Financing the Gig Economy

Greg Buchak[1]

Presenter: Xiangqing Wang (WISE), Jifan Wu (CHOW)

May 21, 2024

[1] Graduate School of Business, Stanford University

Outline

Outline

Background

- Firms like UBER, LYFT, AND AIRBNB have created convenient markets for households to sell capital services with their **durable consumption goods**.
- Individuals could joined the so-called **gig economy** in droves as drivers, delivery people, and hosts.
- Key distinguishing characteristics:
  - Gig economy workers provide and finance their own physical capital
  - Households can use one asset for two purposes: **durable consumption** and **capital income**
  - At the cost of requiring that households finance the capital
- Ride-sharing drivers are largely financially constrianed.

This paper: figure out the importance of financing in gig economy

Main Findings

Reduced-Form

- Entry leads to a 1.6% increase in new auto sales, a 0.60% increase in employment, and among low-income individuals with ride-share-eligible vehicles, an additional 2,000 miles driven per year
- Financing: auto loan originations increase by 1%

Main Findings

Structural-Model

- Rideshare entry led to **large welfare gains** of roughly $25 billion annually among potential drivers and roughly $30 billion annually among riders
- Counterfactually eliminating the need for financing leads to ride quantity and welfare increases on the order of less than 1%
- Counterfactually without finance, equilibrium ride quantities would be 40% lower and prices 90% higher, and only higher-income households could participate as drivers
- Counterfactually allowing car owners to hire minimum-wage drivers to use their cars could reduce ride-share prices by 12% and increases quantities by 7%, leading to aggregate welfare gains

Contributions

- Highlights and quantifies important costs and benefits of ride-share entry
- Help explain why techonologies **allowing durable consumption goods** to be used to produce capital income (such as Airbnb) have succeeded, while other seemingly similar technologies that do not (such as WeWork) haven't succeeded
- Hightlights the important role of **consumer finance**
  - Financial system was largely effective in allocating physical capital
  - Allowing car owners to hire drivers to use their cars leads to aggreagte welfare gains

Related Literature

1. Household and coporate finance(*Egan et al. (2017), Benetton and Fantino (2021), Benetton (2021), Buchak et al. (2018a), and Di Maggio et al. (2022), Campbell (2006), etc.*)
   - This paper: focus on consumers who **finance the capital good** for production
2. Financial system for growth and finance for productivity (*Mian et al. (2017), Kaplan and Zingales (1997), Jayaratne and Strahan (1996), Hsieh and Klenow (2009), Lenzu and Manaresi (2018), Buera et al. (2011), Midrigan and Xu (2014)*)
   - This paper: highlighting the importance of ex ante factor misallocation when a disruptive technological change is introduced that impacts how capital can be used
3. Impact of ride share platform (*Cohen et al. (2016), Cramer and Krueger (2016), Calder-Wang (2021) Hall et al. (2017), Benjaafar et al. (2022), Cook et al. (2021), Cook et al. (2019), and Chen et al. (2019) Barrios et al. (2023)*)
   - This paper: on the benefits of **dual asset use** and **consumer finance**

Outline

Institutional Background

- Uber began operations in San Francisco in 2010, with Lyft following shortly thereafter
- Both services expanded rapidly to other cities. By the end of 2016, there were nearly 800,000 registered Uber drivers
- **Ride-share entry is not random**, which may cause an identification challenge
  - Entry is more likely in **large cities** with high mobile broadband penetration, suggesting that these services entered areas with **large potential markets**
  - **Vehicle ownership rates** or **access to finance** do not predict entry

▸ Figure of Entry Time

▸ Regression Table

Data

For Reduced-Form Estimation

- Staggered entry dates of Uber and Lyft
- Number of registered drivers
- Auto sales, auto loans, vechile utilization (registration)
  - Vechile data is merged with physical attributes of each car
- Individual's borrowing activity (Employment) and past bankruptcy filings

For Structual Estimation

- Auto loan interest rates
- Market-level income of ride-share drivers
- Local demographic information

Selected Summary Statistics

Panel A: R.L. Polk and Equifax data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Sales	567,874	132.367	305.593	0	10	172	34,019
New originations	567,874	126.713	166.496	0	13	186	2,889
Outstanding loans	567,874	2,266.832	2,944.440	1	235	3,392	32,959
Sales per capita	567,874	0.011	0.017	0.000	0.006	0.013	0.988
New loans per capita	567,874	0.012	0.007	0.000	0.008	0.015	0.273
Outstanding loans per capita	567,874	0.208	0.091	0.0001	0.156	0.242	0.998

Panel B: DMV vehicle registration data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
New registrations	74,761	279.814	584.161	0	5	305	9,789
New eligible registrations	74,761	229.941	496.153	0	3	244	9,264
Percent eligible	63,972	0.789	0.140	0.000	0.747	0.852	1.000

Outline

Reduced-Form Estimation

- Empirical effects of ride-share entry on sales, employment, and vehicle utilization
  - Whether ride share's entry prompted lower-income households to **purchase cars**
  - Whether entry corresponded to increases in **vehicle utilization** and **employment**

Identification

$$Y_{zt} = \beta Post_{zt} + \gamma_t + \gamma_z + \epsilon_{zt} \quad (1)$$

$$Y_{zt} = \beta_1 Post_{zt} + \beta_2 Post_{zt} \times Low\ Income_z + \gamma_z + \gamma_{Income,t} + \epsilon_{zt} \quad (2)$$

Notation:

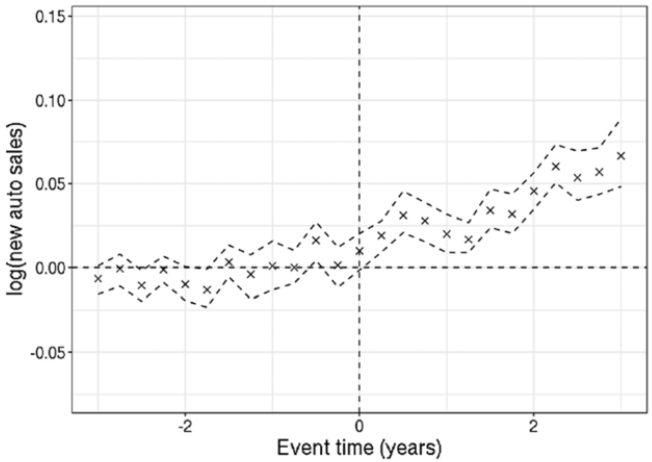
- Y_{zt}: the outcome variable of interest at ZIP z and time t
- $Post_{zt}$: an indicator for ride-share entry
- $Low\ Income_z$: an indicator for whether the ZIP code's median income is in the bottom 50% of ZIP codes in the MSA
- γ_z: ZIP fixed effects
- $\gamma_t, \gamma_{Income,t}$: quarter fixed effects and quarter $\times Low\ Income_z$ fixed effects

Log Auto Sales

Panel A: New Nationwide Auto Sales, R.L. Polk Data

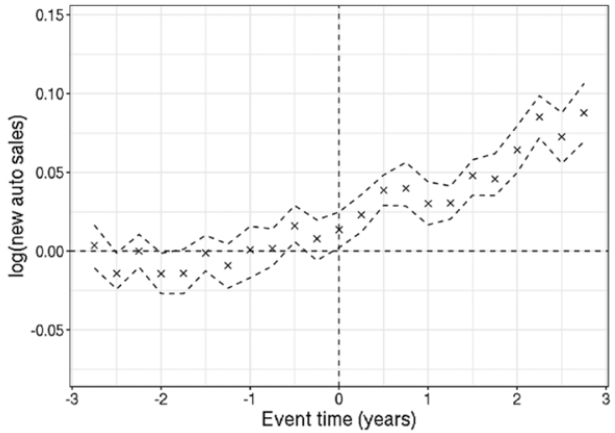
	Log Sales		
	(1)	(2)	(3)
Post	0.016***	0.006***	0.004
	(0.002)	(0.002)	(0.003)
Post × Low Income	–	0.020***	–
	–	(0.004)	–
Post × High Transport Share	–	–	0.025***
	–	–	(0.004)
ZIP fixed effects (FE)	Y	Y	Y
Qtr FE	Y	N	N
Qtr × Low-income FE	N	Y	N
Qtr × High-transport FE	N	N	Y
Observations	244,153	244,153	244,153
R^2	0.971	0.972	0.972

Panel A: New auto sales

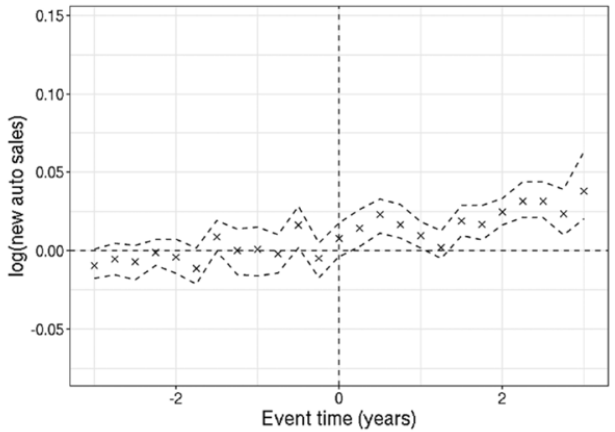


By Income

Panel C: Auto sales growth in low-income ZIPs



Panel E: Auto sales growth in high-income ZIPs



Log Auto Sales: Robustness

1. Vechile Eligibility
   - To be eligible for ride share, a vehicle must be no older than 15 years, have four doors, and be a sedan, SUV, or minivan.
   - Outcome: increases in vehicle registrations correspond entirely to eligible vehicles in low-income ZIP codes ▸ Event Study
2. ZIP-level income measure: wage $\Rightarrow$ 2010 transportation worker share
3. Placebo Test
   - Randomly assign the dates of ride-share entry across locations ▸ Placebo Test

