Does bike sharing increase house prices? Evidence from micro-level data in Shanghai

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Motivation

- As a healthy and sustainable transportation mode, bike sharing has become popular in **thousands of cities** around the world since its first appearance in Amsterdam in the 1960s (Gu, Kim, Currie, 2019).
- Theoretically, sharing economy improves economic efficiency by **reducing frictions** that cause capacity to go underutilized (Barron, Kung, and Proserpio, 2018).

--e.g. Bike sharing facilitates commutes by **solving the "last mile" problem** associated with public transit stations.

- But dockless sharing bikes may also generate negative externalities, such as **misuse of the scarce public space**.


华强南路
Huaqiang S Rd

Motivation

- **In this paper, we study the externality of bike sharing by analyzing house prices.**

--House prices are routinely used to value welfare benefits from local public goods (Teulings, Ossokina, de Groot, 2018): e.g.,

- Zheng, Kahn (2013, PNAS): High-speed rail

- Zhou, Chen, Han, Zhang (2019, Real Estate Economics): Subway

--Sharing bikes are not public goods, but they bring “housing externality” (Rossi-Hansberg, Sarte, and Owens III, 2010).

Motivation

We use Shanghai, China, as our research setting for several reasons:

- China has the **largest bike sharing market** in the world (Gu, Kim, Currie, 2019); Shanghai is one of the first Chinese cities to introduce dockless bike sharing.

  --Wide acquisition of cycling skills → Large pool of potential users

- The **benefits and costs of sharing bikes in Shanghai are both obvious**.

  --The world's largest rapid transit system by route length →The value of bike sharing as a complement to the public transportation network is large

  --High population density → High social cost caused by public space misuse

Outline of empirical tests

- **House-level:** Does bike sharing affect prices of individual houses? What's the role of its interaction with subway stations?

  --IV approach

- **Aggregate-level:** Does bike sharing affect house price indexes? If yes, does the effect vary with the distance to the city center?

- **Robustness checks**

  --Placebo test: Does bike sharing increases house prices by interacting with bus stations? (Our expectation: No)

