Your Uber Has Arrived
Ridesharing and the Redistribution of Economic Activity

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Urban Accessibility and Economic Activity

Accessibility: *how easy or difficult a location is to reach*

- Where we live, work and consume
- Billions in public spending
  - Transmilenio
  - US Highway Network
  - 2nd Avenue Subway Line

$\rightarrow$*Ridesharing, the newest private-sector innovation in transportation, has the potential to reshape our cities by changing access continuously in space*

Research Question

How does the spatial distribution of consumption change with respect to a continuous and unexpected increase in accessibility?

- How do firms and house prices respond to the advent of ridesharing?
  - Inaccessibility varies within cities across neighborhoods
  - Post period defined by a city's specific UberX entry date

- How does welfare change as inaccessible locations become more attractive?
  - Spatial equilibrium model to derive local demand
  - Shock travel times and costs using UberX natural experiment
  - Estimate distribution of welfare improvements (in $'s)

Preview of Methodology

This paper: Exploits natural experiment independent of urban planning and physical infrastructure which rolls out quickly

- **Data and Setting**
  1. 34 U.S. CBSAs with at least 2 million residents in 2010
  2. Novel inaccessibility measure: Google Maps API, County Business Patterns
  3. Outcomes sensitive to travel mode choice: County Business Patterns
  4. Allow neighborhood response: House Prices (CoreLogic) and Rents (Zillow)
- **Research Design**
  1. Differences-in-Differences Design: compares economic outcomes in *inaccessible* and *accessible* locations
  2. Spatial Equilibrium: allows for continuous changes in accessibility, recovers resident net welfare benefits

Preview of Findings

The spatial distribution of consumption changes with respect to an increase in accessibility.

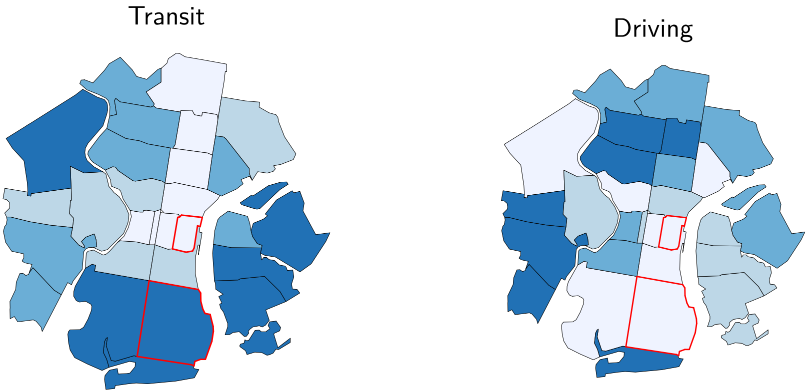
1. Measuring the costs and benefits w.r.t. inaccessibility:
   - Restaurants *disperse*
     - inaccessible restaurant net creation higher by 0.63 establishments in post-period $\rightarrow$ nearly **doubles** in inaccessible locations (6% to 10%)
   - Location values *increase* in inaccessible locations
     - House Prices: **4%**
     - Rents: **1%**
2. Weighing the costs vs. benefits w.r.t. inaccessibility:
   - all residents willing to pay for improvements in access induced by ridesharing
   - Net Welfare Benefits: Homeowners (\$110/month) $>$ renters (\$28/month)

Related Literature

This paper: Short run impact of change in **inaccessibility**, independent of infrastructure, on demand for **consumption**.

- Accessibility and Economic Activity
  - New Economic Geography: Fujita & Ogawa (1980), Lucas & Rossi-Hansburg (2002)
  - Live and Work: Baum-Snow (2007); Ahlfeldt, Redding, Sturm & Wolf (2015); Heblich, Redding & Sturm (2017); Tsivanidis (2018)
  - Daily Travel: Athey et al (2018); Kreindler and Miyauchi (2019)
- Consumption in Cities
  - Glaeser, Kolko, Saiz (2000)
  - Davis, Dingel, Monras, and Morales, (2017); Couture (2016); Couture and Handbury (2017)
- Uber papers
  - Cohen et al. (2016); Hall and Krueger (2016), Cook et al. (2018); Moskatel and Slutsky (2017); Hall Palsson and Price (2018); Barrios, Hochberg and Yi (2019)