Employment

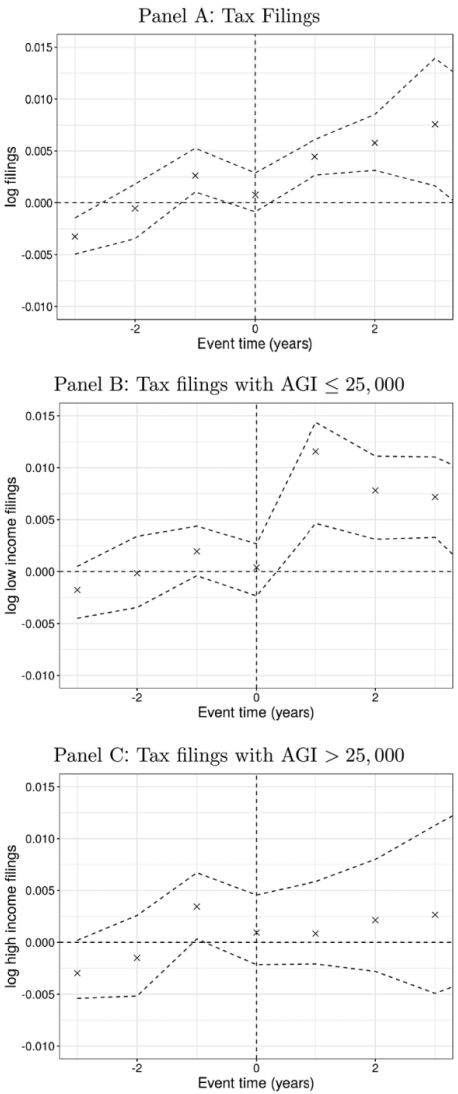
- Whether ride-share entry coincides with increases in low-income employment
- Outcome variable: log number of tax filings
- Low Income indicator: whether the AGI[2] bucket is below $25,000 per year[3]

	Log Filings		
	(1)	(2)	(3)
Post	0.006***	0.001	–
	(0.002)	(0.003)	–
Post × (AGI ≤ 25k)	–	0.011**	0.011**
	–	(0.004)	(0.004)
(AGI < 25k)×Year FE	Y	Y	Y
(AGI < 25k)×ZIP FE	Y	Y	Y
ZIP×Year FE	N	N	Y
Observations	172,127	172,127	172,127
R^2	0.996	0.996	0.998

[2] Adjusted Gross Income

[3] The $25,000 income level is the relevant threshold because full-time ride-share driving pays slightly below this level on average.

Employment: Event Study & Robustness



Robustness

- Outcome variable: log number of **total** tax filings ⇒ log number of **business income** tax filings[a]
- Placebo tests show no effect.

	Dependent variable:		
	log filings	log wage or salary filings	log business filings
	(1)	(2)	(3)
Post	0.003	0.003	0.013***
	(0.002)	(0.002)	(0.004)
ZIP FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	72,646	72,646	72,646
R^2	0.999	0.999	0.989
Residual Std. Error (df = 58,820)	0.041	0.040	0.165
Note:			*p<0.1; **p<0.05; ***p<0.01

[a]Ride-share drivers report earnings as business rather than wage income, which the IRS data report separately

Vechile Utilization

- Whether ride-share cars see higher utilization rates after entry

	Miles per Year (Thousands)					
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.175	−0.156	−1.033**	–	0.299	–
	(0.160)	(0.282)	(0.444)	–	(0.659)	–
Post × Low Income	–	0.381	–	–	−1.518**	–
	–	(0.279)	–	–	(0.605)	–
Post × Eligible	–	–	1.350***	1.186**	−0.561	−0.922
	–	–	(0.469)	(0.543)	(0.714)	(0.905)
Post × Low Income × Eligible	–	–	–	–	2.185***	2.372***
	–	–	–	–	(0.663)	(0.866)
ZIP × Eligible FE	Y	Y	Y	Y	Y	Y
Qtr × Eligible FE	Y	Y	Y	Y	Y	Y
ZIP × Quarter FE	N	N	N	Y	N	Y
Observations	129,215	129,190	129,215	129,215	129,190	129,190
R^2	0.036	0.036	0.036	0.158	0.036	0.158

- Vehicle utilization may not be an important factor in a consumer's decision to purchase a car for durable consumption

Financing Ride-Share Growth

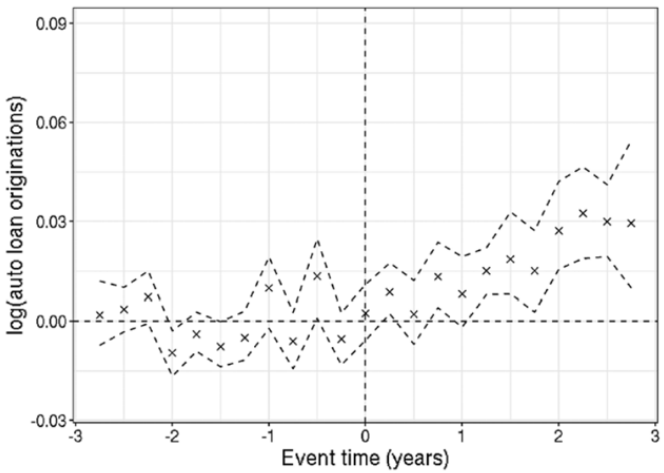
- How **auto lending** contributed to the real effects
- Whether **lack of access to finance** on the extensive margin inhibits gig economy growth

Log Auto Loans

Panel B: New Nationwide Auto Loan Originations, Equifax Data

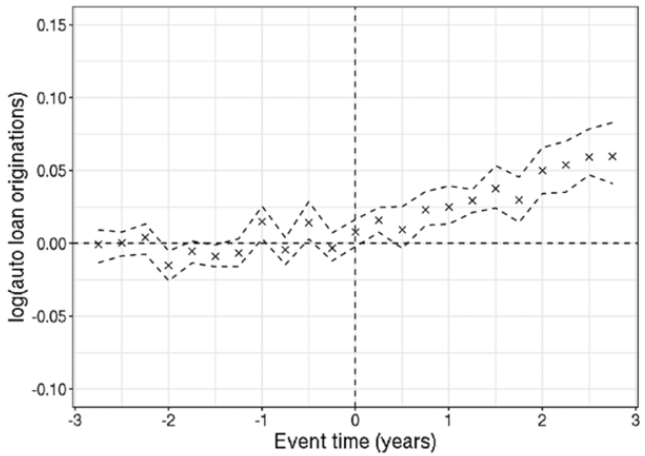
	Log New Originations		
	(1)	(2)	(3)
Post	0.010***	−0.001	−0.002
	(0.002)	(0.002)	(0.002)
Post × Low Income	–	0.021***	–
	–	(0.003)	–
Post × High Transport Share	–	–	0.024***
	–	–	(0.003)
ZIP FE	Y	Y	Y
Qtr FE	Y	N	N
Qtr × Low-wage FE	N	Y	N
Qtr × High-transport FE	N	N	Y
Observations	244,153	244,153	244,153
R^2	0.979	0.979	0.979

Panel B: New auto loan originations

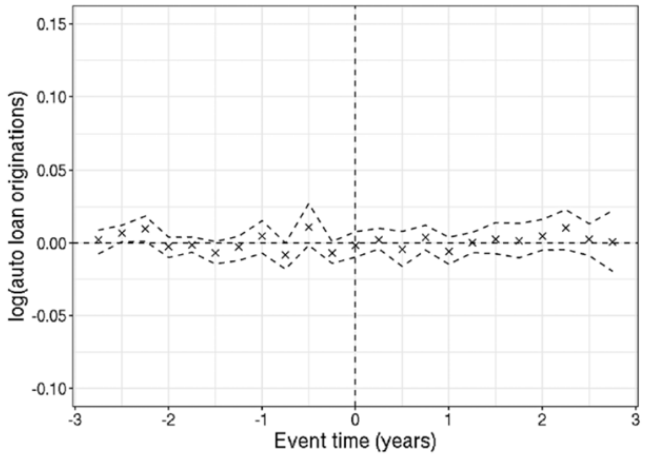


By Income

Panel D: Auto loan growth in low-income ZIPs



Panel F: Auto loan growth in high-income ZIPs



Direct Financial Constraint and Ride-Share Growth

Borrower-Level Analysis

- FCRA requires that credit agencies remove Chapter 7 bankruptcy filings[4] from credit reports 10 years after filing
- Serves as an exogenous variation in borrowing costs

[4] This chapter of the Bankruptcy Code provides for "liquidation" - the sale of a debtor's nonexempt property and the distribution of the proceeds to creditors.

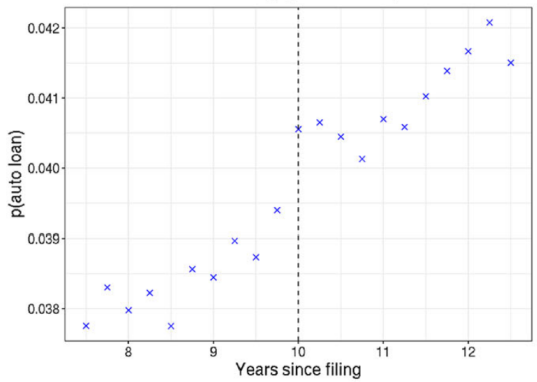
Borrower-Level: Exogeneity & Validity

$$Origination_{izt} = \beta \mathbf{I}(YearsSinceFiling \geq 10) + \gamma_{zt} + \epsilon_{izt} \quad (3)$$

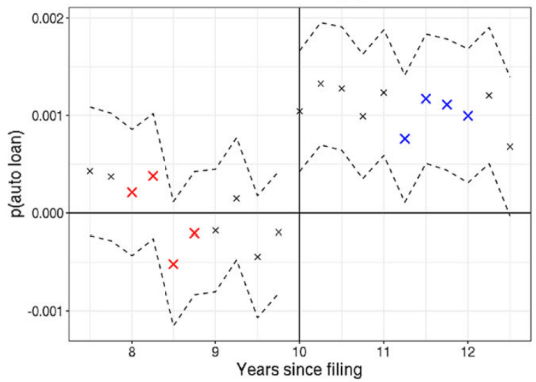
Panel A: Bankruptcy Flag and Auto Originations

	P(Auto Loan) (%)				
	(1)	(2)	(3)	(4)	(5)
Window (years)	±0.25	±0.50	±1.00	±1.50	±2.50
≥ 10 years	0.132***	0.149***	0.132***	0.136***	0.115***
	(0.032)	(0.021)	(0.015)	(0.012)	(0.010)
ZIP-Time FE	Y	Y	Y	Y	Y
Observations	2,052,307	4,021,994	7,799,010	11,303,095	17,332,333
R^2	0.228	0.146	0.091	0.068	0.049

Panel A:
Auto lending probability



Panel B:
Residualized auto lending probability



Borrower-Level Analysis

$$Origination_{izt} = \beta_1 Post_{zt} + \beta_2 Post_{zt} \times Constrained_i + \gamma_{gt} + \gamma_{gz} + \gamma_{zt} + \epsilon_{izt} \quad (4)$$