  --Others

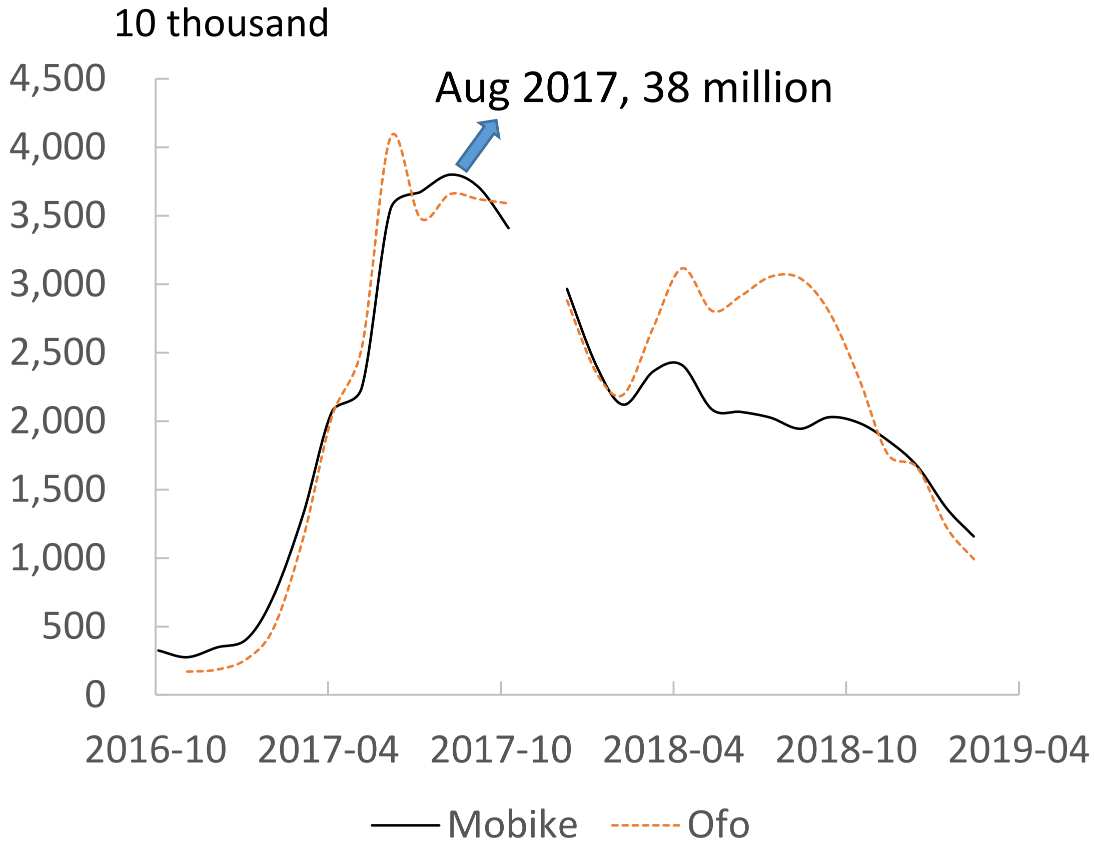
Data 1: Mobike

➢ **Source**: Mobike

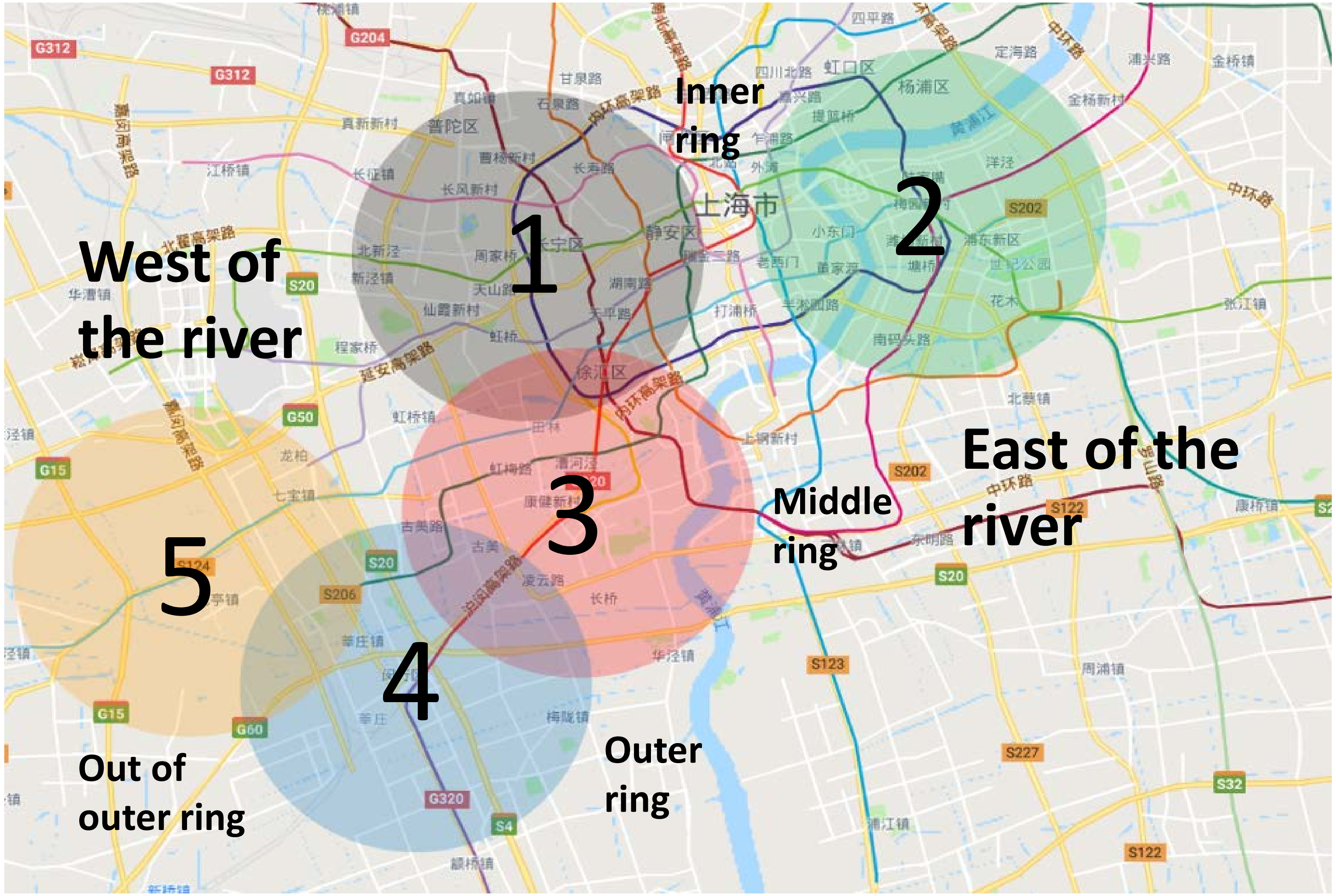
--The largest sharing bike brand in China (till May 2017)

--The first sharing bike brand in Shanghai ; launched on 22 April, 2016

- **Variables**: Order ID, Bike ID, User ID, the location and time of the starting of a riding, the location and time of the ending of a riding, and the riding distance
- **Period**: May 2016 - June 2016



