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

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Abstract: This paper studies the impact of bike sharing on house prices. We combine the order-level records of a major sharing bike company with the house-level listing data and the Baidu Map point-of-interest (POI) data. We find that bike sharing has a negative effect on house prices. For an average house, the net house price premium caused by bike sharing is -0.48% in the post-launch period. However, the interaction of bike sharing with subway stations has an offsetting positive effect, indicating that bike sharing is a good solution to the "last-mile" problem. Unlike subway stations, the interaction between bus stations and bike sharing does not lead to a premium. At an aggregate level, the net effect of bike sharing is positive (negative, respectively) in zones that are close to (far from, respectively) the city center. This is consistent with our micro-level findings, because the density of subway network decreases with the distance from the city center, and that bike-sharing is more likely to be a complement to the subway network in downtown than in the suburbs.

Keywords: Bike sharing; Public transportation; House price; Benefits; China
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I. Introduction

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, and Currie, 2019). Theoretically, sharing economy improves economic efficiency by reducing frictions that cause capacity to go underutilized (Barron, Kung, and Proserpio, 2018). However, dockless sharing bikes may generate negative externalities, such as misuse of the scarce public space. So the net social benefit is unclear.

In this paper, we study the net welfare effect of bike sharing by focusing on house prices. House prices are routinely used to value welfare benefits from local public goods (Teulings, Ossokina, de Groot, 2018). While bike sharing is not considered public goods, it does bring "house externality" (Rossi-Hansberg, Sarte, and Owens III, 2010). So we can still study the welfare effect of sharing bikes by examining house prices.

We use Shanghai, China, as our research setting. China has the largest bike sharing market in the world (Gu, Kim, and Currie, 2019), and Shanghai is one of the first Chinese cities to introduce dockless bike sharing. On one hand, bike sharing is expected to bring large welfare benefits to Shanghai residents. There are two reasons. First, as in other Chinese cities, a large proportion of residents have acquired the skill of cycling. Prior to the popularization of private cars, cycling was one of the most important transportation modes in China. For example, in 2004, about 25.2% of the travel in Shanghai was cycling.[1] Because of the wide acquisition of cycling skills, bike sharing is a feasible transportation mode for a large proportion of residents. In August 2017, there were already 38 million Chinese users of Mobike, a major sharing bike brand in China.[2] Second, Shanghai has the world's largest rapid transit system by route length (Zhou, Chen, Han, and Zhang, 2019); as a result, the value of bike sharing as a complement to the public transportation network is potentially great. On the other hand, as mentioned above, dockless bike-sharing occupies public space in Shanghai, which features high population density. In short, Shanghai is an interesting city to research as both the benefits and costs of bike sharing is obvious.

Our micro-level datasets consist of three parts. The first part is the riding records of Mobike, which accounts for about half of the market share in the bike-sharing industry of China. The second part is house listing data from Lianjia, one of the most important real estate brokerage in China. The third part is point-of-interest (POI) data from Baidu Map, a Chinese counterpart of Google Map.

With the above datasets, we estimate the net welfare benefit of bike sharing in the following steps. First, we calculate the growth rate of Mobike usage from May 2016 to June 2016, which are the first two months after Mobike's launch in Shanghai on 22 April 2016. We denote the growth rate as *Grow*. We calculate two versions of *Grow*, one at neighborhood level and the other at zone-level.

Second, we do a micro-level analysis. To examine whether sharing bikes benefit local residents by solving the "last mile" problem, we look at the interaction term

[1] The source of this number is Wind database, which collects the information from Shanghai Municipal Transportation Commission.

[2] According to Sohu News (a major news portal in China), Mobike became the largest sharing bike company of China in May 2017. See: http://business.sohu.com/20170517/n493354558.shtml

between neighborhood-level *Grow* and the number of subway/bus stations with a distance suitable for riding. We expect that the interaction term is positively correlated with house prices. To mitigate the endogeneity concern, we compute the density of parking lots in the zone where the neighborhood is located. When calculating the density, we exclude the parking lots around the neighborhood itself. This density is used as a (negative) instrument variable for neighborhood-level *Grow*.