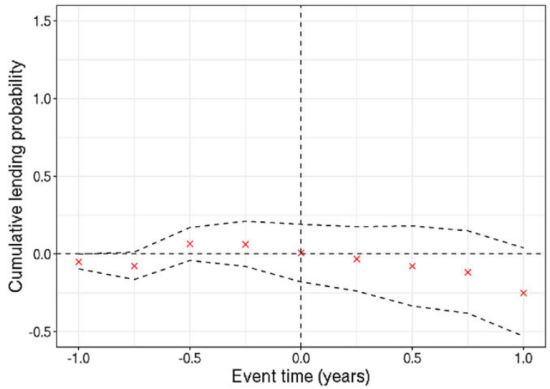
- $Constrain_i = 1$: filed for bankruptcy between 8 and 9 years prior to ride-share entry
- $Constrain_i = 0$: filed for bankruptcy between 11 and 12 years prior to ride-share entry

Borrower-Level Analysis

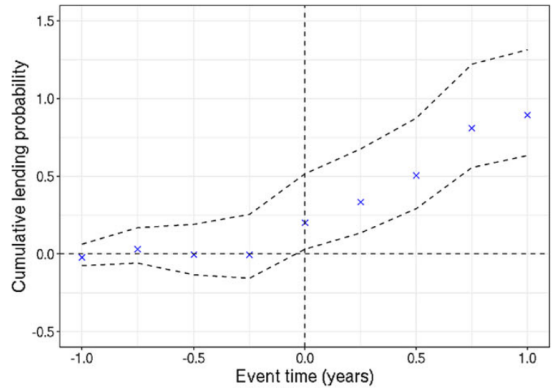
Panel B: Bankruptcy Flag Removal and Ride-Share Entry

	P(Auto Loan) (%)					
	Window = ±1 year			Window = ±0.50 years		
	(1)	(2)	(3)	(4)	(5)	(6)
Post_{zt}	0.085	0.243***	–	0.093	0.255**	–
	(0.059)	(0.083)	–	(0.081)	(0.109)	–
$\text{Post}_{zt} \times$ Constrained	–	−0.316**	−0.317**	–	−0.310*	−0.326*
	–	(0.128)	(0.142)	–	(0.171)	(0.197)
ZIP-Group FE	Y	Y	Y	Y	Y	Y
Date-Group FE	Y	Y	Y	Y	Y	Y
ZIP-Time FE	N	N	Y	N	N	Y
Observations	1,920,408	1,920,408	1,920,408	1,073,389	1,073,389	1,073,389
R^2	0.019	0.019	0.073	0.028	0.028	0.115

Panel C:
Cumulative auto lending for constrained borrowers



Panel D:
Cumulative auto lending for unconstrained borrower



Direct Financial Constraint and Ride-Share Growth

ZIP-Level Analysis

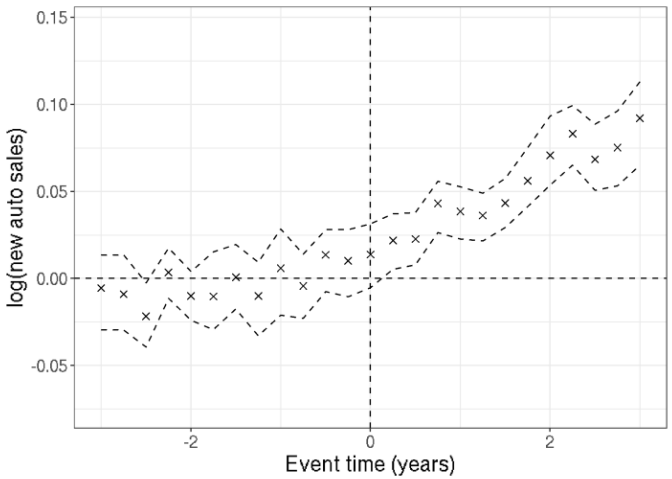
Whether variation in credit access leads to smaller real effects

- The share of consumer loans that became seriously delinquent in 2010 and
- The 2010 bank share of auto lending[5]

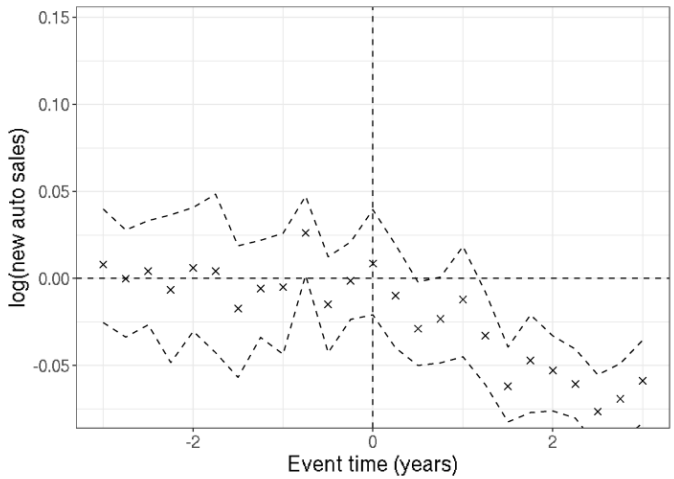
[5] Following the financial crisis, new banking regulations such as increased capital requirements and stricter supervision reduced banks' ability to lend

ZIP-Level Analysis: Auto Sales

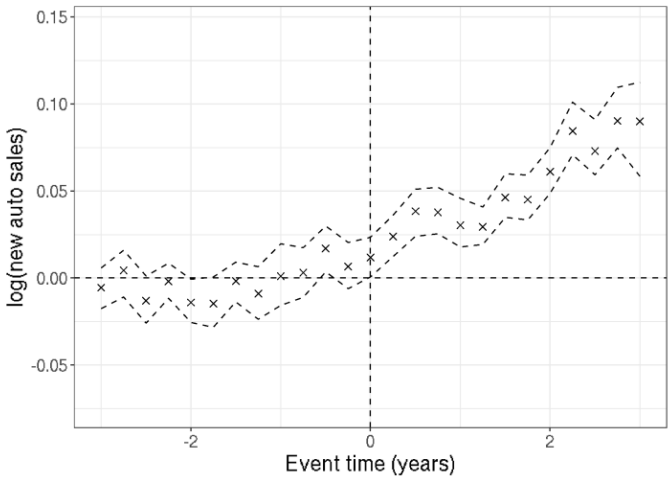
Panel A. Vehicle sales in low-bank ZIP codes



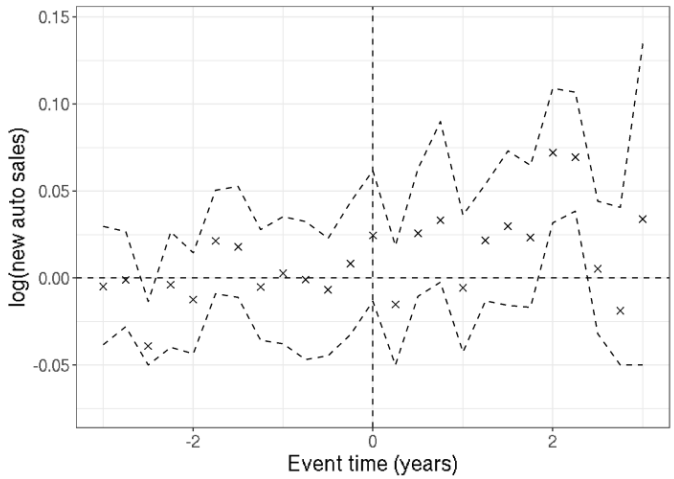
Panel B. Vehicle sales in high-bank ZIP codes



Panel C. Vehicle sales in low-default ZIP codes



Panel D. Vehicle sales in high-default ZIP codes



Outline

Structural Model

- Analyze the aggregate equilibrium effects of limiting access to finance on outcomes such as ride quantities, prices, welfare, and substitution patterns across the income distribution
- Examine the welfare and distributional impacts of a key technological limitation of gig economy production, namely, that workers must own the capital
- Model Setup
  - **Supply side:** discrete choice model added with financing and ride-share driving decisions to an individual's vechile ownership decision
  - **Demand side:** binary choice of whether to utlize the ride-share service

Ride-Share Supply

- A ride-share market $m \in \{1, ..., M\}$ is characterized by a distribution of individual demographics $F_m(D_i)$ and an indicator for ride share presence ϕ_i
- Individual i's demographics D_i map to preferences θ_i
- Individuals preferences determine the individual's three decisions
  1. whether to acquire a vehicle
  2. whether to finance the car or pay cash outright
  3. whether to become a ride-share driver

Individual's Problem: Indirect Utility

Individual i obtains utility from

- car ownership for durable consumption

$$u_c(\theta_i, \epsilon_i^c) = \beta_i^c + \epsilon_i^c \tag{5}$$

  - β_i^c: the value of car ownership relative to the outside option of not owning a car

- how the vehicle is financed (cash or loan)

$$u_f^{finance}(\theta_i, r_m, \epsilon_i^f) = -f_i^0 - \alpha_i^f r_m + \epsilon_i^f, \tag{6}$$

$$u_f^{cash} = 0 \tag{7}$$

  - f_i^0 captures financial constraints in reduced form; r_m is the market insterest rate on an auto loan
  - Individual is endowed with liquidity l_i, which serves as a threshold to loan

Individual's Problem: Indirect Utility

Individual i obtains utility from

- using the car for income producing activities

$$u_I^R(p_m, \theta_i, \epsilon_i^R) = \alpha_i(w^R(p_m) - w_i) + \gamma_i^R + \epsilon_i^R \tag{8}$$

$$u_I^T(p_m, \theta_i, \epsilon_i^T) = \alpha_i(w^T - w_i) + \gamma_i^T + \epsilon_i^T \tag{9}$$

$$u_I^0 = 0 \tag{10}$$

- $w^R(p)$: wage as a function of equilibrium ride-share price p
- w^T: prevailing wage for other transportation activities, assumed to be fixed
- w_i: individual's outside-option wage, assumed to be fixed
- α_i: individual's price sensitivity
- γ_i: nonmonetary net benefits like flexible hours