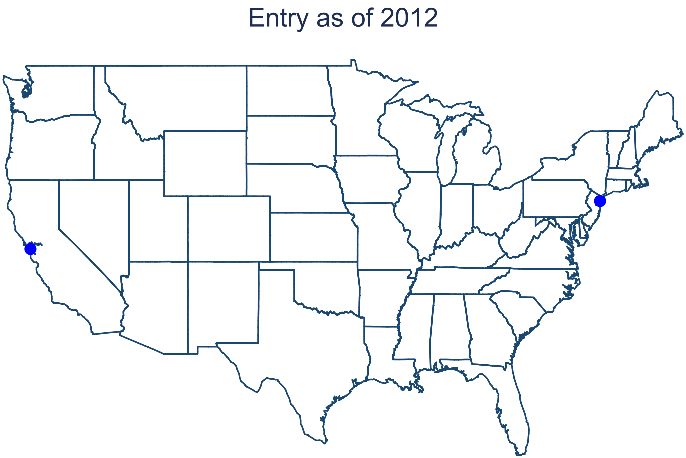
Inaccessibility Intuition: Travel in Philadelphia



$Inaccess_j$: a zipcode's public transit time for the average city resident is above the median time it takes to get to a restaurant in 2010

Darker the blue, longer the average travel time.

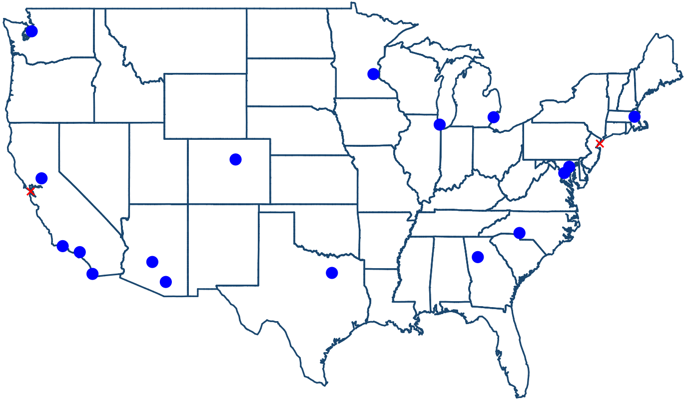
$Post_t$ Variation: Staggered UberX Entry



Source: Local new outlets, Uber's city-specific blog for later entries.

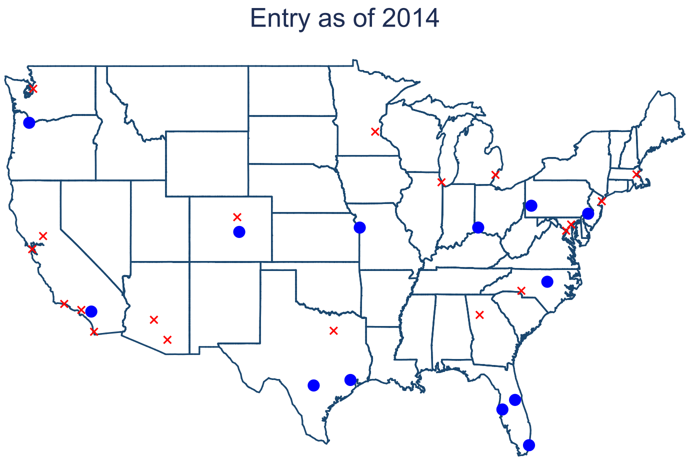
$Post_t$ Variation: Staggered UberX Entry

Entry as of 2013



Source: Local new outlets, Uber's city-specific blog for later entries.