Third, we conduct aggregate-level analysis. With house listing prices, we construct a house price index for each zone with the hybrid approach of Fang, Gu, Xiong, and Zhou (2016). Then, we test if house price indexes grew faster during the post-launch period in zones with higher *Grow*. We also test if the relationship between index growth and *Grow* varies with a zone's distance to the city center. To cope with the collinearity between *Grow* and the distance to the city center, we use the residual approach as in Zhou, Chen, Han, and Zhang (2019) and Ibeas, Cordera, dell'Olio, Coppola, and Dominguez (2012).

We find that *Grow* has a negative effect on house prices. For an average house listed in the post-launch period, the net premium associated with bike sharing is -0.48%. This is consistent with the intuition that dockless bike-sharing misuses public space, thus generating a negative externality. However, the interaction between *Grow* and the number of subway stations with a distance suitable for riding (i.e. 1 km to 2 km) has an offsetting and positive effect on house prices. This indicates that bike sharing generates a positive externality by solving the "last mile" problem associated with subway stations. In addition, we find no evidence that the interaction between sharing bikes and the number of medium-distance bus stations has any positive effect on house prices.

At an aggregate level, the relationship between *Grow* and the post-launch house price growth varies with the distance to the city center. In zones close to (far from) the city center, the relationship is positive (negative). This is consistent with our micro-level findings, because the density of subway network decreases with the distance from the city center, and bike-sharing is more likely to be a complement to the subway network in downtown than in the suburbs. This is also consistent with Li, Ren, Zhao, Duan, Zhang, and Zhang (2017), who show that the transfer stations exhibit the highest level of radiation accessibility while the first/last stations have the lowest. First/last stations are usually located in suburbs.

The contribution of this paper lies in several aspects. First, this paper is among the first studies to quantitatively analyze the welfare benefit of sharing bikes in an emerging economy. Unlike in developed countries, private bikes used to be one of the most important transportation tools in developing cities like Shanghai in the 1990s. Therefore, the base of potential users with riding skill is large. Second, we shed light on the underlying mechanism through which bike sharing affects residents' benefits. With micro-level datasets, we show that bike-sharing generates a positive externality by serving as a complement to the public transportation network. Here we look at both bus stations and subway stations and examine the modes separately. And our identification is strong. With POI information from Baidu Map, we construct an instrument variable for *Grow*, thus alleviating the endogeneity concern. Third, we contribute to the literature on the effect of transportation on house prices. While the house price implications of road, airport, high-speed rail, and subway have been well studied, there are few studies about the impact of bike sharing – we can now fill this gap.

The rest of the paper is arranged as follows. Section II reviews the literature. Section III provides background knowledge about the bike-sharing market in Shanghai, China. Section IV develops the hypothesis. Section V displays our major empirical results. Section VI presents robustness checks and additional tests, and Section VII concludes.

II. Literature review

In recent years, there has been emerging literature on shared economy. Benjaafar, Kong, Li, and Courcoubetis (2019) build an equilibrium model to investigate the implications of peer-to-peer product sharing on ownership and usage. Jiang and Tian (2018) develop an analytical framework to examine the strategic and economic impact of product sharing among consumers. Guda and Subramanian (2019) offers insights for effectively managing on-demand service (e.g., Uber, Lyft) with independent workers. Burtch, Carnahan, and Greenwood (2018) study the impact of the entry of the ridesharing platform Uber X on local entrepreneurial activity. Unlike these papers, we focus on bike sharing. It differs from peer-to-peer product sharing or on-demand service like Uber, because the providers of shared bikes are not independent individuals. We are also different from these papers in that we study the net social benefits by looking at house prices.

To the extent that we look at house prices, we are related to Pelechrinis, Kokkodis, and Lappas (2015). With data from Pittsburgh, the US, they find that the bike-sharing system leads to an increase in the housing prices in the zip codes where sharing bike stations were installed. Unlike them, we consider dockless sharing bikes. Moreover, we conduct a house-level analysis, which enables us to explore the underlying mechanism through which bike-sharing affects house prices.[3]

This research also relates to that of Chu, Duan, Yang, and Wang (2018). They conduct an event study for the launch of sharing bikes. Using resale apartment data in 10 major cities of China, they regress logarithm of price per square meter on the interaction between distance to subway and a dummy indicating the post-launch period. They estimated that the entry of dockless bike sharing reduces the subway premium in house prices by about one-third.