Individual's Problem: Optimal Solution

- Financing Choice

$$u_f^*(\theta_i, r_m, \epsilon_i^f) = \begin{cases} u_f^{finance}(\theta_i, r_m, \epsilon_i^f) & l_i < 0 \\ \mathbf{max}\{u_f^{finance}(\theta_i, r_m, \epsilon_i^f), 0\} & l_i \geq 0 \end{cases} \tag{11}$$

- Income-producing Choice

$$u_I^*(\mathbf{p}, \theta_i, \phi_m, \epsilon_i^R, \epsilon_i^T) \tag{12}$$

$$= \begin{cases} \mathbf{max}\{0, u_I^T(p_m, \theta_i, \epsilon_i^T)\} & \phi_m = 0 \\ \mathbf{max}\{0, u_I^T(p_m, \theta_i, \epsilon_i^T), u_I^R(p_m, \theta_i, \epsilon_i^R)\} & \phi_m = 1 \end{cases} \tag{13}$$

Assumption: ϵ_i follows a type-I extreme value distribution

Individual's Problem: Optimal Solution

- Car ownership choice

$$u(p_m, \theta_i, r_m, \phi_m, \epsilon_i^c) = u_c(\theta_i, \epsilon_i^c) + Eu_f(\theta_i) + Eu_I(p_m, \theta_i, \phi_m) + \epsilon_i^c \tag{14}$$

$$\mathbf{max}\{0, u(p_m, \theta_i, r_m, \phi_m, \epsilon_i^c)\} \tag{15}$$

Assumption: ϵ_i follows a type-I extreme value distribution

Aggregation

Assume the distribution of θ_i:

$$\theta_i = \bar{\theta} + (D_i - \bar{D})'\Pi \tag{16}$$

- $\bar{\theta}$: $n \times 1$ vector if preference means
- D_i: $d \times 1$ vector of individual demographics[6]
- Π: $n \times d$ matrix mapping demographics to characteristics Π governs

Key set of structral parameters: $\Theta = (\bar{\theta}, \Pi)$

[6] $D_i \sim F_m(D_i)$, measured directly in the data

Aggregation

The fraction of people purchasing a car

$$s_m^{own}(p_m, r_m, \phi_m; \Theta) = \int p(p_m, \theta_i, r_m, \phi_m) dF_m(\theta_i; \Theta) \tag{17}$$

Obtaining financing, becoming transportation workers, becoming ride-share drivers

$$s_m^f(r_m) = \int p(p_m, \theta_i, r_m, \phi_m) p_f(\theta_i, r_m) dF_m(\theta_i; \Theta) \tag{18}$$

$$s_m^T(p_m, \phi_m) = \int p(p_m, \theta_i, r_m, \phi_m) p_T(p_m, \theta_i, \phi_m) dF_m(\theta_i; \Theta) \tag{19}$$

$$s_m^R(p_m, \phi_m) = \int p(p_m, \theta_i, r_m, \phi_m) p_R(p_m, \theta_i, \phi_m) dF_m(\theta_i; \Theta) \tag{20}$$

Ride-Share Demand and Equilibrium

Assume: the aggregate demand has a logit form

- Individual's demand function:

$$q(p_m) = \frac{exp(\delta_m^0 - \delta_1 p_m)}{exp(\delta_m^0 - \delta_1 p_m) + 1} \tag{21}$$

  - δ_m^0: a market-specific constant
  - δ_1: the price sensitivity for ride-share services
- market demand: $q \times M$[7]
- market supply: $s_m^R(p_m, \phi_m) \times M$
- Producer Surplus

$$\int_i Eu(p_m, \theta_i, r_m, 1) - \int_i Eu(p_m, \theta_i, r_m, 0) \tag{22}$$

[7] M is the number of working-age adults

Estimation

- Methodology: GMM (minimizing the distance from moments in the model to their empirical analogs)
- Key parameters: the mapping between demographics D_i and individual preferences + the preference means
  1. The only relevant demographic characteristic is **outside-option income**
  2. Only β_i^c (consumption value of car ownership), l_i (access to liquidity) and f_i^0 (the presence of financial constraints) vary directly with income
  3. Normalize the variance of ϵ_i^c to be 1
- 12 parameters to estimate: $\bar{\theta} = \{\bar{\beta}^c, \bar{f}^0, \bar{\alpha}^f, \bar{l}, \bar{\alpha}, \bar{\gamma}^R, \bar{\gamma}^T\}$, $\Pi \equiv \{\pi^{\beta^c}, \pi^l, \pi^{f^0}\}$, $\Sigma \equiv \{\sigma^F, \sigma^I\}$

Estimation

Minimizing the distance from moments in the model to their empirical analogs

- Vechile sales $\rightarrow \bar{\beta}^c$
  ZIP codes vary in median incomes $\rightarrow \pi^{\beta^c}$
- Financing shares $\rightarrow \{\bar{f}^0, \bar{\alpha}^f, \bar{l}, \pi^{\beta^c}, \pi^l, \pi^{f^0}\}$
  - Instrument for interest rates using deposit-weighted bank capitalization in the ZIP code $\rightarrow \bar{\alpha}^f$
- Sales versus financing $\rightarrow \{\bar{f}^0, \bar{l}, \pi^{\beta^c}, \pi^l, \pi^{f^0}\}$
- Transportation worker and Uber driver share $\rightarrow \{\bar{\alpha}, \bar{\gamma}^R, \bar{\gamma}^T\}$
  - Instrument for transportation worker wages using the fraction of workers that walk or bike to work as of 2000
- Minimizing market-level residuals of predicted financing and transportation work $\rightarrow \{\sigma^F, \sigma^I\}$

Estimated Parameters

Panel A: Estimated Parameters

Parameter	Description	$\bar{\theta}$	Π
β^c	Own consumption value	3.50 (0.22)	2.35 (0.24)
f^0	Nonrate financial cost	−1.10 (0.25)	0.005 (0.22)
α^f	Rate sensitivity	0.91 (0.21)	–
l	Liquidity	0.44 (0.25)	1.31 (0.18)
γ^T	Other transportation work preference	−3.49 (0.02)	–
γ^R	Ride-share driving preference	−3.16 (0.01)	–
α	Wage sensitivity	0.06 (0.003)	–
σ^F	Financing shock variance	0.81 (0.10)	–
σ^I	Driving shock variance	0.41 (0.19)	–

Panel B: Other Parameters

Parameter	Description	Value	Source
ζ	Uber commission	0.25	Mishel (2018)
ξ	Booking fee	1.55	Mishel (2018)
$f(\delta^1)$	Demand elasticity	0.57	Cohen et al. (2016)

Model Validation

The change in vehicle sales and loans after ride share entry, both overall and by income level

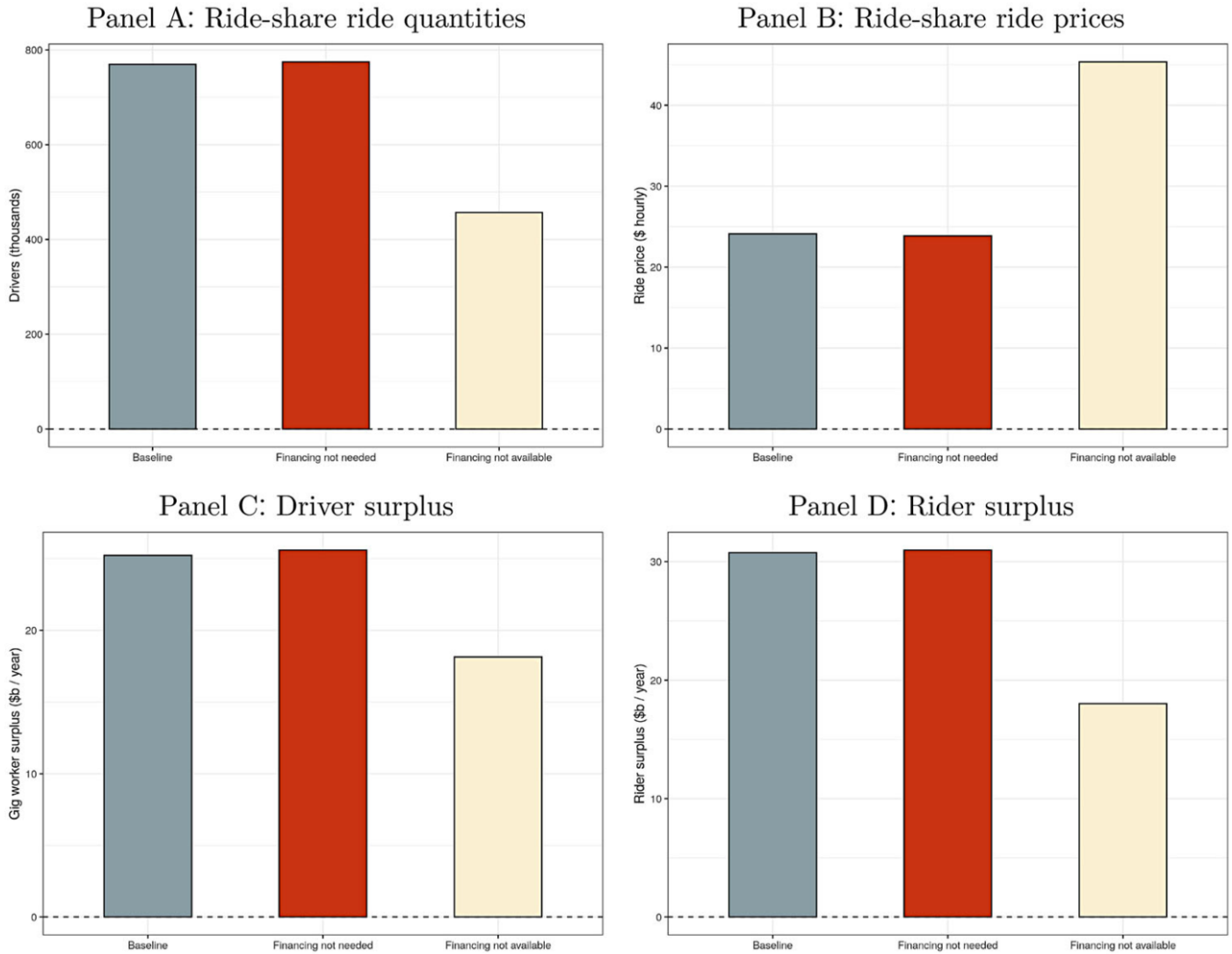
Panel C: Model Validation—Untargeted Moments