$Post_t$ Variation: Staggered UberX Entry



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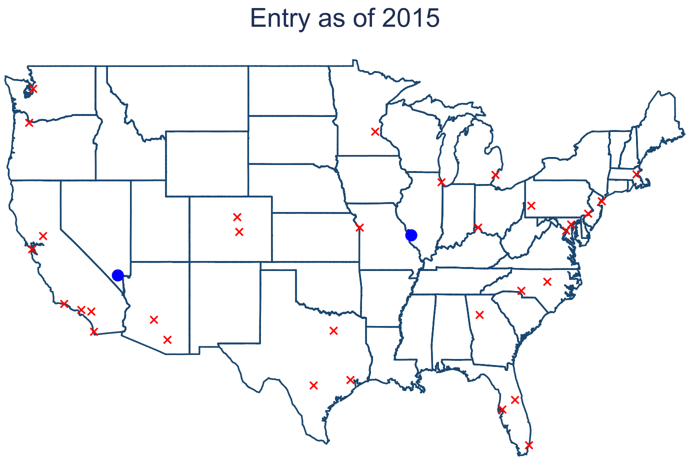
$Post_t$ Variation: Staggered UberX Entry



Source: Local new outlets, Uber's city-specific blog for later entries.

Research Design: Difference-in-differences

Exploit staggered and quick UberX entry into 34 US cities:

$$Y_{jt} = \beta Inaccess_j \times Post_t + year_t + zip_j + \varepsilon_{jt}$$

- $Post_t$: city-specific UberX entry year
- $Inaccess_j$: zipcode has above-median $\overline{m}_j$
- Y_{jt}:
  - Restaurant net creation: County Business Patterns (2010-2017)
  - House Prices: Hedonic HPI from CoreLogic Deeds (2010-2018)
  - Rents: Zillow Rent Index (ZRI) (2010-2018)

Summary Stats

Assumptions for a Valid Difference-in-difference

1. **Parallel Trends:** inaccessible and accessible zipcodes have parallel rates of restaurant creation, absent UberX entry Testing Trends

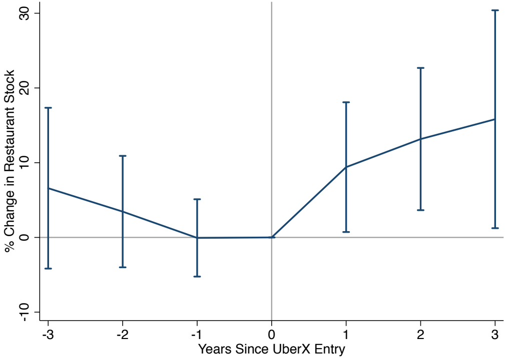
2. **Exogeneity:** UberX did not enter when it observed restaurant dispersion Testing Exogneity

3. **Demand Shock:** Residents do not re-optimize their work location or commute Testing Demand Shock

Restaurant Net Creation: from 6% to 10% growth per year

Pre-period stock: 14 restaurants per zipcode

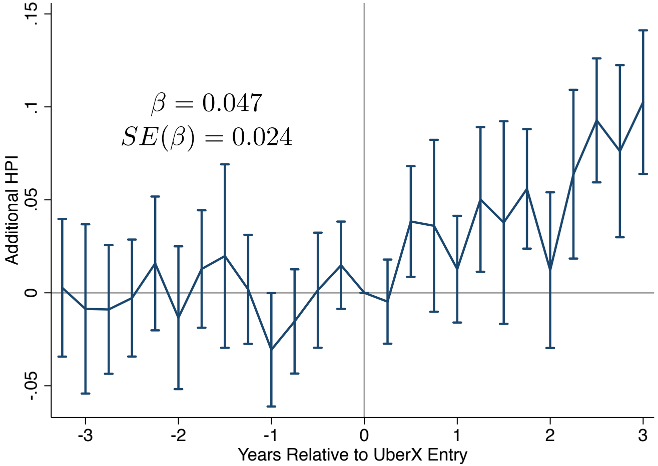
	(1)	(2)	(3)
$Post_t \times Inaccess_i$	0.652***	0.602***	0.627***
	(0.191)	(0.203)	(0.179)
$Post_t$	-0.0577	0.221	0.255
	(0.293)	(0.287)	(0.398)
$Inaccess_i$			0.829*
			(0.425)
R-Squared	0.283	0.305	0.179
Observations	3091	2827	3091
Year FE	X	X	X
Zip FE	X	X	
$Inc_{it}, Edu_{it}, Pop_{it}$		X	



note: All specifications include $CBSA_c$ fixed effects, $CBSA_c \times Post_t$, and $CBSA \times Inacces_i$ controls. Standard errors clustered at the CBSA-post level. Standard errors in parentheses. Observations at the zipcode-year level. Balanced panel covers 32/34 cities.