Our paper is different from that of Chu, Duan, Yang, and Wang (2018) in several aspects. First, in terms of research question, they do not investigate whether bike-sharing reduces a subway premium by decreasing the value of houses close to subway stations or by increasing the value of houses far from subway stations. It is important to distinguish between these two alternatives. While the former suggests a negative externality, the latter channel suggests a positive one, and the policy implication corresponding the two alternatives are obviously different. We try to distinguish between the two alternatives. With order-level information of Mobike, we are able to examine how *Grow* and its interaction with subway stations affect house prices.

Second, since Chu, Duan, Yang, and Wang (2018) conduct event studies, they are

[3] As described in detail below, a "house" or "house unit" in our context refers predominantly to an apartment unit.

subject to the noise caused by time varying unobserved attributes (Bajari, Fruehwirth, Kim, and Timmins, 2012) and time-varying parameters (Knight, Dombrow, and Sirmans, 1995). An example of the former issue is the upward trend of car ownership rate, which can lead to a decline in a subway premium even without bike sharing. The latter issue is also worth noting as the launch of sharing bikes in Chinese cities mostly occurred between 2016 and 2017. The post-launch period coincided with a bull housing market. If the pricing gradients associated with transportation amenity are flatter in a bull market than in normal times, the estimated effect of bike sharing on a subway premium can also be biased. We are less subject to the time-trend problem because we use a shorter sample period; our micro-level data already contains enough variation. We alleviate the second problem by running regressions separately for the prior-launch period and the post-launch period, which allows for time-varying prices of house characteristics.

Third, we introduce an instrument variable (IV). Particularly, we innovatively use the density of parking lots around a neighborhood as a negative IV for *Grow*. This IV enables us to establish a causal relationship between bike sharing and house prices, and also suggests a useful tool for relevant studies in the future.

To the extent that we consider residents' benefit from sharing bikes, this paper is associated with Wang and Zhou (2017). They show that public bike-sharing systems (BSSs) have mixed impacts on congestion in general. Larger cities become better off but richer cities become worse off. Instead of solely focusing on the aspect of congestion, we consider the general welfare benefit delivered by bike sharing, which is reflected in house prices.

Furthermore, this research is related to the literature on house price heterogeneity. Housing prices in China have experienced rapid and prolonged growth in the past decade (Chen and Wen, 2017). However, the growth is highly imbalanced across regions (Fang, Gu, Xiong, and Zhou, 2016). It has been well documented that the geographical relationships between a housing unit and its major surrounding sites are fundamental factors that determine housing value (e.g. Sadayuki, 2018; McIntosh, Alegría, Ordóñez, and Zenteno, 2018). So one possible reason for the heterogeneous growth is the imbalanced public infrastructure investment across regions. With evidence from a metropolis in an emerging economy, we show that sharing bikes contributes to within-city house price heterogeneity.

Finally, we contribute to the literature about the effect of transportation on house price and economic growth. Many studies have investigated the effects of road, airport, high-speed rail, rail rapid transit line, and subway on house prices (e.g. McMillen, 2004; Li, Chen, Wang, Lam, and Wong, 2013; Zheng and Kahn, 2013; Cohen and Brown, 2017; Zhou, Chen, Han, and Zhang, 2019; Jing and Liao, 2019). The effects of roads, railroads, and highway on economic growth is also well documented (e.g. Duranton and Turner, 2012; Donaldson, 2018; Donaldson and Hornbeck, 2016; Baum-Snow, Brandt, Henderson, Turner, and Zhang, 2017; Baum-Snow, Henderson, Turner, Zhang, and Brandt, 2018). We add to this literature by looking at the impact of bike-sharing on house prices and, thus, social welfare.

III. Background and data description

We first provide the background knowledge of the bike sharing industry in Shanghai, China. Then we describe our data.

III.1. Bike sharing in Shanghai

In China, dockless bike sharing is operated by private firms. Although these firms are not state-owned, they receive government subsidies to the extent that dockless sharing bikes use public space freely. In Shanghai, Mobike is one of the biggest bike-sharing brands. It was introduced on April 22, 2016 - earlier than Ofo, which is another major bike-sharing brand.