Coefficient	Sample	Data	Model
DnD on log sales	All	0.058	0.045
DnD on log sales	Bottom income quartile	0.068	0.063
DnD on log sales	Top income quartile	0.014	0.020
DnD on log loans	All	0.047	0.045
DnD on log loans	Bottom income quartile	0.080	0.066
DnD on log loans	Top income quartile	0.001	0.020

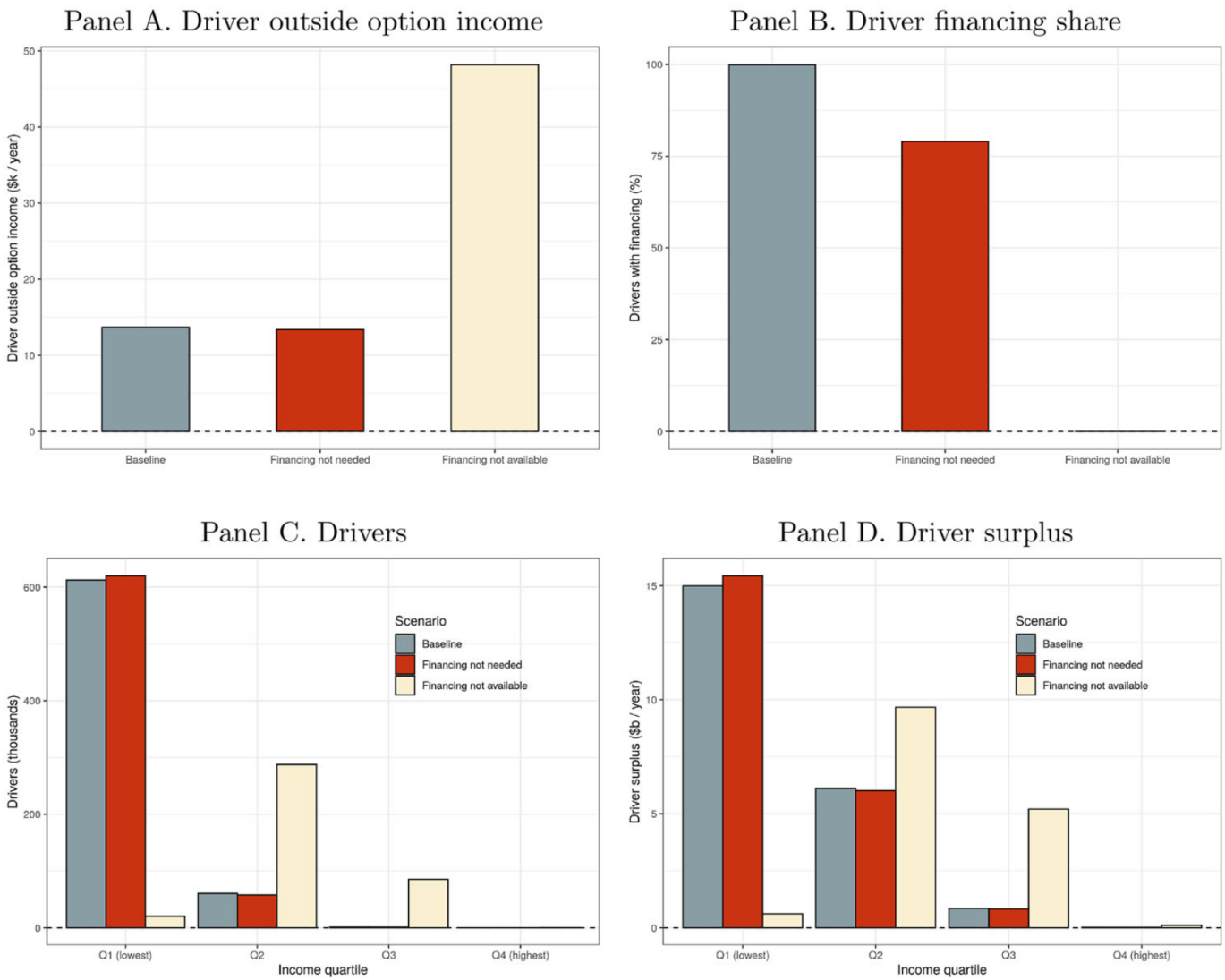
Counterfactual I: Different Financing Environments

- Financing environments
  1. **Unnecessary financing:** endow all individuals with sufficient liquidity $\bar{l} \to \infty$
  2. **Unavailable financing:** making financing unavailable $\bar{f}^0 \to \infty$

Counterfactual I: Different Financing Environments



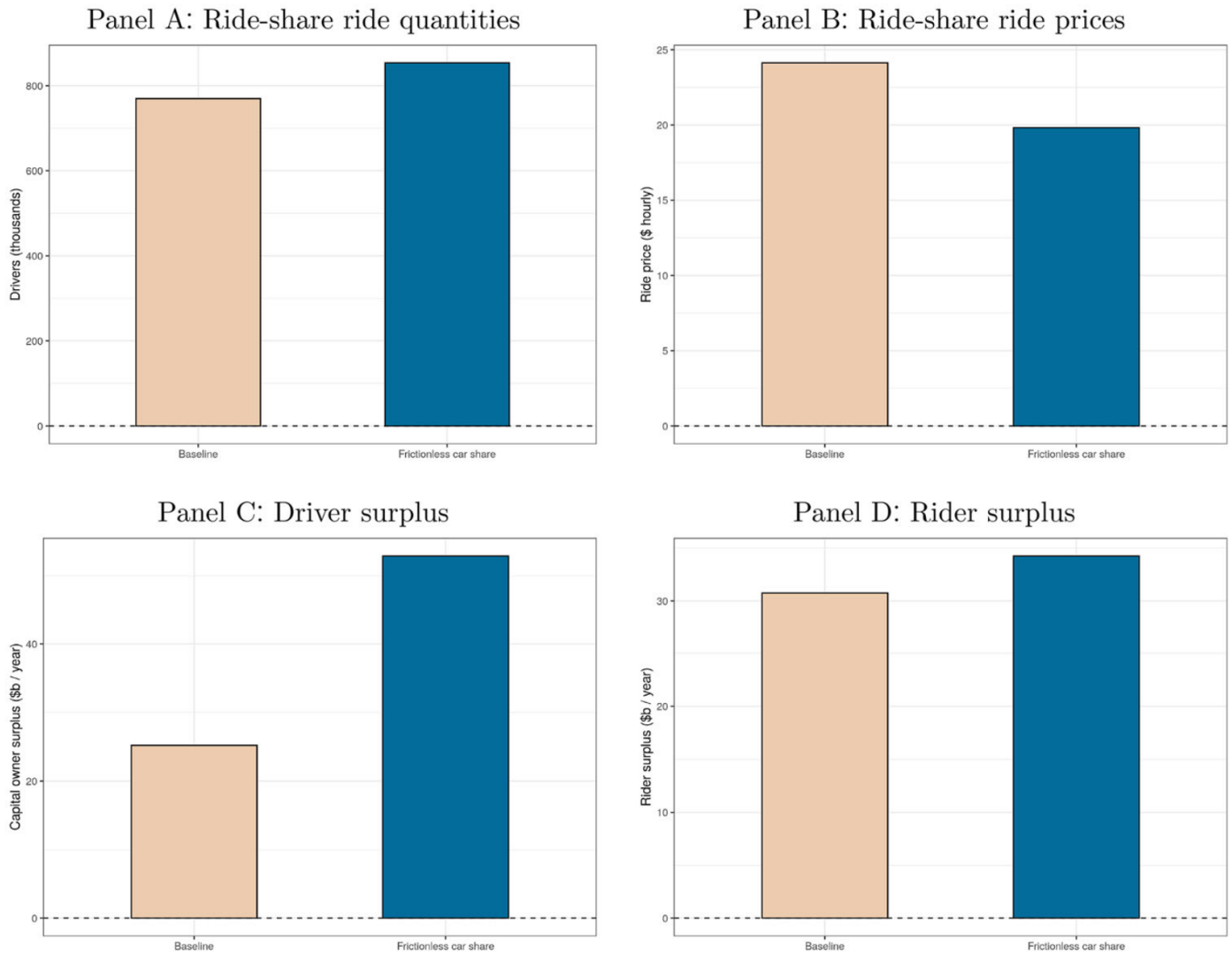
Counterfactual I: Different Financing Environments



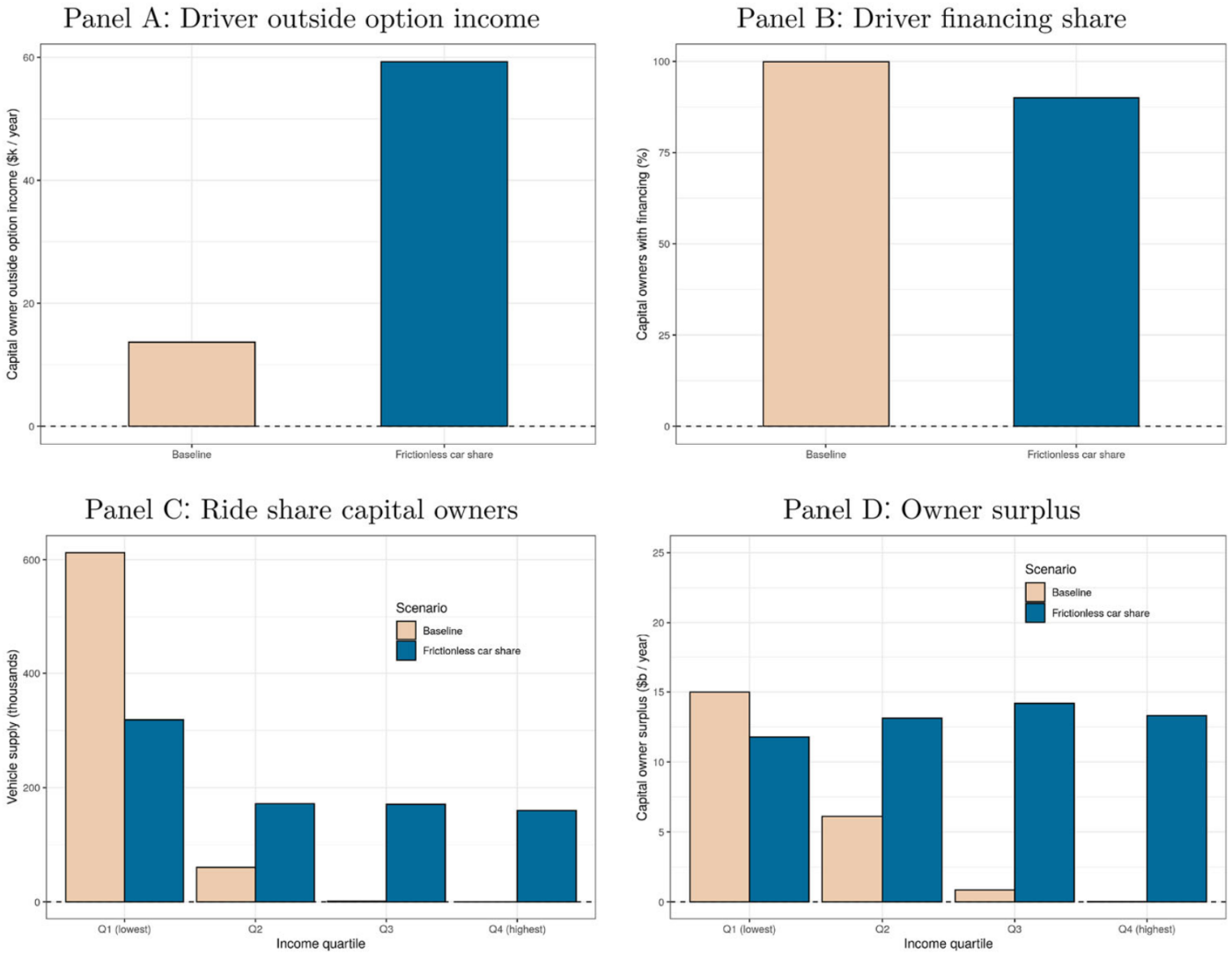
Counterfactual II: Alternate Ownership Structures

