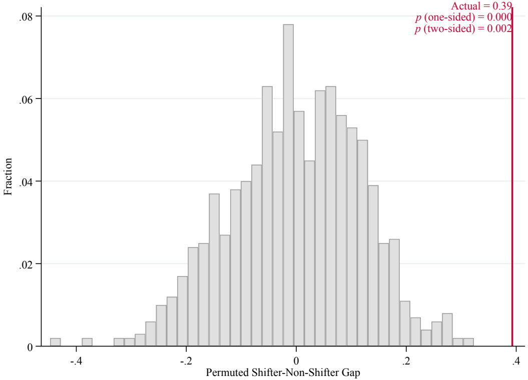
Back

	Offered $\log(1-\kappa)$	$\mathbf{1}\{\text{Accepted}\}$	$\log(1-\kappa)$	$\log(W)$
	(1)	(2)	(3)	(4)
Treated	0.24***	0.65***	0.16***	0.18***
	(0.001)	(0.010)	(0.002)	(0.010)
Observations	4,910	4,910	4,910	3,730
Strata Dummies	✓	✓	✓	✓

Adjusted Shifter–Non-Shifter Gaps Back



Permutation Inference Back



Propensity-Score Reweighting Back

	Propensity Score Quartile				Reweighted
	Q1	Q2	Q3	Q4	Estimate
Non-Shifter (τ_{non})	0.44***	0.67***	0.44	-0.00	0.35***
	(0.13)	(0.22)	(0.54)	(0.41)	(0.07)
Shifter (τ_{shift})	0.92***	0.79**	1.32***	1.28***	0.75***
	(0.31)	(0.36)	(0.30)	(0.19)	(0.12)
$\tau_{\text{shift}} - \tau_{\text{non}}$	0.49	0.12	0.88	1.28**	0.40***
	(0.37)	(0.51)	(0.61)	(0.50)	(0.13)
Observations	2,063	1,756	1,653	1,704	7,158

Alternative Specifications, Shifter Gap Back

	Pooled		Male		Female	
	$\mathbf{1}\{\text{Drive}\}$	Log(Hours)	$\mathbf{1}\{\text{Drive}\}$	Log(Hours)	$\mathbf{1}\{\text{Drive}\}$	Log(Hours)
	(1)	(2)	(3)	(4)	(5)	(6)
Just-Identified Model						
Non-Shifter	0.25***	0.38***	0.18**	0.27*	0.30***	0.46***
	(0.06)	(0.09)	(0.09)	(0.15)	(0.07)	(0.12)
Shifter	0.20	1.03***	-0.00	1.16***	0.51*	0.68***
	(0.18)	(0.13)	(0.23)	(0.14)	(0.28)	(0.26)
Shifter – Non-Shifter	-0.05	0.65***	-0.18	0.89***	0.21	0.22
	(0.18)	(0.16)	(0.25)	(0.21)	(0.29)	(0.28)
Observations	6,140	7,026	3,227	4,598	2,913	2,428
Strata Only						
Non-Shifter	0.23***	0.39***	0.14	0.30*	0.30***	0.47***
	(0.06)	(0.10)	(0.09)	(0.16)	(0.07)	(0.12)
Shifter	0.20	1.02***	0.01	1.14***	0.51*	0.69***
	(0.17)	(0.12)	(0.23)	(0.14)	(0.28)	(0.25)
Shifter – Non-Shifter	-0.03	0.63***	-0.13	0.85***	0.21	0.23
	(0.18)	(0.16)	(0.24)	(0.21)	(0.29)	(0.28)
Observations	6,140	7,026	3,227	4,598	2,913	2,428
Houston EA	✓	✓	✓	✓	✓	✓
Boston EA		✓		✓		✓