The bike-sharing market is highly concentrated on the supply side. According to the 2017 China Household Finance Survey (CHFS), about 55.4% (55.0%, respectively) of bike-sharing riders in China (Shanghai, respectively) choose Mobike.[4] In **Figure 1**, the solid line shows the number of active users of Mobike in China; the dash line shows the number of active users of Ofo. In August 2017, the number of Mobike users peaked at 38 million, which is followed by a gradual decline. Such decline has also been experienced by Ofo. One reason for the decline is that bike-sharing brands attracted customers by large discounts when they first launched but such discounts are not sustainable. Another reason is the restriction erected by the government. As dockless sharing bikes' misuse of public space became more and more severe as time goes by, the government has started to prohibit the parking of sharing bikes in some areas. This limits the use of bike-sharing.

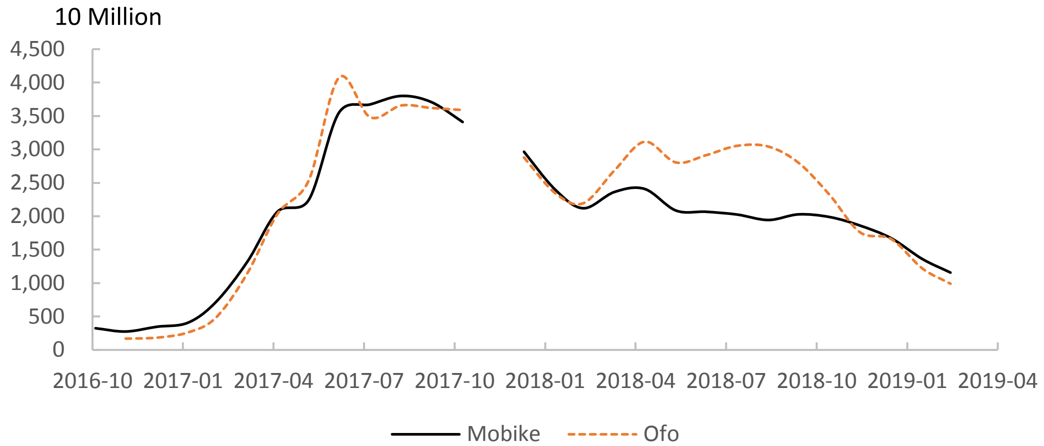

Figure 1 The number of active users of Mobike and Ofo

Note. The figure shows the number of active users of two major brands of sharing bikes in China: Mobike and Ofo. The sample period spans from October 2016 to February 2019. The data source is Wind database; the values in November 2017 are missing in the database.

III.2. Data

This section introduces three micro-level datasets that we combine together: Mobike usage records, listing prices of individual houses, and POI information.

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[4] See more details about the survey data in Gan, Yin, Jia, Xu, Ma, and Zheng (2014).

III.2.1 Mobike usage records

Our Mobike data covers the riding records in five regions. In **Figure 2**, we mark these regions by circles numbered from 1 to 5. The radium of each circle is 5 km. Regions 1 and 2 involve the inner-ring and middle-ring of Shanghai. Region 3 lies between the middle-ring and the outer-ring. Regions 4 and 5, especially the latter, are mostly outside of the outer-ring.[5] The sample period is from May 2016 to June 2016. These are the first two (full) months after the launch of Mobike in Shanghai. During the period 1996-2017, the average temperature of May (June) is 21℃ (24℃), which is suitable for bike riding. The available variables include Order ID, Bike ID, User ID, the location and time of the start of a ride, the location and time of the end of a ride, and the ride distance.

The centers of the five regions are five subway stations surrounded by a large number of residential houses. Among the 311 subway stations in Shanghai, the above five stations have the 21^{st}, 20^{th}, 10^{th}, 1^{st}, and 3^{rd} largest number of house units nearby.[6] Sharing bikes are supposed to solve the "last mile" problem associated with the subway network. In these five regions, the demand for the solution of the "last mile" problem should be strong, and the benefit of sharing bike should be large.

Regarding the geographic distribution of rides, we display the starting location and ending location of rides in each region by **Fig. A1** to **Fig. A10** in **Appendix A**. In all the five regions, the number of rides witnessed an obvious growth during the period from May 2016 to June 2016. Furthermore, the number of rides in Regions 1 to 3 is generally greater than that in Regions 4 to 5, implying that bike sharing is more popular in regions closer to downtown.