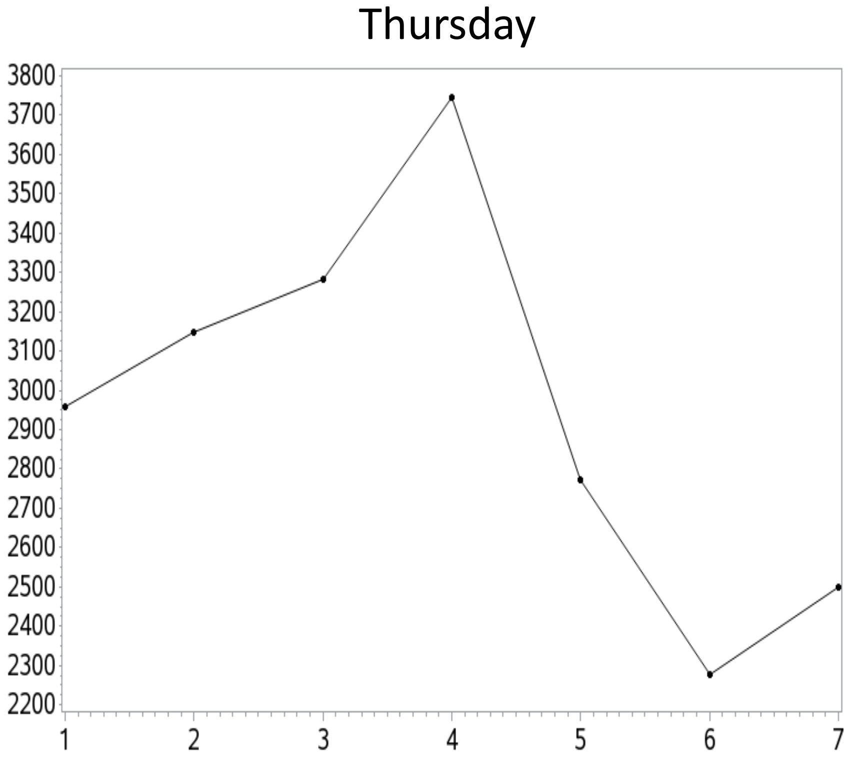
Data 1: Mobike



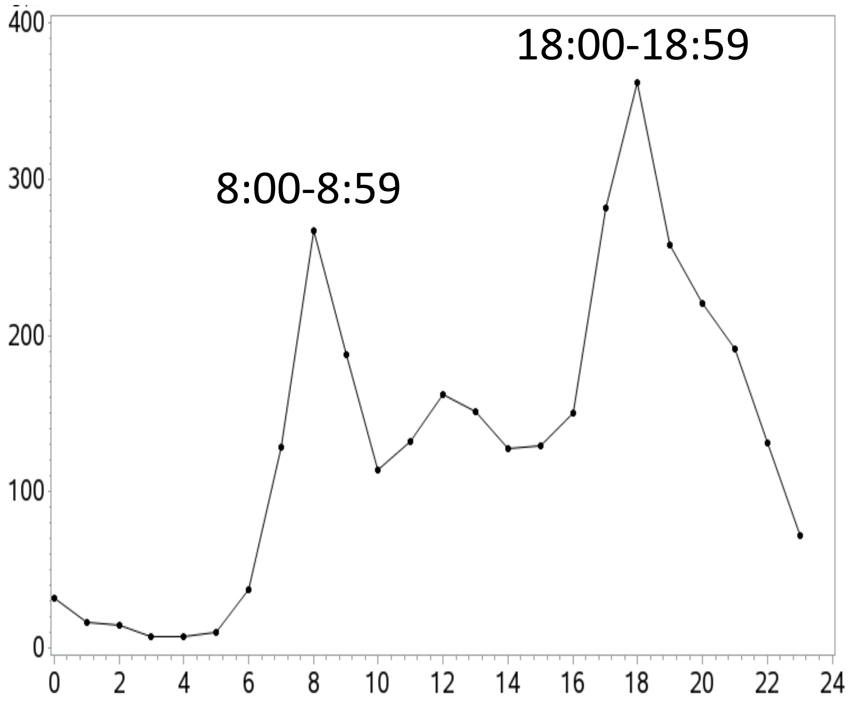
Radius = 5km

Note. The choice of the five stations is supported by our transportation card usage data

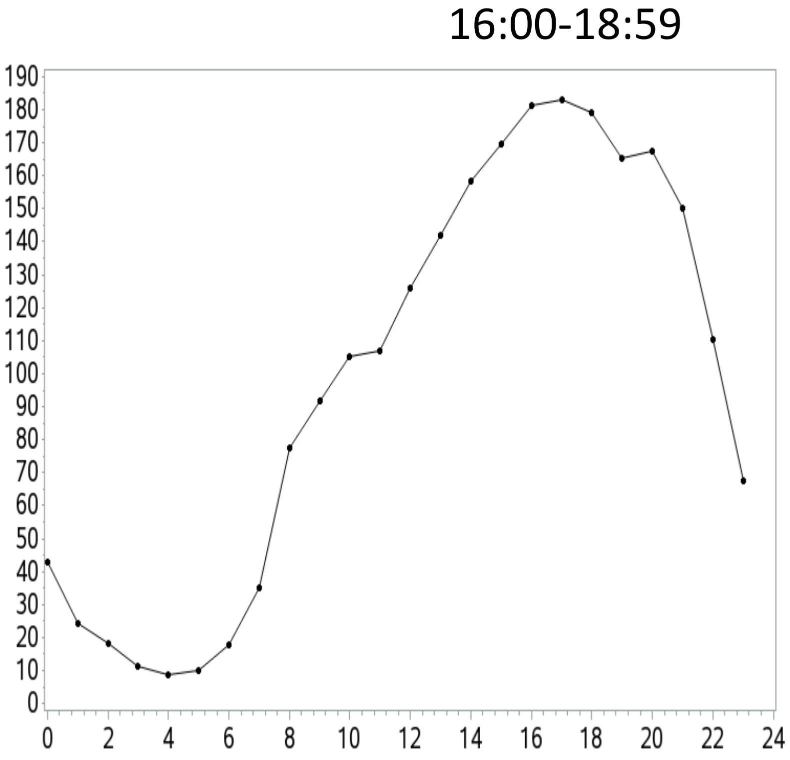
Data 1: Mobike



Number of ridings on weekdays and weekends



Number of Ridings by hour on weekdays



Number of Ridings by hour at weekends

Data 1: Mobike

Table 1 Summary statistics of Mobike usage records

	Region 1	Region 2	Region 3	Region 4	Region 5	Total
Number of ridings	115277	30409	30776	863	379	177704
Number of users	27302	10808	9565	506	225	48406
Number of bikes	3875	3357	2650	288	111	10281
Median distance (km)	1.6070	1.6190	1.6030	1.7315	1.8020	1.6100
First mile ridings	0.0879	0.1153	0.0611	0.0278	0.0158	0.0875
Last mile ridings	0.0909	0.1262	0.0540	0.0185	0.0079	0.0900
Morning rush hour	0.1340	0.1151	0.1761	0.1664	0.0935	0.1381
Evening rush hour	0.2041	0.2065	0.2043	0.2041	0.2014	0.2045

