The Last Mile Matters: Impact of Dockless Bike Sharing on Subway Housing Price Premium

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Motivation

- **Bike sharing as an effective solution to the last-mile problem**
  - With urban public transits, the first/last mile (door to station) of a trip is particularly costly
  - Dockless bike sharing offers a convenient and affordable means of transportation from/to subway stations
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- **Effects on the Housing Market**
  - To avoid the last mile commuting costs, urban dwellers prefer to live close to subway stations $\Rightarrow$ housing price premium
  - In the presence of shared bikes, living close to subway stations becomes less attractive $\Rightarrow$ attenuate the housing price premium

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- **Research Question**
  - How does bike sharing affect subway housing price premium?
  - Does the effect imply a reduction in commuting costs/solution to the last-mile problem?

Related Literature

- **Hedonic prices and equilibrium sorting**: Use housing prices to reflect the "value" of living amenities (Rosen 1974, Chay and Greenstone 2005, Bayer et al. 2008, Freeman et al. 2017, etc.)

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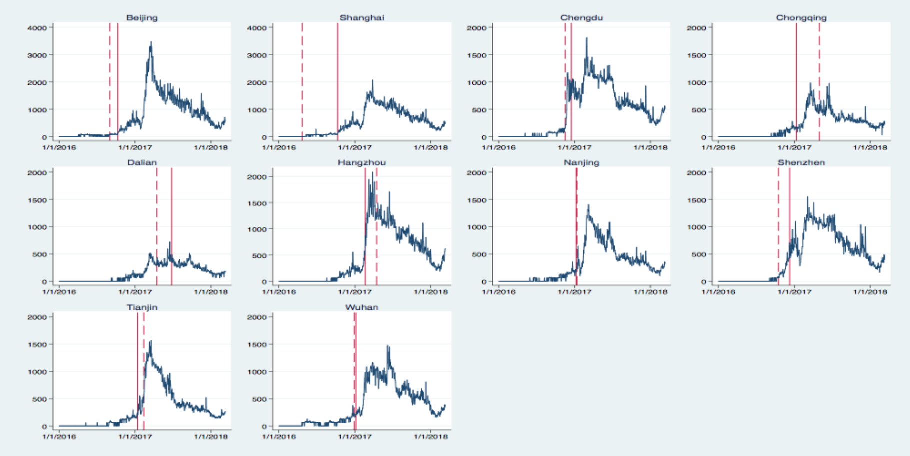
- **Sharing economy**: Impact of Airbnb, Uber and bike sharing on related businesses, markets and local amenities (Zervas et al. 2017, Greenwood and Wattal 2017, Hall et al. 2017, Pelechrinis et al. 2017, etc.)

Empirical Strategy

- A quasi-natural experiment: entry of bike sharing to 10 Chinese cities
- Exploit the difference in entry dates to implement DID



Solid lines: Ofo, Dashed lines: Mobike, Trends: Internet search

Empirical Strategy

$$Y_{it}^{cs} = \beta_1 Dist_{it}^{cs} + \beta_2 Bike_t^c + \beta_3 Dist_{it}^{cs} Bike_t^c + \gamma X_{it}^{cs} + \alpha_s + t_c + \epsilon_{it}^{cs}$$

- Y_{it}^{cs}: apartment i's (log) price at time t, in city c
- $Dist_{it}^{cs}$: distance from apartment i to its nearest station s at time t
- $Bike_t^c$: indicator of bike sharing's entry to city c by time t
- X_{it}^{cs}: apartment i's characteristics at time t
- α_s and t_c: subway station F.E. and city-year-month F.E.
- ϵ_{it}^{cs}: standard errors clustered by subway station

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  - Limit to apartments within 3km to the nearest station
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- Sample: 617,271 price records from 399,840 apartments
  - Two-thirds apartments have 1 record $\Rightarrow$ apartment F.E. not feasible
  - Can identify "building F.E." from geo-coordinates

Results

Variables	Geodesic distance	Walking distance	Building F.E.	Bootstrap std. err.
Distance	-0.042	-0.026	0.006	-0.041
	(0.003)	(0.002)	(0.004)	(0.004)
Bike sharing	-0.011	-0.014	-0.003	-0.002
	(0.005)	(0.005)	(0.004)	(0.006)
Distance	0.012	0.009	0.012	0.011
× Bike sharing	(0.003)	(0.002)	(0.003)	(0.004)
Housing characteristics	Yes	Yes	Yes	Yes
Subway station F.E.	Yes	Yes	Yes	Yes
City-year-month F.E.	Yes	Yes	Yes	Yes
Observations	617,271	593,429	617,271	617,271
Subway stations	1,424	1,424	1,424	1,424
R^2	0.91	0.91	0.98	0.91