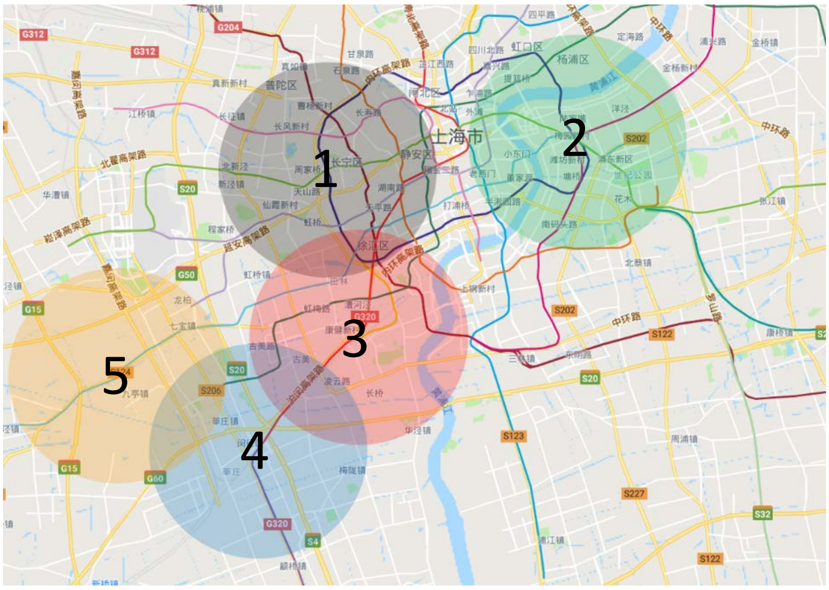

Figure 2 Sample regions of Mobike data

[5] Shanghai is divided into four parts by the inner-ring, middle-ring, and outer-ring. The area inside the inner-ring is the traditional downtown. The area outside the outer-ring is the suburb. Middle-ring lies between the inner-ring and the outer-ring.

[6] We have the records of transportation card usage on 13 April 2015, an ordinary Monday. We look at the last subway station where a passenger use his/her transportation card. We assume that the station is close to his/her home. Then, for each subway station, we calculate the number of passengers whose home is nearby.

Note. The center of Region 1 is Zhongshan Park station of subway Line 2. The center of Region 2 is Century Avenue station of subway Line 6. The center of Region 3 is Shanghai South Railway Station of subway Line 1 and subway Line 3. The center of the Region 4 is Xinzhuang Station of subway Line 1. The center of Region 5 is Jiuting Station of subway Line 9.

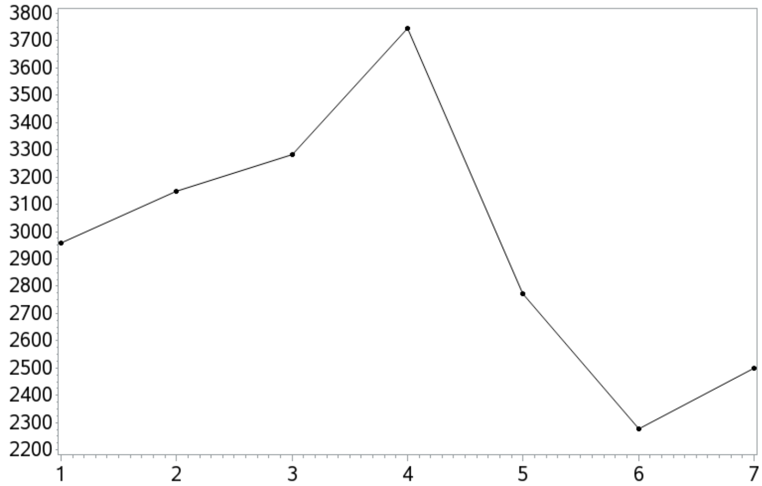

Figure 3 Number of rides on weekdays and weekends

Note. The figure shows the average number of rides on Monday through Sunday. Holidays that coincide with Monday to Friday are excluded. The sample period spans from May 2016 to June 2016.

We summarize the time distribution of rides. **Figure 3** plots the average number of rides on Monday to Sunday. There are more rides on weekdays than on weekends. **Figure 4** displays the average number of rides per hour. On weekdays, the number of rides peeks at 8:00-8:59 and 18:00-18:59. This "dual peaks" pattern of the morning and evening rush hours indicates that commuting is an important purpose of using shared bikes. During the weekend, on the other hand, the number of rides peeks at one period, i.e. 16:00-18:59.