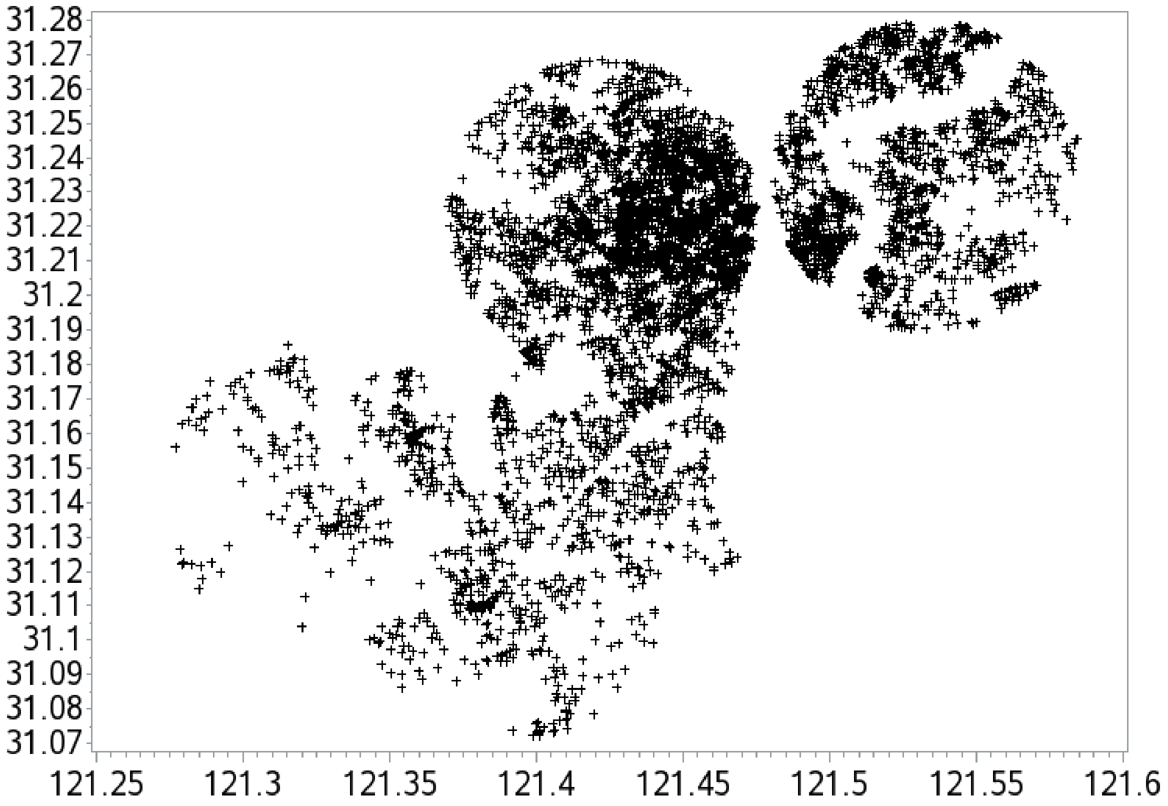
Note. "First mile ridings" is the percentage of ridings that ends within a distance of 0.2 km from a subway station. "Last mile ridings" is the percentage of ridings that starts within a distance of 0.2 km from a subway station. "Morning (evening) rush hour" shows the percentage of rides between 7:30 and 9:30 (17:30 and 19:30) on weekdays. The ridings that started in the overlapping area between Region 1 and 3 are classified into Region 1. The ridings that started in the overlapping area between Region 3 and 4 are classified into Region 3. The ridings that started in the overlapping area between Region 4 and 5 are classified into Region 4.