Complier-Mean Elasticities Back

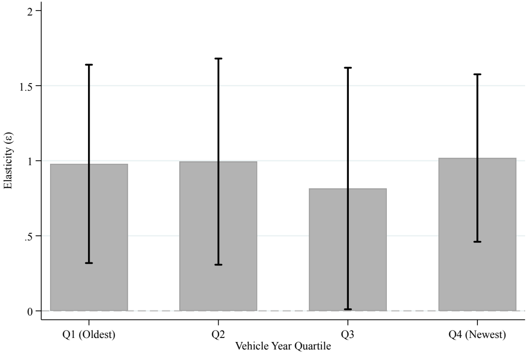
	Complier Hours			Impact & Elasticity		
	Untreated Mean	Treated Mean	% Increase	Impact on $\log(1-\kappa)$	Implied τ_{non} or τ_{shift}	Implied σ
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Shifter	18.81	21.74	16%	0.30***	0.53	
	(0.59)	(0.46)		(0.002)		
Shifter	14.50	18.77	29%	0.24***	1.21	8.45
	(0.48)	(0.39)		(0.001)		
Male						
Non-Shifter	20.47	22.62	11%	0.28***	0.38	
	(1.00)	(0.71)		(0.003)		
Shifter	15.94	20.47	28%	0.25***	1.16	9.95
	(0.59)	(0.45)		(0.001)		
Female						
Non-Shifter	17.52	21.12	21%	0.31***	0.67	
	(0.69)	(0.60)		(0.002)		
Shifter	10.53	14.16	35%	0.24***	1.45	9.68
	(0.74)	(0.70)		(0.003)		

Placebo: Vehicle Age When Lyft Is Absent Back

	$\mathbf{1}\{\text{Drive}\}$	log(Hours)		IV-Tobit	Poisson
	(1)	(2)	(3)	(4)	(5)
Pseudo Non-Shifter	0.15^{**}	0.39^{***}	0.69^{***}	0.95^{***}	0.44^{***}
	(0.07)	(0.14)	(0.15)	(0.28)	(0.14)
Pseudo Shifter	0.14^{***}	0.44^{***}	0.69^{***}	0.97^{***}	0.50^{***}
	(0.05)	(0.11)	(0.11)	(0.21)	(0.11)
p-value (equal)	[0.921]	[0.790]	[0.985]	[0.936]	[0.752]
Observations	3,108	2,766	4,650	3,108	3,108
Fee-Free Driving Data	✓	✓	✓	✓	✓
Taxi Data			✓		
Strata Dummies	✓	✓	✓	✓	✓
Baseline Covariates	✓	✓	✓	✓	✓

Pseudo-shifter and pseudo-non-shifter elasticities are indistinguishable ($p > 0.75$ throughout).

Vehicle-Year Gradient (Placebo) Back



Houston Spring 2017 (Lyft absent). Whiskers = 95% CI.
Joint test of equal elasticities: p = 0.98

Flat across quartiles; $p = 0.98$ for joint equality.

Markdown Sensitivity Back

	2SLS				Poisson			
Calibration anchor ϕ_0	0.67	0.72	0.83	0.93	0.67	0.72	0.83	0.93
Panel A: Inputs								
τ_{non} (non-shifter elasticity)	0.42				0.47			
Non-shifter markdown	70.2%				67.8%			
$\varepsilon + \lvert\sigma\rvert$ (calibrated at ϕ_0)	0.79	1.00	1.90	5.17	0.80	1.01	1.92	5.22
Panel B: Shifter Markdown at ϕ, by Calibration Anchor								
$\phi = 0.67$	55.1%	52.1%	42.3%	25.2%	53.5%	50.7%	41.3%	24.7%
$\phi = 0.72$	57.7%	55.1%	46.2%	29.1%	56.0%	53.5%	45.0%	28.5%
$\phi = 0.83$	63.0%	61.4%	55.1%	40.2%	61.0%	59.5%	53.5%	39.3%
$\phi = 0.93$	67.4%	66.7%	63.8%	55.1%	65.1%	64.5%	61.8%	53.5%

The Individual Driver Bonus
Back

An Uber-run promotion in San Francisco — independent variation

- Lump-sum bonus for exceeding a trip threshold $\Rightarrow$ notch in the budget set $\hookrightarrow$
- Random assignment to high vs. low bonus within 8 strata; 58,928 drivers
- Shifters $=$ vehicle model year 2004$+$ (Lyft-eligible in SF)

Lyft access varies across drivers in the same city at the same time — the Houston contrast varies across time