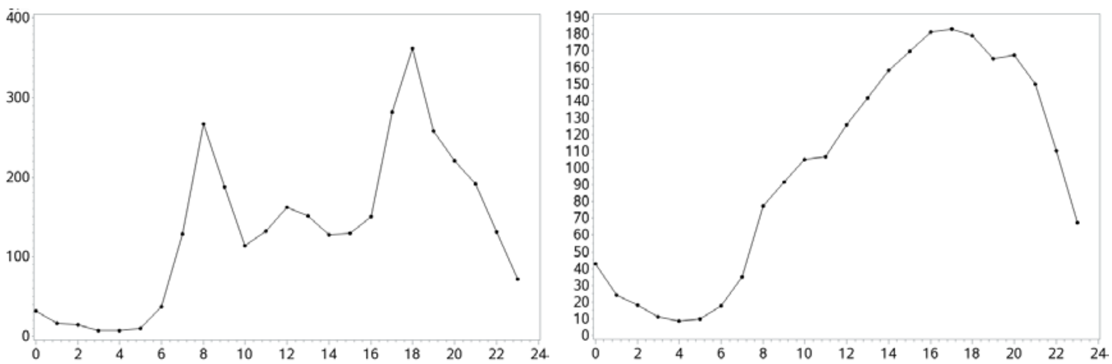

Figure 4 Number of Ridings by hour

Note. The figure shows the average number of rides by hour. For example, on the x-axis, "8" refers to 8:00-8:59. The left panel shows the case of weekdays, whereas the right panel shows the case of weekends and holidays. Note also that the vertical scales of the two graphs are different. The sample period is May 2016 to June 2016.

Table 1 Summary statistics of Mobike usage records

	Region 1	Region 2	Region 3	Region 4	Region 5	Total
Number of rides	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 rides	0.0879	0.1153	0.0611	0.0278	0.0158	0.0875
Last-mile rides	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. "Median distance" is the median ride distance. "First-mile rides" is the percentage of rides that end within 0.2 km from a subway station. "Last-mile rides" is the percentage of rides that start within 0.2 km from a subway station. "Morning (evening) rush hour" shows the percentage of rides between 7:30 and 9:30 (between 17:30 and 19:30). The rides that started in the overlapping area between Regions 1 and 3 are classified into Region 1. The rides that started in the overlapping area between Regions 3 and 4 are classified into Region 3. The rides that started in the overlapping area between Regions 4 and 5 are classified into Region 4.

To have a more accurate picture of the ride patterns of each region, we provide some summary statistics in **Table 1**. In regions closer to downtown, the numbers of rides, users, and bikes are larger, and the median ride distance is shorter. We also calculate the percentage of rides that end within 0.2 km from a subway station; it measures the importance of bike sharing as a solution to the "first mile" problem. The percentage ranges from 1.58% to 11.53%, becoming higher in regions closer to downtown. Similarly, the percentage of rides starting within 0.2 km from a subway station measures the importance of sharing bikes as a solution to the "last mile" problem. This percentage ranges from 0.79% to 12.62%, which is also higher in regions closer to downtown. Therefore, bike-sharing is more likely to be a complement to the subway network in downtown than in suburb. In suburb, bike-sharing is mostly a substitute to other transportation modes. If residents value the complementary role more than the substitute role, then we expect higher house price appreciation associated with bike sharing in downtown.

Regarding the usage time, more than one third (34.26%) of the rides occur during the rush hours, i.e. 7:30-9:30 and 17:30-19:30. The percentage of rides during the evening rush hours are similar across the regions, while that during the morning rush hours is lowest in Region 5. If people value easier commutes more than other benefits brought by bike sharing, then we expect lower house price appreciation associated with bike sharing in suburb.

3.2.2 Listing price of individual houses

The data of house listings is from Lianjia, which is the largest real estate brokerage in China, holding more than 50% market share in Shanghai and Beijing (Li, Wei, Wu, and Tian, 2018). Our sample period spans from 17 March 2016 to 14 November 2017, which straddles the date when Mobike entered Shanghai. In the five regions covered by our Mobike data, there are 214,775 listings. They are located in 6,117 neighborhoods, which belong to 127 zones.[7] **Figure 5** shows the location of listed houses.