- Alternate ownership structure that allows car owners to rent their vehicles to other drivers for use in the gig economy
  - Allow car owners to hire drivers at the market-level minimum wage $\underline{w}_m$ and earn the residual or to drive themselves
  - Car owner's utility: $\alpha_i(w^R(p_m) - \mathbf{min}\{w_i, \underline{w}_m\}) + \gamma_i^R + \epsilon_i^R$
  - Here keep γ_i^R constant

Counterfactual II: Alternate Ownership Structures



Counterfactual II: Alternate Ownership Structure



Additional Tests

Sensitivity of Counterfactuals

- Demand elasticities established in Cohen et al. (2016)
- Assumes fixed fees and commissions with values from Mishel (2018)

▸ Outcome

Additional Counterfactuals

- Ride share's growth was aided by the fact that people like owning cars for their own consumption and incidentally choose to supply ride-share services ▸ Outcome
- Ride share's growth was aided by a nonmonetary hedonic preference of workers to drive for ride share (due to, for example, flexible working conditions) over similar, less flexible jobs ▸ Outcome

Outline

Contributions

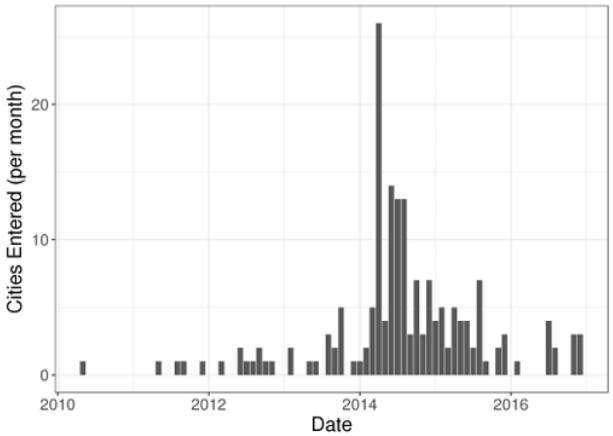
- Main Findings ▸ Main Findings
- Contributions ▸ Contributions

Acknowledgement

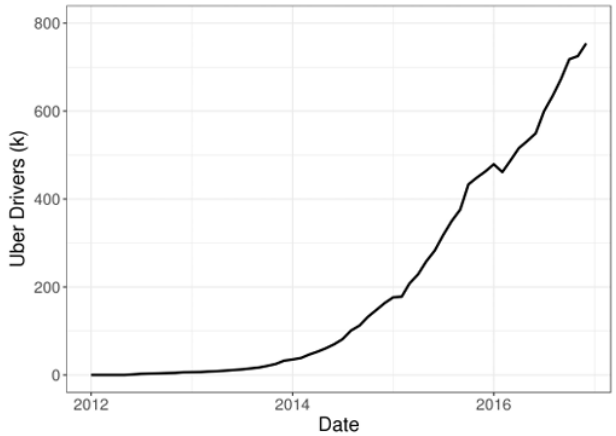
Thank you!

Timing of ride-share entry and ex-ante vehicle ownership

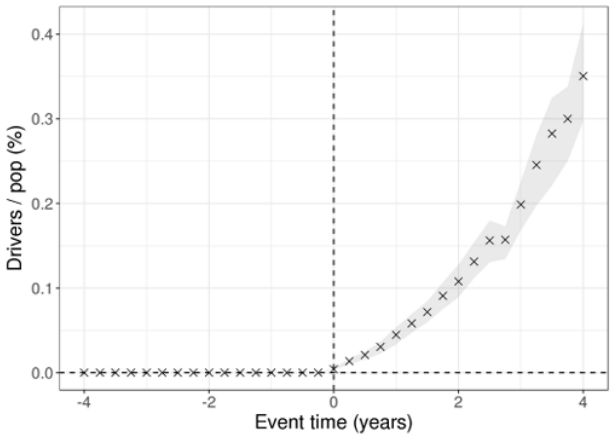
Panel A. New markets entered by month



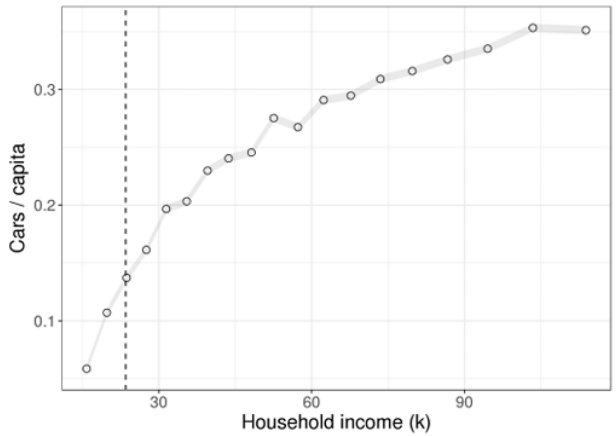
Panel B. Total Uber drivers in the United States



Panel C. Driver share of population around entry



Panel D. Vehicles per household versus household incom



Back

Timing of ride-share entry

	Entered		Years to entry	
	(1)	(2)	(3)	(4)
log population	0.229***	0.235***	−0.799***	−0.739***
	(0.021)	(0.025)	(0.071)	(0.088)
Δ population	1.450	0.815	−4.209	−0.498
	(1.261)	(1.436)	(4.508)	(5.173)
HH with mobile broadband (%)	0.754**	0.925**	−5.905***	−5.150***
	(0.332)	(0.377)	(1.202)	(1.457)
Δ % HH with mobile broadband	0.064	0.159	−2.486*	−2.861*
	(0.319)	(0.341)	(1.412)	(1.500)
HH with vehicles (%)	0.364	1.266	−0.619	−2.092
	(1.000)	(1.073)	(3.285)	(3.580)
Δ % HH with vehicles	−1.322	−0.678	8.664	7.715
	(1.326)	(1.447)	(5.872)	(6.216)
Bank share of auto financing	0.009	0.098	−0.955	−0.204
	(0.186)	(0.218)	(0.691)	(0.861)
Other controls	N	Y	N	Y
Observations	470	460	215	214
R^2	0.320	0.334	0.523	0.542
Note:			*p<0.1; **p<0.05; ***p<0.01	

Back

Vechile Eligibility

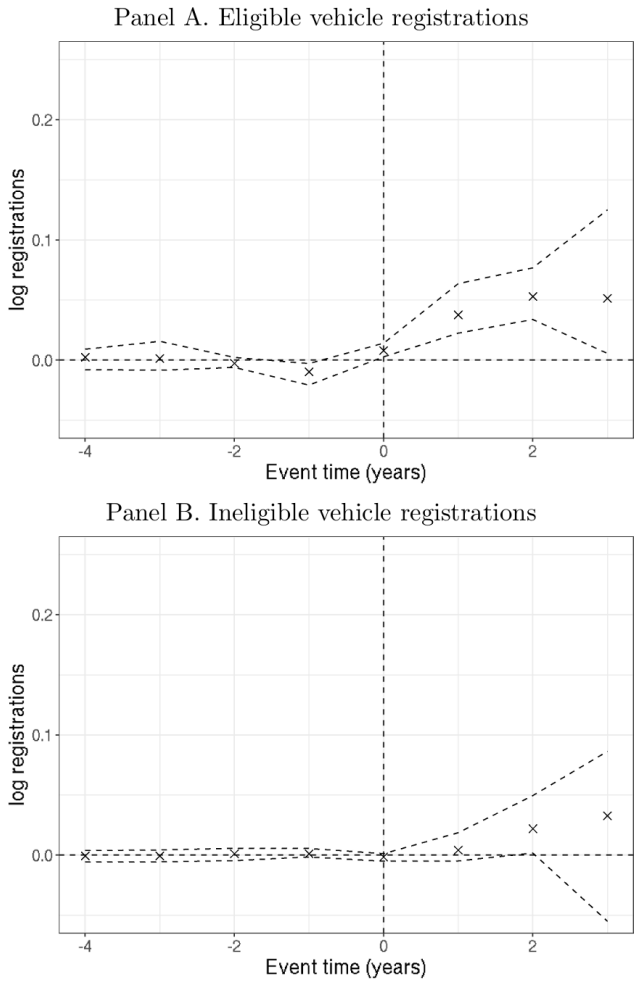
$$\log Regs_{mezt} =$$

$$\sum_{\tau=-4}^{4} \beta_\tau \mathbf{I}(t - ET_z = \tau) \times Low\ Income_z \times Eligible_{me}$$

$$+ \gamma_{tme} + \gamma_{zme} + \epsilon_{mezt}$$

- $\log Regs_{mezt}$: the log of the number of new registrations of manufacturer m, of eligibility status e, in ZIP code z, at time t