Visualization

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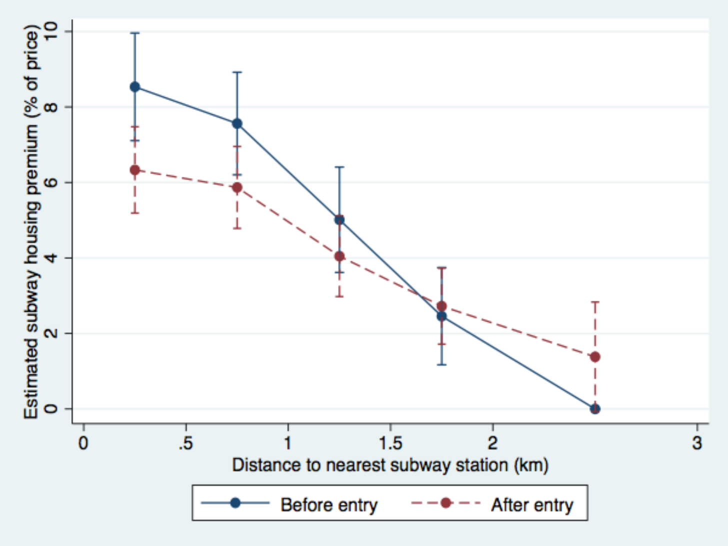
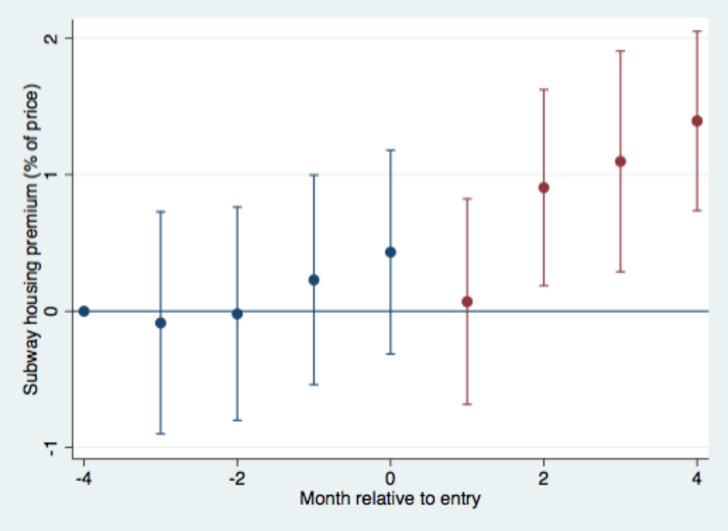
▸ Visualization

- Implied willingness-to-pay for lower commuting costs $\approx$ 1,893–2,127 CNY (282–317 USD) per household per year over 30 years

Non-linear Estimates



Parallel Trends



Alternative Explanations

- **Endogenous entry (e.g. anticipated entry, housing market price control, other confounding)**:
  - City characteristics in 2015 cannot predict entry dates
  - Estimates robust to narrower time windows (90 or 183 days) and district-year-month fixed effects

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- **Non-transiting rides**: 68% users ride shared bikes for transiting purpose; estimates robust to excluding stations near shopping malls
- **Reduced transaction costs for distant apartments**:
  - Frequency of visits by potential buyers does not increase
  - For the same potential buyer, the average distance-to-subway of his/her visits does not increase

Robustness & Additional Estimates

Variables	Ofo entry	Mobike entry	Internet search	Within 2km	Within 4km	Within 5km
Distance	-0.042	-0.042	-0.040	-0.041	-0.040	-0.039
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Distance	0.013	0.011	0.010	0.014	0.008	0.007
$\times$ Bike sharing	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Observations	617,271	617,271	617,271	541,482	655,719	676,231
Subway stations	1,424	1,424	1,424	1,417	1,424	1,425
R^2	0.91	0.91	0.91	0.91	0.91	0.91

Conclusion

- **Main findings**
  - Exploiting the entry of bike sharing to 10 Chinese cities as a quasi-natural experiment, we find bike sharing reduces subway housing price premiums by approximately one-third
  - Various robustness checks validate that our estimates represent a causal effect
  - Using the estimates, we quantify the monetary value of bike sharing on solving the last mile problem

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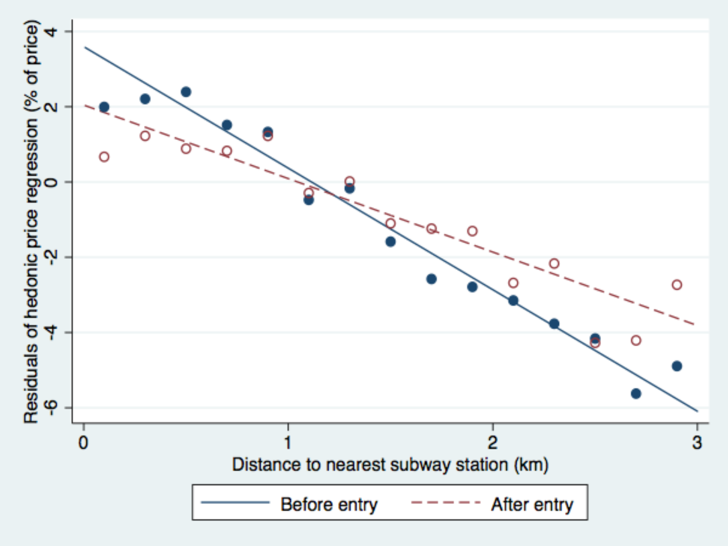
  - Various robustness checks validate that our estimates represent a causal effect
  - Using the estimates, we quantify the monetary value of bike sharing on solving the last mile problem
- **Contributions**
  - We provide the first empirical evidence on the causal effect of dockless bike sharing on subway housing price premium & commuting costs
  - The findings deliver policy implications for bike sharing companies (pricing and operation), policy makers (regulation and subsidy), urban residents and housing market practitioners (housing amenities)

Visualization



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