Data 2: House listing price

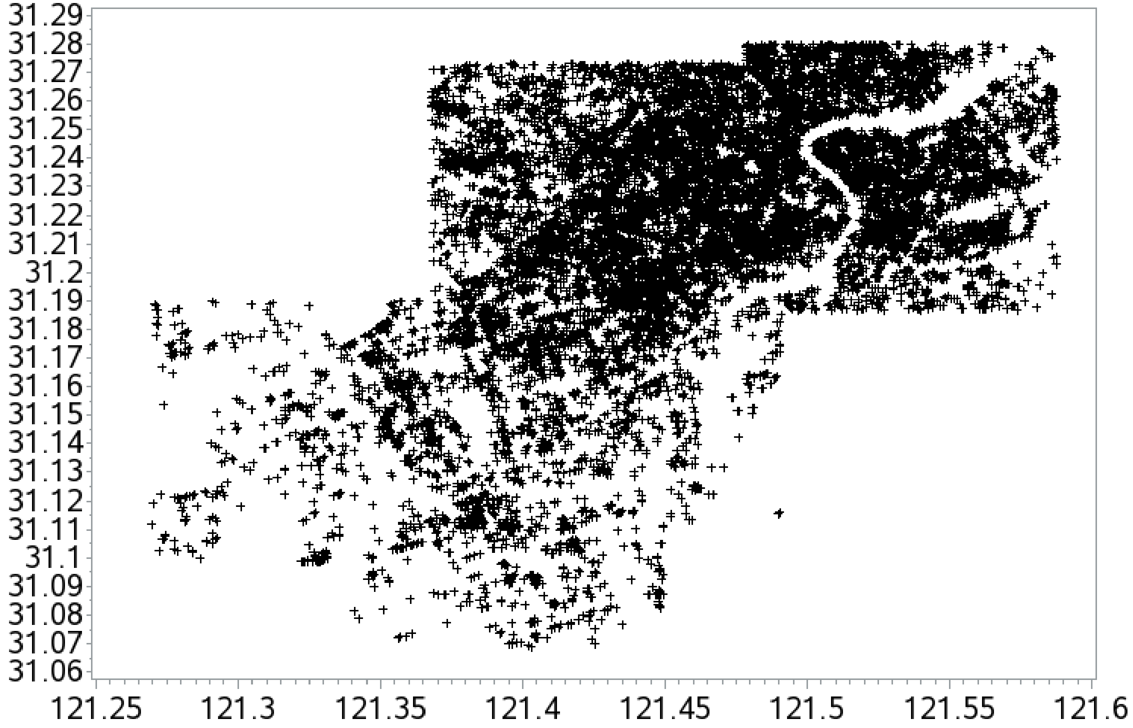
- **Source**: Lianjia

  --The largest real estate brokerage in China, holding more than 50% market share in Shanghai and Beijing (Li, Wei, Wu, Tian, 2018)

- **Period**: March 2016 - November 2017
- In the 5 regions: 214,775 listings in 6,117 neighborhoods of 127 zones



Data 3: Point of Interest (POI)



Location of parking lots around the 5 regions

Data source: Baidu Map

- **Key variable**: *Grow*= The growth rate of Mobike usage from May 2016 to June 2016 (the first two months after launch)
- **IV**: $\ln AvgP = \log(1 + AvgP)$

For neighborhood *n*, ***Parking*** is the number of parking lots that are less than 200m away from it.

AvgP is the average *Parking* of **other** neighborhoods in the same zone as *n*, weighted by the inverse of the distance to neighborhood *n*.

Empirical results

- **Mobike, subways, and house prices:**

$$\ln prc_{i,n,z,t} = c + \boxed{\beta_1 Grow_n} + \beta_2 Grow_n * ClsSub_n + \beta_3 \boxed{Grow_n * MidSub_n} + \beta_4 DisSub_n + + \beta_5 DisCenter_n$$
$$+ \beta_6 Size_i + \beta_7 Size_i^{\,2} + \beta_8 Age_i + \beta_9 Rooms_i + \beta_{10} East_i + \beta_{11} South_i + \beta_{12} West_i + \beta_{13} North_i + \beta_{14} Floor_i$$
$$+ \beta_{15} Totfloor_i + \beta_{16} Floor_i * Totfloor_i + \beta_{17} Decoration_i + \beta_{18} Villa_i + \beta_{19} LuxVilla_i + \beta_{20} LiLong_i$$
$$+ \beta_{21} DualHouse_i + \lambda_z + \tau_t + \varepsilon_{i,n,z,t}$$

i: house *n*: neighborhood *z*: zone *t*: month

Empirical results

OLS: The dependent variable is ln*Prc*

	2016.3.17-2016.4.21		2016.3.4.22-2016.10.31	
	Prior-launch		**Post-launch**	
	Coeff.	p-value	Coeff.	p-value
Grow	-0.0001	0.9711	-0.0007	0.6458
Grow*ClsSub	-0.0037**	0.0423	-0.0024**	0.0421
Grow*MidSub	0.0010**	0.0249	0.0007**	0.0137
ClsSub	0.0112	0.3274	0.0015	0.8726
MidSub	-0.0088	0.1634	-0.0038	0.4463
Other controls	Y		Y	
Zone FE & Month FE	Y		Y	
Obs	12423		28480	
R^2	80.37%		76.00%	

Note. Standard errors are clustered by neighborhood.

Empirical results

✓**Interpretation:**

1. Bike sharing generates negatively affects house prices in areas close to subway stations.

2. Bike sharing is a good solution to the “last mile” problem of subway stations.

3. The market overestimated both the positive and negative effects in the prior-launch period.

4. For an average house listed in the post-launch period, the house price premium associated with bike sharing is -0.48%.