Estimates Bunching Balance

IDB: Shifters Are More Elastic

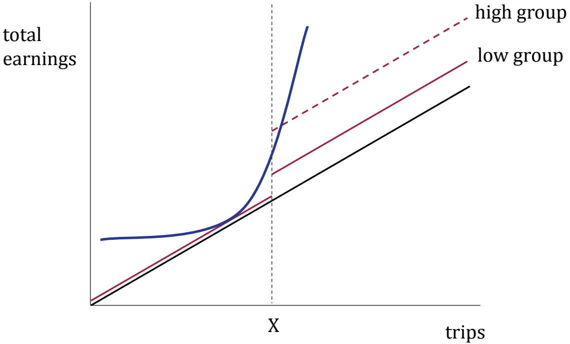
Back

	(1)	(2)	(3)	(4)	(5)
Non-Shifter	0.602*	0.419	0.859**	0.895***	0.916**
	(0.364)	(0.283)	(0.400)	(0.182)	(0.359)
Shifter	1.100***	1.062***	1.399***	1.349***	1.314***
	(0.188)	(0.177)	(0.210)	(0.174)	(0.178)
Shifter – Non-Shifter	0.498	0.643**	0.539	0.454*	0.398
	(0.416)	(0.327)	(0.443)	(0.267)	(0.399)
Elasticities	216	216	227	221	220
Driver-Periods	878,323	878,323	965,714	943,769	934,926
Threshold Dummies	✓	✓	✓	✓	✓
Sample-Size Weighted	✓		✓	✓	✓
Width	50	50	50	100	100
Degree	3	3	3	3	4
Excluded Bins	4	4	3	3	3

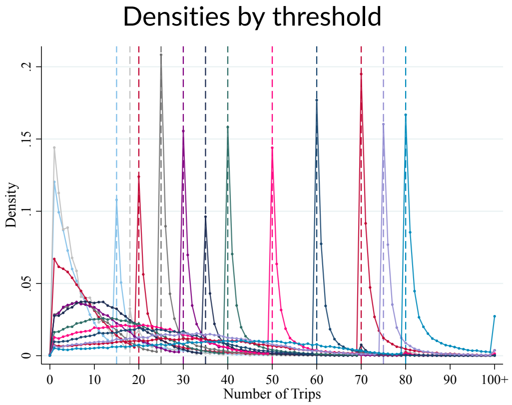
Non-shifters 0.60, shifters 1.10; gap 0.50 (bootstrap SE 0.42).

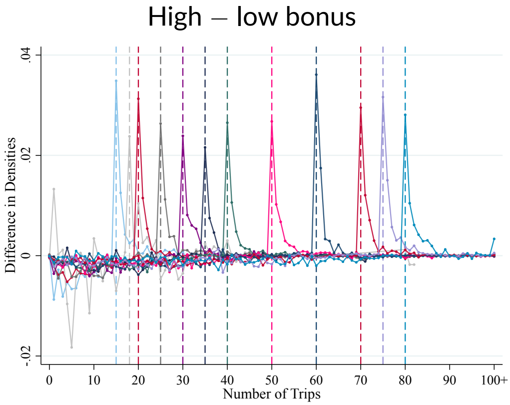
IDB Budget Sets

Back



Bunching in the IDB Back





IDB Balance Back

	Control Mean (1)	Difference (2)
Female	0.14	-0.000 (0.001)
Experience (months)	18.75	0.010 (0.027)
Vehicle Year	2013.79	0.001 (0.006)
Lag Trips	30.33	0.021 (0.048)
Lag Earnings ($)	350.86	-0.107 (0.586)
Previously Treated	0.50	0.000 (0.001)
F-statistic		1.07
p-value		[0.378]
Unique Drivers	55,671 (control), 58,928 (total)	
Observations	513,356 (control), 1,036,336 (total)	

How to Multi-App

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How to run the apps at the same time

Once you have everything set up you will need to actually open and run both apps at the same time. This is pretty easy for the most part, but there are a few tricks that will help you out.

First, close out any apps you have open. Driving for Lyft and Uber at the same time requires you to keep both apps open until you get a request, which puts quite a bit of strain on your phone, sucks the battery dry, and uses a ton of data in the process. So bring a charger, stay on task, and be prepared to pull down a lot of data. And I mean, a TON.

Second, try to minimize surfing the web or being active on social media. Keep in mind you have two apps that are constantly talking to their respective platforms, so the chance of your phone crashing or glitching out becomes much higher than usual. The last thing you want is to get a ride request and have your phone freeze up or crash, costing you both time and money.

It is also worth noting that when you have both of the apps open, you will need to have Uber open on the main screen, with Lyft running in the background behind it. Uber will automatically close out after a minute or two if it is running in the background, but Lyft will stay open.

Accepting ride requests

When you get a ride request, make sure to accept one and immediately log right out of the other. It won't take long to get a ride request, and on a busy night you may get two at the same time. If this happens, pick the once closest to you and decline the other. As every driver knows, the best way to make money is in volume, and the less dead miles you have, the better.