Access Industries NYC

HPI increased in inaccessible areas post UberX entry



Translates to a 3% faster increase in HPI

ZRI

Model Overview

1. Adapt Ahlfeldt et al. (2015) **spatial equilibrium framework** to derive local demand functions:
   - Residents: Choose quantities of housing, tradable goods, and service amenities to consume
   - Producers: scale up production to meet local demand
   - Land Markets: segmented and fixed
2. **Estimate local demand function** to recover key parameters in consumer's optimization problem
3. Use data and recovered parameters to **calculate residents' net welfare benefit** (\$'s)

Resident Welfare

$$V_{ij} = \frac{I_i z_{ij}(\varepsilon, E_j)}{q_i^{\beta} p^{\alpha} e^{\tau m_{ij}}}$$

$$z_{ij} \sim F(z_{ij}) = e^{-E_j z_{ij}^{-\varepsilon}}$$

- I_i: endowed income
- z_{ij}: preference shock ($\sim$ Frechet)
- E_j: destination value
- ε: preference for heterogeneity

- q_i: housing rents
- p: tradables price
- m_{ij}: travel time (minutes)
- β: housing share of income
- α: tradables share of income
- τ: opportunity cost of travel minute

Inputs needed in calculating resident welfare

Welfare calculated using estimated and borrowed inputs:

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Estimate to recover E_j (destination value), τ (time cost):

$$n_j^d = E_j \sum_i \frac{R_i I_i (e^{-\varepsilon \tau m_{ij}})}{\sum_s E_s (e^{-\varepsilon \tau m_{is}})}$$

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Additional inputs:

- ε: preference for heterogeneity, set to 8
- β: housing share of budget, set to 0.3
- α: tradable share of budget, set to 0.6
- q_j: predicted $\hat{q}_j$ from UberX natural experiment
- m_{ij}: predicted $\hat{m}_{ij}$ from UberX natural experiment

Est. Eqtn. Est. Parms.

Resident Net Welfare Benefit

1. To create money metric, log-linearize $E(V_{ij})$:

$$ln(E(V_{ij})) = ln(I_i) + ln(\Gamma\left(\frac{\varepsilon - 1}{\varepsilon}\right)) + \frac{1}{\varepsilon}ln(E_j) - \beta ln(q_i) - \alpha ln(p) - \hat{\tau}m_{ij}$$

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2. Calculate income needed to balance benefits and costs of access:

$$ln(I_i) = \Big[\ \beta ln(q_i) + \alpha ln(p) + \tau m_{ij}\ \Big] \ - \Big[\ \frac{1}{\varepsilon}\ln(E_j) - ln(\Gamma\Big(\frac{\varepsilon - 1}{\varepsilon}\Big))\Big]$$

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3. The Net Welfare Benefit (NWB_i) is the difference in compensation:

$$NWB_i = I_i^{pre} - I_i^{post}$$

renters vs. owners

Homeowners' NWB (per month), $t = -1$ to $t = 3$

Varied	NWB_i^{Access} (\$)	$NWB_i^{Inaccess}$ (\$)
Cost: $\hat{\tau}$	63	55
Times & cost: $\hat{m}_{ij}, \hat{\tau}$	64	55
Times, cost, house prices: $\hat{m}_{ij}, \hat{\tau}, \hat{q}_i$	111	96
Full Model: $\hat{m}_{ij}, \hat{\tau}, \hat{q}_i, \hat{E}_j$	123	101

- All homeowners benefit from improvements in access
- Benefits of amenity improvement accrue more to *accessible* areas

Renters' NWB (per month), $t = -1$ to $t = 3$

Varied	NWB_i^{Access} (\$)	$NWB_i^{Inaccess}$ (\$)
Cost: $\hat{\tau}$	52	52
Times & cost: $\hat{m}_{ij}, \hat{\tau}$	53	52
Times, cost, house prices: $\hat{m}_{ij}, \hat{\tau}, \hat{q}_i$	24	24
Full Model: $\hat{m}_{ij}, \hat{\tau}, \hat{q}_i, \hat{E}_j$	30	26

- All renters benefit from improvements in access
- Benefits of amenity improvement accrue marginally more to *accessible* areas
- Homeowners benefit more than renters due to equity gains
- Renters show more spatial arbitrage than homeowners

Summary of Findings & Conclusion

The spatial distribution of economic activity has responded to improvements in accessibility.