Empirical results

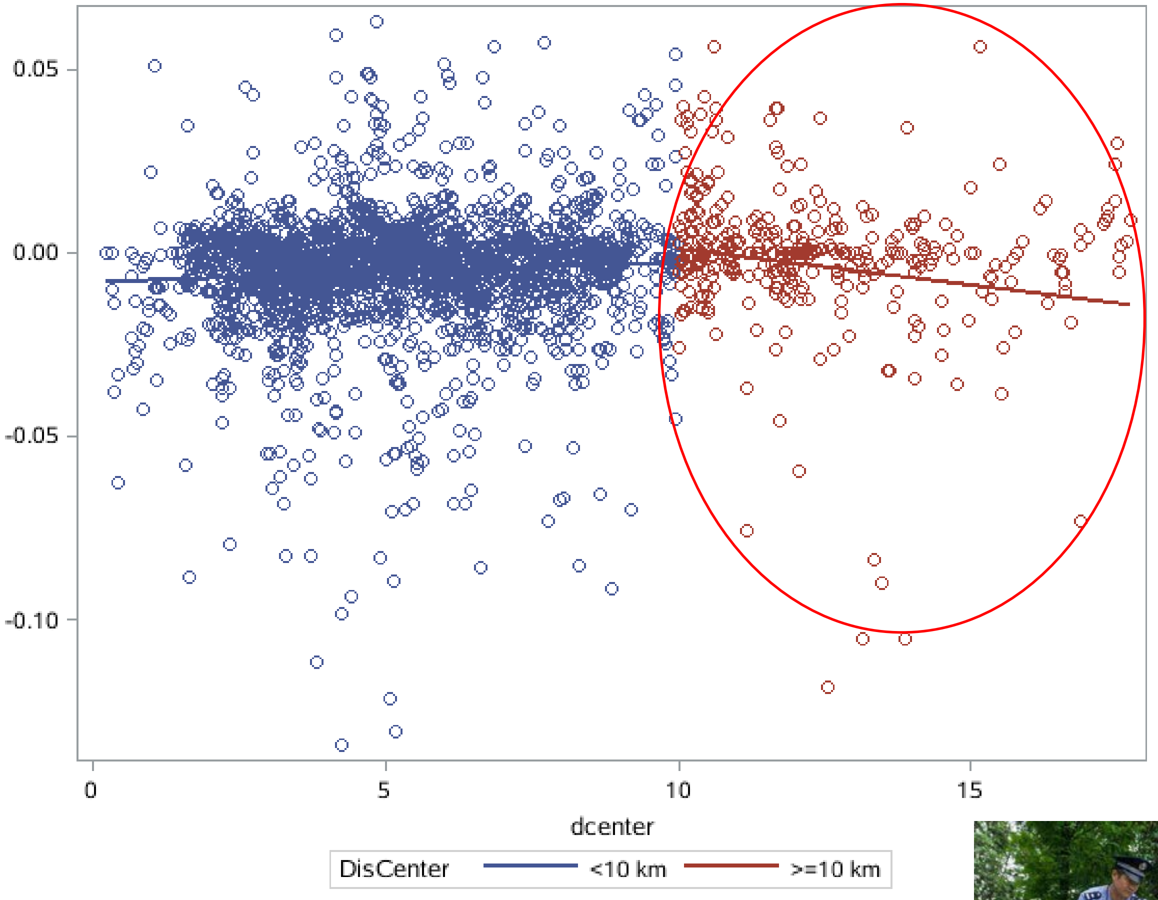


Figure 6A Prior-launch

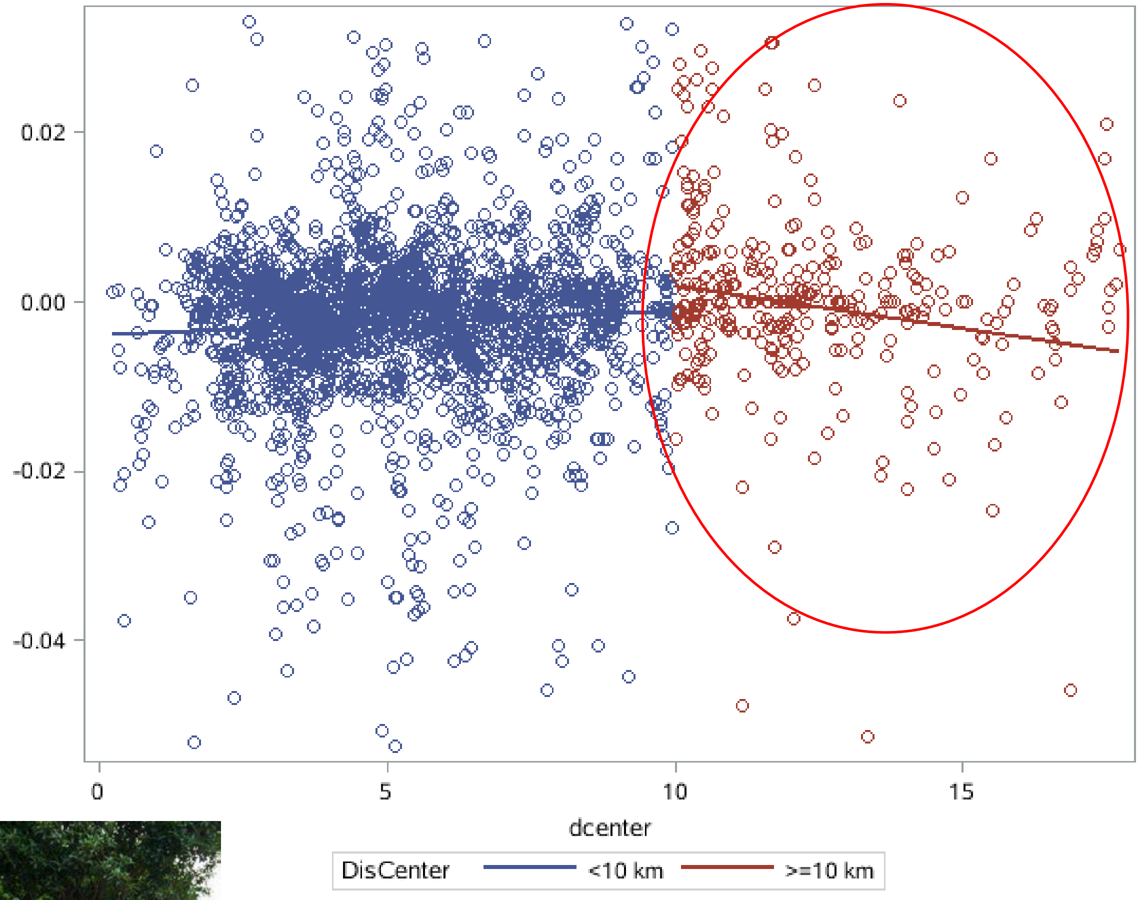


Figure 6B Post-launch

Empirical results

- **IV approach: 1st stage**

$$Grow_{i,n,z} = c + \beta_1 \ln AvgP_n + \beta_2 Age_i + \beta_3 Totfloor_i + \beta_4 Villa_i + \beta_5 LuxVilla_i + \beta_6 Commhouse_i + \beta_7 Xinli_i + \varepsilon_{i,n,z}$$

The coefficient of ln*AvgP* is -0.80, its *t*-value is -4.16; R^2 is 6.18%.