Back



Placebo Test

Panel A: New auto sales nationwide, R.L. Polk data

	Log sales		
	(1)	(2)	(3)
Post	0.0004	0.001	0.001
	(0.002)	(0.002)	(0.003)
Post × Low income	-	−0.002	-
	-	(0.004)	-
Post × High transport share	-	-	−0.001
	-	-	(0.004)
ZIP FE	Y	Y	Y
Qtr FE	Y	N	N
Qtr × Low income FE	N	Y	N
Qtr × High transport FE	N	N	Y
Observations	299,332	299,332	299,332
R^2	0.967	0.967	0.967

Panel B: New auto loan originations nationwide, Equifax data

	Log new originations		
	(1)	(2)	(3)
Post	−0.002	−0.001	−0.004
	(0.002)	(0.002)	(0.002)
Post × Low income	-	−0.002	-
	-	(0.003)	-
Post × Transport share	-	-	0.003
	-	-	(0.003)
ZIP FE	Y	Y	Y
Qtr FE	Y	N	N
Qtr × Low income FE	N	Y	N
Qtr × High transport FE	N	N	Y
Observations	299,332	299,332	299,332
R^2	0.974	0.974	0.974

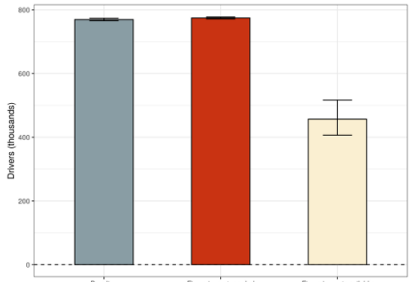
Note: *p<0.1; **p<0.05; ***p<0.01

Back

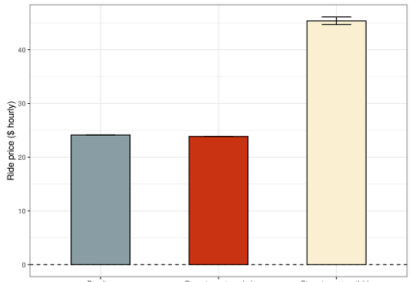
Sensitivity of Counterfactuals

Demand Elasticity: δ_m^0 and δ^1

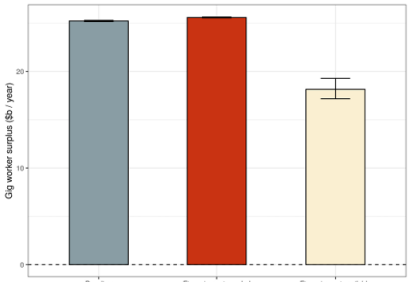
Panel A. Ride-share ride quantities



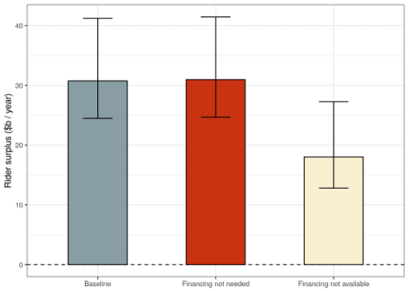
Panel B. Ride-share ride prices



Panel C. Driver surplus

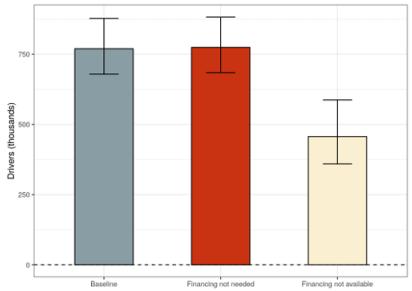


Panel D. Rider surplus

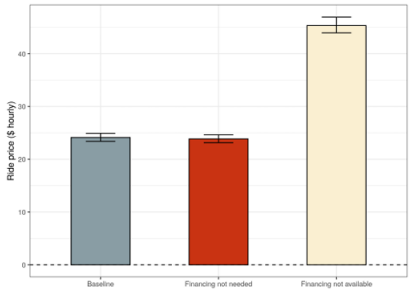


Demand Elasticity: δ^1 only

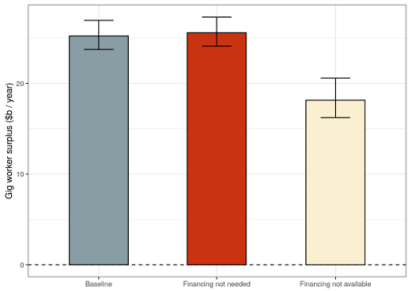
Panel E. Ride-share ride quantities



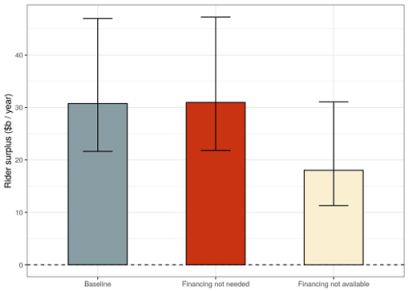
Panel F. Ride-share ride prices



Panel G. Driver surplus

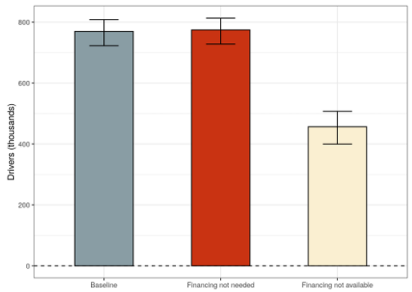


Panel H. Rider surplus

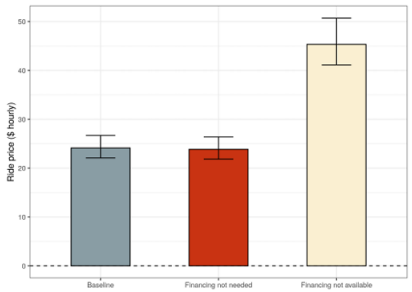


Commission sensitivity: ζ

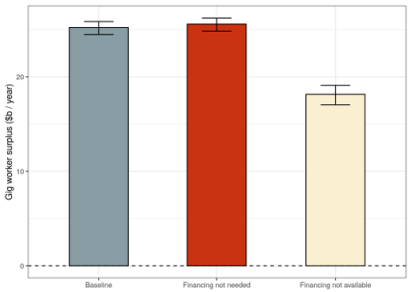
Panel I. Ride-share ride quantities



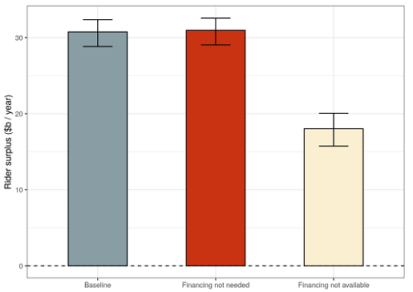
Panel J. Ride-share ride prices