1. Measuring costs and benefits in inaccessible locations:
   - In inaccessible locations: restaurant net creation nearly **doubled**, house prices and rents increase **4%, 1%**
   - Robust to different travel metrics and controlling for transit usage
   - Lower impacts on industries less sensitive to travel choice

2. Weighing costs vs. benefits in inaccessible locations:
   - All residents benefit from improvements in access induced by ridesharing's entry
   - Homeowners benefit more than renters after accessibility improvements, at **$110** and **$28** respectively

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Thank you!

Summary Statistics: Accessible and Inaccessible Locations are Different

More amenity activity in *accessible* zipcodes in the pre-period

	Outcome Variables		
	Access.	*Inaccess.*	*Difference*
Δ(# Restaurants)	1.43	0.67	0.76***
	(0.15)	(0.07)	(0.15)
HPI	1.74	1.72	0.02
	(0.02)	(0.02)	(0.03)
ZRI	0.95	0.96	-0.004***
	(0.00)	(0.00)	(0.00)

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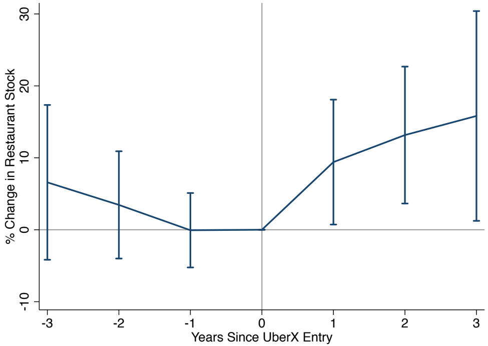
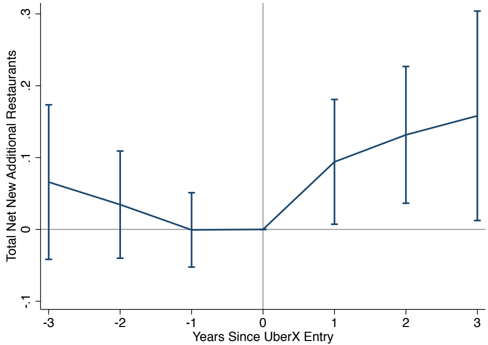
Testing Parallel Trends: Annual and Total Restaurant Net Creation

Annual



Cumulative



After 3 years: ∼20% more restaurants relative to entry year[1]

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[1] Sample includes only 32/34 cities to capture 3 years of post data. 95% confidence intervals shown.

Testing Exogeneity: UberX entry uncorrelated with *within* city restaurant dispersion

$$Month_c = \beta Depvar_c + \varepsilon_c$$

	population	earnings	fraction bachelor's degree	restaurant net creation
		City Wide		
β	-3.23**	-0.47**	-0.44**	-0.11***
		Within City		
β_{access}	-5.6	-0.25	-0.02	$\boxed{-0.17}$
$\beta_{inaccess}$	-16.6	-0.06	-0.44**	$\boxed{-0.17}$

Hall, Palsson and Price (2018): the probability that UberX entered the larger city first is 68%

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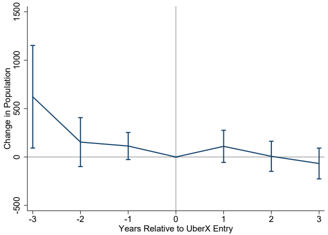
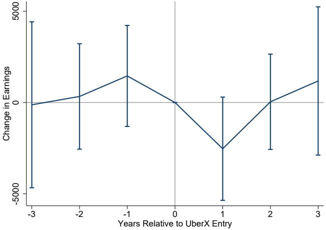
Testing Demand Shock: No evidence of neighborhood sorting

Demographic characteristics of $Inaccess_j$ locations:

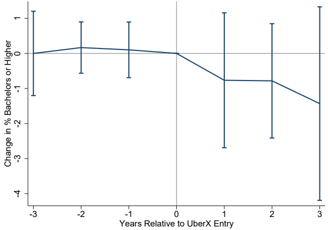
Population



Earnings



Education



95% confidence intervals shown

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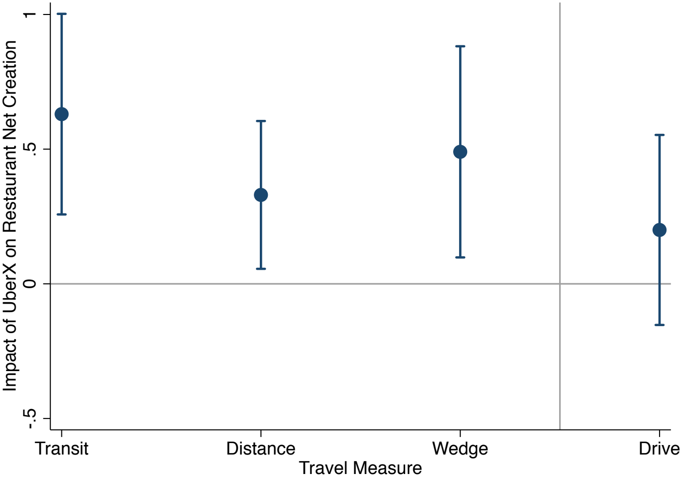
Robust to different measures of inaccessibility



Robustness

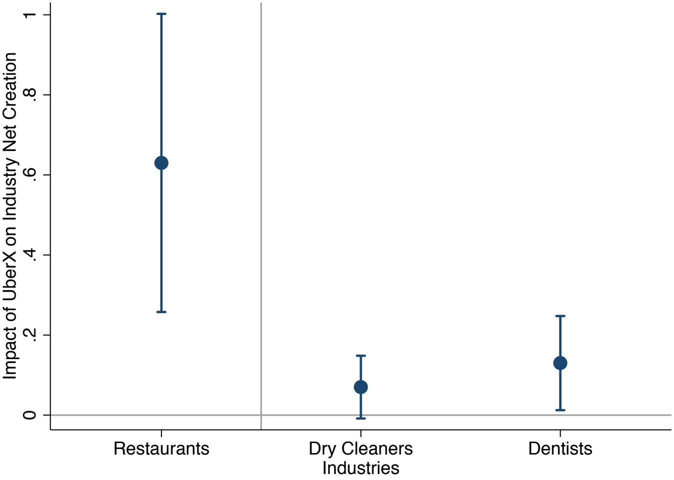
- Transit: 0.63^{***}
- Distance: 0.33^{**}
- Wedge: 0.49^{**}

Placebo:

- Driving: 0.20

95% confidence intervals shown Back

Results not driven by general urbanization or gentrification

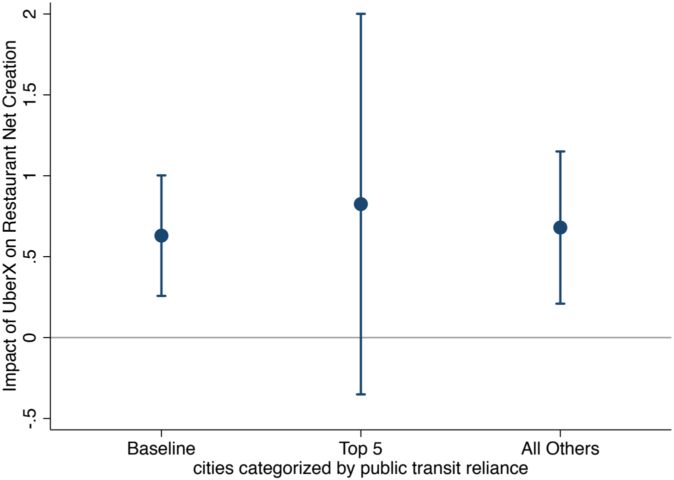


95% confidence intervals shown Back

Industry

- Restaurants: 0.63^{***}
- Dry Cleaners: 0.07^{*}
- Dentists: 0.13^{**}

Main Results not limited to big public transit cities

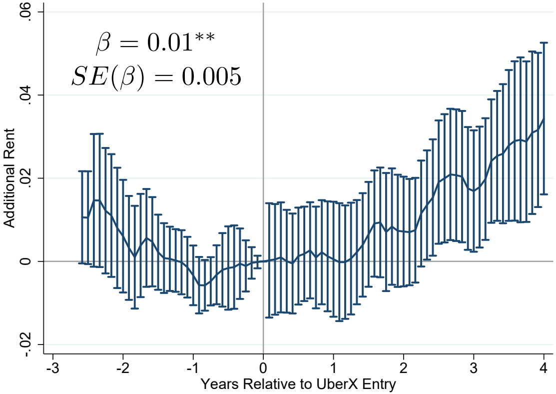


95% confidence intervals shown Back

Estimate

- Baseline: 0.63^{***}
- Top5: 0.83
- All others: 0.68^{***}

ZRI increases in inaccessible areas post UberX entry



ZRI increases by 3.5% after 4 years[2] back

[2] Balanced sample includes 27/34 cities. 95% confidence intervals shown.

Estimating Equation

$$ln(n_j^c) = \kappa^c + ln\left(\sum_{i \in c} R_i^c I_i^c (e^{-\varepsilon\tau m_{ij}^c})\right) + ln(E_j^c) \tag{1}$$

Parameters to estimate:

- $\varepsilon\tau$: combined preferences and travel costs parameters
- $ln(E_j^c)$: destination value
- κ^c: $\sum_s E_s(e^{\tau m_{is}})^{-\varepsilon}$, city-level fixed effect

Use nonlinear least squares (NLS) for estimation.

Back m_{ij} const.

Constructing m_{ijt}

- m_{ij}: Google maps API
- η: NHTS surveys, 2009 & 2017

For each city, c, and period, t, $\exists\ \eta_c^t$:

- Estimate: $\eta_c^t = \omega + Post_t + \nu_{ct}$
- Predict: $\hat{\eta_c}^t$
- Construct: $m_{ijt} = \hat{\eta}_c^t m_{ij}^{drive} + (1 - \hat{\eta}_c^t) m_{ij}^{transit}$

Back

Estimation Results: Travel Costs Fall after UberX Entry

	source		
Parameter	Estimation	Calibration	Value (S.E.)
$\widehat{\varepsilon\tau}_{pre}$	✓		0.17 (0.02)
$\widehat{\varepsilon\tau}_{post}$	✓		0.12 (0.02)
β		✓	0.30
ε		✓	8.00
α		✓	0.6
$\hat{\tau}_{pre}$			0.021
$\hat{\tau}_{post}$			0.015

- ε: governs preferences for amenity heterogeneity across neighborhoods
- τ: measures cost of marginal travel minute
- β: income share devoted to housing
- α: income share devoted to tradable goods

Back Other parm. est.

$\hat{\varepsilon}$ and $\hat{\tau}$ in related literature

$\hat{\varepsilon}$

- Alhfeldt et al. (2015): 6.83
- Eaton and Kortum (2002): 3.6–12.86
- Su (2018): 7.5
- Couture (2016): 8.8
- Couture et al. (2019): 6.5

$\hat{\tau}$

- Ahlfeldt et al. (2015): 0.01
- Tsivanidis (2019): 0.012
- Couture (2016), Couture et al. (2019): 0.2

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Estimating q_i for Renters

q_i for renters is the UberX component of rent increase:

$$q_{it}^{R} = \lambda m_j^N \times Post_t + year_t + zip_i + \epsilon_{it}$$

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Estimating q_i for Homeowners

1. q_i for homeowners: *User Cost*, $UC_i(\hat{q}_{it}^{HP})$

$$q_{it}^{HP} = \lambda m_j^N \times Post_t + year_t + zip_i + \epsilon_{it}$$

Estimating q_i for Homeowners

1. q_i for homeowners: *User Cost*, $UC_i(\hat{q}_{it}^{HP})$

$$q_{it}^{HP} = \lambda m_j^N \times Post_t + year_t + zip_i + \epsilon_{it}$$

2. UC_i depends on your mortgage payment, opportunity cost of capital, property taxes, etc:

$$UC_i = (1 - \tau_I) r \hat{q}_i^{HP} + (1 - \tau_I) \tau_p \hat{q}_i^{HP} + (\mu + \delta + \gamma) \hat{q}_i^{HP} - \pi^e q_i^{HP}$$

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3. As $\hat{q}_i^{HP}$ increases, as long as $(1 - \tau_I)\tau_p < \pi^e$, UC_i falls

Back