Empirical results

2nd stage:

	Prior-launch		Post-launch	
	Coeff.	p-value	Coeff.	p-value
Grow	-0.0230	0.4163	-0.0360*	0.0640
Grow*ClsSub	-0.0130*	0.0543	-0.0103*	0.0928
Grow*MidSub	0.0069*	0.0507	0.0046*	0.0877
ClsSub	0.0377*	0.0731	0.0169	0.4157
MidSub	-0.0290**	0.0195	-0.0218**	0.0261
Other controls	Y		Y	
Zone FE & Month FE	Y		Y	
Obs	12423		28480	
R^2	80.37%		76.00%	

Note. Numbers in italics are p-values.

Empirical results

- **Subsample analysis: Shopping-mall or not?**

	Prior-launch		**Post-launch**	
	Coeff.	p-value	Coeff.	p-value
c	5.2785***	<.0001	5.2320***	<.0001
Grow	-0.0044	0.1001	-0.0029	0.1043
Grow*SClsSub	-0.0027	0.3399	-0.0031	0.1712
Grow*NSClsSub	-0.0046**	0.0247	-0.0028**	0.0332
Grow*SMidSub	-0.0009	0.2388	-0.0001	0.8866
Grow*NSMidSub	0.0014***	0.0087	0.0008*	0.0612
SClsSub	0.0236	0.1534	0.0137	0.3152
NSClsSub	0.0210	0.1178	0.0077	0.5065
SMidSub	0.0131*	0.0832	0.0082	0.2041
NSMidSub	-0.0024	0.6964	0.0026	0.6204
Other controls	Y		Y	
Zone FE & Month FE	Y		Y	
Obs	12423		28480	
R^2	80.41%		76.03%	

Empirical results

✓**Interpretation:**

1. The negative externality concentrates in areas close to non-shopping-mall stations.

--Shopping malls often have staff who keep the surrounding area tidy.

2. The positive externality concentrates in areas with many medium-distance non-shopping-mall subway stations.

--There are usually bus lines that connects neighborhoods with major shopping malls nearby.

汇金百货门口（徐家汇）

Empirical results

➢ **Aggregate-level analysis**

- Using house listing prices, we construct a house price index for each of the 80 zones involved in the 5 regions.
- We adopt the hybrid approach of Fang, Gu, Xiong, and Zhou (2016).

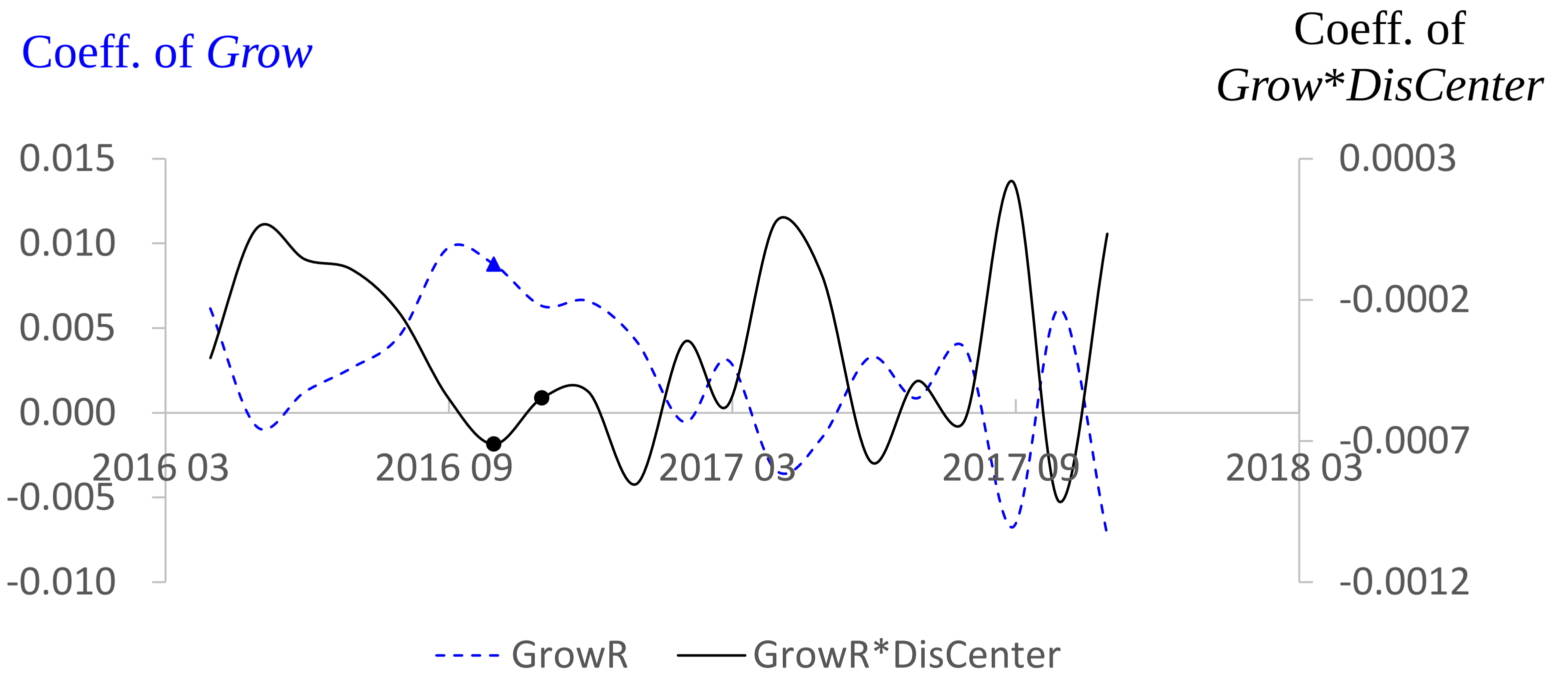
$$\ln unitprc_{i,n,z,t} = c + \beta_{1,z} Size_i + \beta_{3,z} Age_i + \beta_{4,z} Rooms_i + \beta_{5,z} Floor_i + \beta_{6,z} Totfloor_i$$
$$+ \beta_{7,z} Floor_i * Totfloor_i + \beta_{8,z} East_i + \beta_{9,z} South_i + \beta_{10,z} West_i + \beta_{11,z} North_i + \eta_n$$
$$+ \boxed{\sum_{s=2}^{T} \lambda_{s,z} \times 1\{s = t\}} + \varepsilon_{i,n,z,t}$$