Panel K. Driver surplus



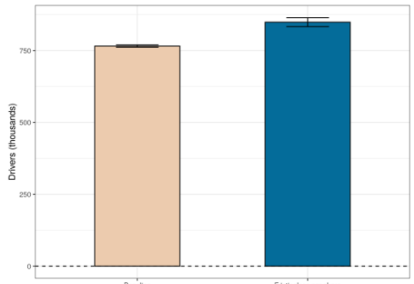
Panel L. Rider surplus



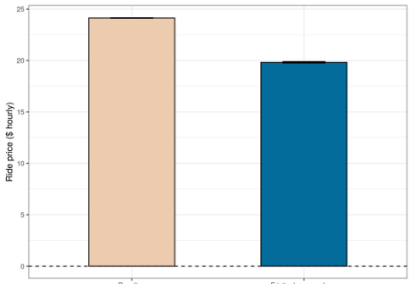
Sensitivity of Counterfactuals

Demand Elasticity: δ_m^0 and δ^1

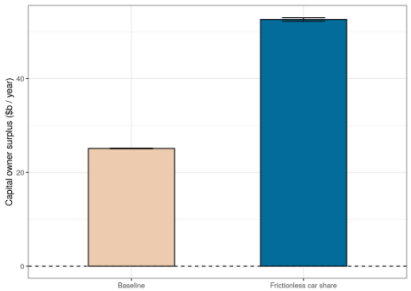
Panel A. Ride-share ride quantities



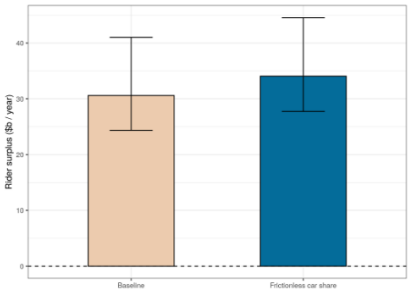
Panel B. Ride-share ride prices



Panel C. Driver surplus

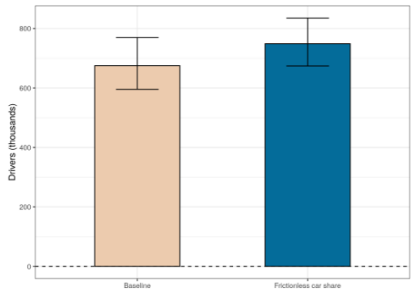


Panel D. Rider surplus

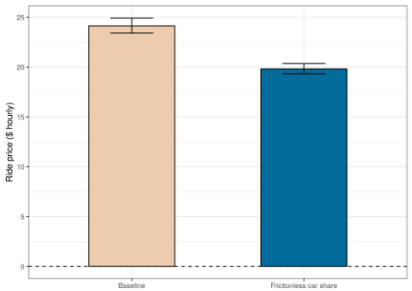


Demand Elasticity: δ^1 only

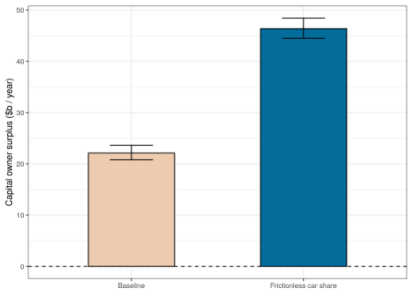
Panel E. Ride-share ride quantities



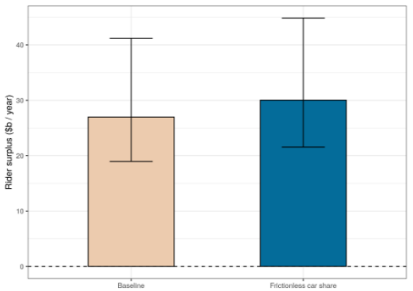
Panel F. Ride-share ride prices



Panel G. Driver surplus

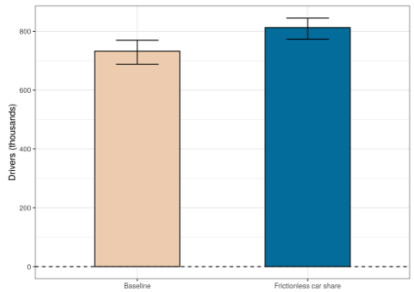


Panel H. Rider surplus

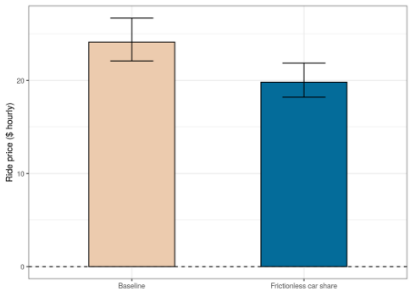


Commission sensitivity: ζ

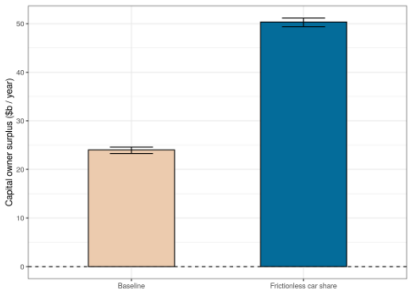
Panel I. Ride-share ride quantities



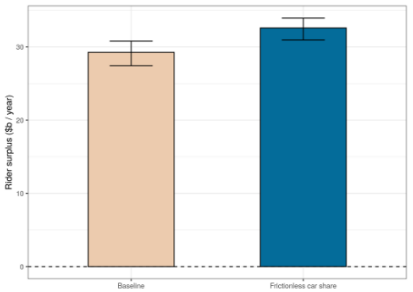
Panel J. Ride-share ride prices



Panel K. Driver surplus

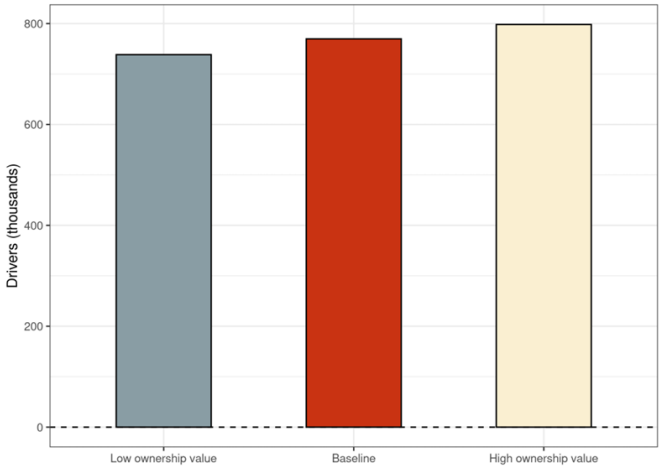


Panel L. Rider surplus

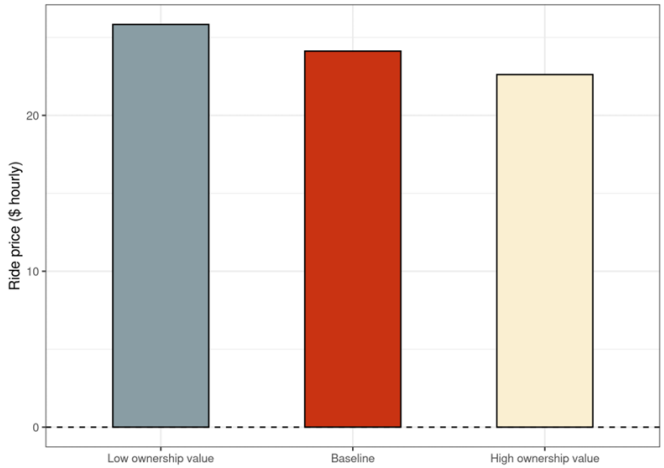


Own Value of Vehicle, Aggregates

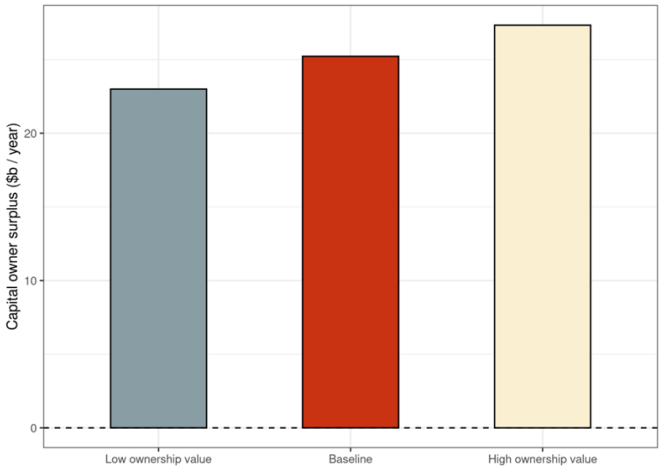
Panel A. Ride-share ride quantities



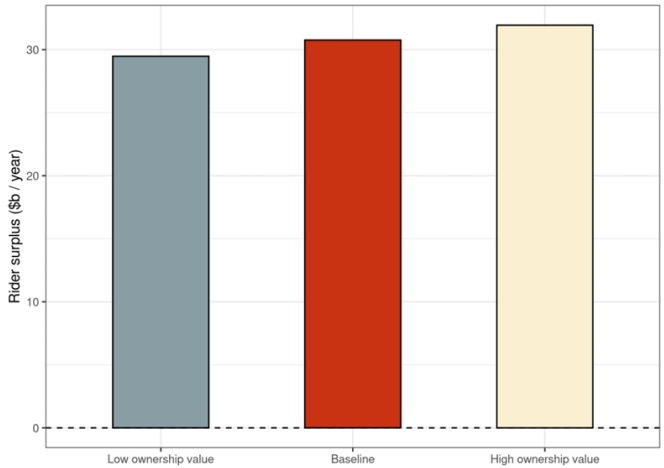
Panel B. Ride-share ride prices



Panel C. Capital owner surplus



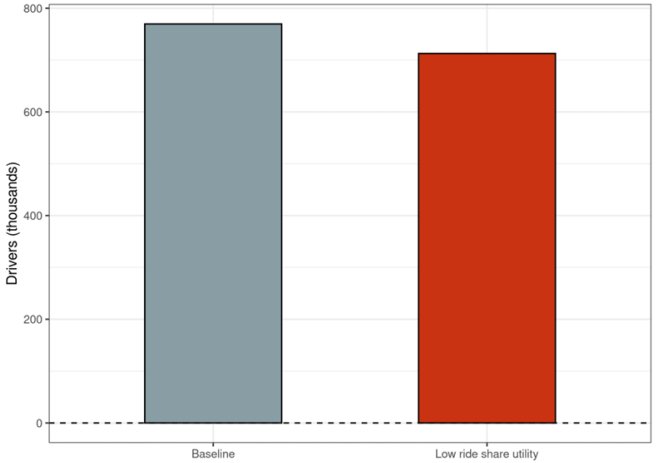
Panel D. Rider surplus



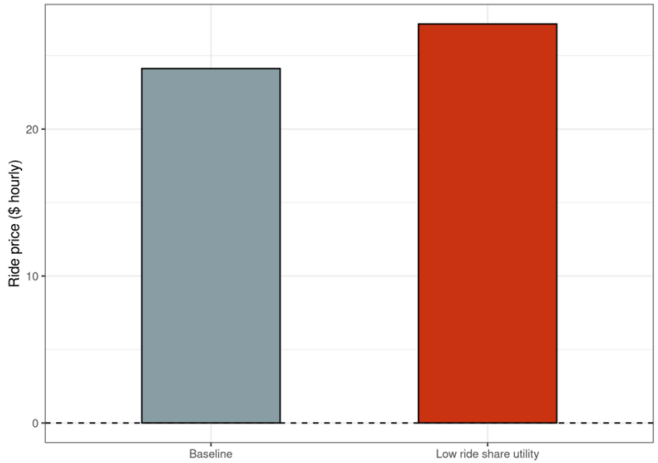
Back

Non-monetary Value of Ride Share Driving, Aggregates

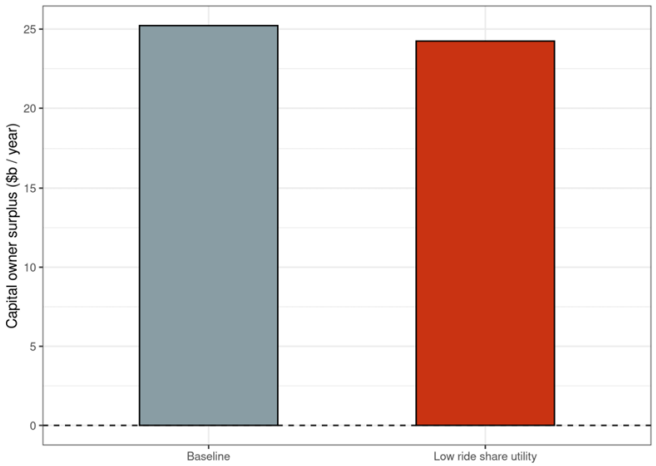
Panel A. Ride-share ride quantities



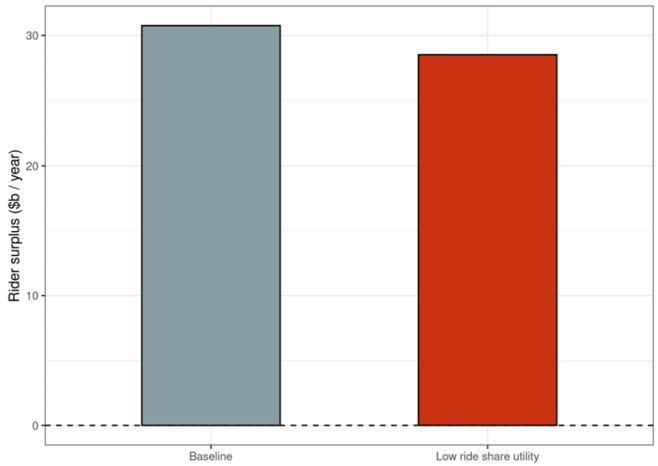
Panel B. Ride-share ride prices



Panel C. Capital owner surplus



Panel D. Rider surplus



Back