$$HPI_{z,t} = \begin{cases} 1 & \text{if } t\text{=1 (i.e. March 2016)} \\ \exp(\lambda_{t,z}) & \text{for } t\text{=2,3,…} \end{cases}$$

Empirical results

$$Grow_z = c + \beta \times DisCenter_z + \varepsilon_z$$

$$HPI_{z,t} = c_t + \beta_{1,t} GrowR_z + \beta_{2,t} GrowR_z * DisCenter_z + \beta_{3,t} DisCenter_z + \varepsilon_{z,t}$$



- The externality of Mobike is positive (negative) in zones close to (far from) the city center.
- Cutoff point: 12 km away from the city center (i.e. People's Square)
- Consistent with micro-level findings

Robustness checks and additional tests

- **Mobike, buses, and house prices: Insignificant, as expected**

	Prior-launch		Post-launch	
	Coeff.	p-value	Coeff.	p-value
Grow	0.0000	0.9991	-0.0027	0.3402
Grow*ClsBus	-0.0006	0.2463	0.0001	0.7840
Grow*MidBus	0.0002	0.2995	0.0001	0.1420
ClsBus	0.0037	0.3174	0.0011	0.6458
MidBus	-0.0029	0.1063	-0.0026*	0.0521
Other controls	Y		Y	
Zone FE & Month FE	Y		Y	
Obs	12423		28480	
R^2	80.34%		75.99%	

Robustness checks and additional tests

- **Sensitivity test regarding band width: Robust**

	Panel 1: (0.8 km, 2.4 km)				Panel 2: (1 km, 2.5 km)				Panel 3: (1 km, 3 km)			
	Prior-launch		Post-launch		Prior-launch		Post-launch		Prior-launch		Post-launch	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Grow	-0.0027	0.1959	-0.0027**	0.0407	-0.0023	0.2884	-0.0019	0.1864	-0.0017	0.2304	-0.0019	0.3782
Grow*ClsSub	-0.0052*	0.0636	-0.0005	0.7144	-0.0047**	0.0134	-0.0030**	0.0238	-0.0030**	0.0241	-0.0045**	0.0137
Grow*MidSub	0.0008**	0.0123	0.0004*	0.0619	0.0010***	0.0023	0.0007**	0.0103	0.0005**	0.0143	0.0006***	0.0033
Controls	Y		Y		Y		Y		Y		Y	
Zone FE	Y		Y		Y		Y		Y		Y	
Month FE	Y		Y		Y		Y		Y		Y	
Obs	12423		28480		12423		28480		28480		12423	
R^2	80.38%		75.99%		80.39%		76.02%		76.03%		80.38%	

El-Geneidy, Grimsrud, Wasfi, Tétreault, and Surprenant-Legault (2014)

Robustness checks and additional tests

➢ **Mobike usage growth at longer horizon**

- So far, we have assumed that the growth of Mobike usage from May 2016 to June 2016 is a good measurement for Mobike density at steady state.
- To see if this assumption is reliable, we look at the growth at a longer horizon.
- We consider Mobike usage on October 9, 2017, which was a cloudy Monday.
- On October 9, 2017, the number of ridings reached 764,802. As a comparison, in May and June of 2016, the total number of ridings was 177,705.
- $Grow^{long} = Num_{171009}/Num_{1605}$-1.
- The correlation between *Grow* and $Grow^{long}$ is 0.4280 ($p<0.0001$).

Robustness checks and additional tests

- **Distance to city center and the tendency of Mobike to solve “last mile” problem: As expected**

- So far, we have found that house prices increase (decrease) with Mobike usage in zones that are close to (far from) the city center.
- We attribute this to the high density of subway network in the downtown area.
- Now we directly test the relationship between the distance to city center and the probability that bike sharing serves as a complement to the subway network.

Robustness checks and additional tests

- *Firstmile* (*Lastmile*) is a dummy that equals 1 if a riding ends (starts) in a place that is less than 0.2 km away from a subway station.

$$Firstmile_i = c + \beta DisCenter_i + \varepsilon_i$$

-0.0086

(p<0.0001)

$$Lastmile_i = c + \beta DisCenter_i + \varepsilon_i$$

-0.0074

(p<0.0001)

Note. Standard errors are clustered by user ID.

Conclusion

- Bike sharing generates a negative externality and hurts house prices.
- But meanwhile, bike sharing is a good solution to the “last mile” problem of subway stations.
- For an average house, the price premium associated with bike sharing is -0.48% in the post-launch period.
- At aggregate level, we find that house prices increase (decrease) with May-to-June growth rate of Mobike usage in zones that are close to (far from) the city center. This is consistent with micro-level findings.

Thank you!