The variables we have included are: house listing ID, listing date, listing price, unit price (yuan/m^2), latitude and longitude of a house, house age, house type, the last transaction time, the number of rooms, direction ("chaoxiang" in Chinese), the house level in a building, the total number of levels in the building, extent of interior decoration, name of the neighborhood ("xiaoqu" in Chinese), name of the zone, etc.

Listing price is an important variable in our analysis. However, it limits our interpretation in two ways. First, listing price is not transaction price. It only reflects the required price of the seller. Many houses finally withdrawn their listing. Second, we only have the last listing price of a house, which is a function of both the initial listing price and the revisions. In Section 6.2, we will discuss about the potential effects of these two issues on our results.

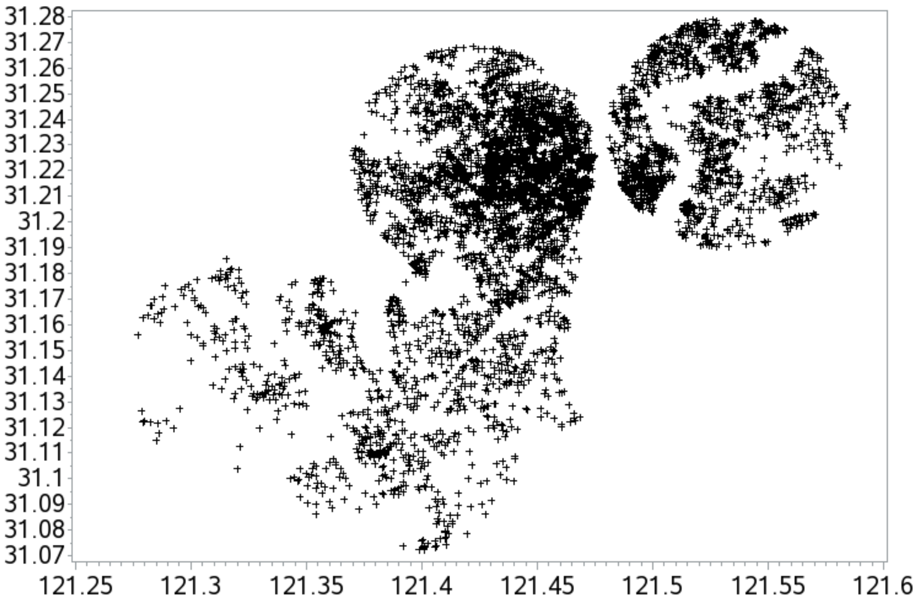

Figure 5 Location of houses listed at Lianjia

Note. The figure shows the latitude and longitude of houses in our sample.

3.2.3 Key variable, instrument variable, and POI information

The key variable in our paper is the growth rate of Mobike usage during the period from May 2016 to June 2016. We calculate the number of rides starting within the 0.2 km distance from each neighborhood. The calculation is done separately for May 2016 and June 2016, which produces Num_{1605} and Num_{1606}. Then *Grow* is defined as (Num_{1606}/Num_{1605}) - 1. This growth rate should be positively correlated with the density of sharing bikes in steady state. In later analysis, we will investigate how *Grow* affects house prices.

Grow may be endogenous, however. For example, rich communities have a high

[7] According to the government, there are 121 zones in Shanghai (Zhou, 2016). But Lianjia defines a zone in a way that is different from the government. A zone defined by Lianjia is typically smaller than a zone defined by the government.

ownership rate of private cars, which leads to a low demand for shared bikes and a low value of *Grow*. CBD zones have large passenger flows, which leads to a high value of *Grow*. In a given period, the house price trends in rich communities and CBD zones may be different from those in other places. Such an endogeneity problem associated with *Grow* may bias our results. To mitigate this concern, we construct an instrumental variable (IV). This IV is based on the point-of-interest (POI) information collected through the API service of Baidu Map, a Chinese counterpart of Google Map.

More specifically, we collect the locations of parking lot POIs in the rectangles covering the five regions involved in our Mobike data.[8] We display the parking lot POIs in **Fig. A11** of **Appendix A**. For each neighborhood, we count the number of parking lots with a distance of less than 0.2 km from the core of the neighborhood. The number is denoted as *Parking*. The core of a neighborhood is defined by the median latitude and longitude of the listed houses in it. Then for neighborhood *i*, we calculate the average of *Parking* around other neighborhoods in the same zone, weighted by the inverse of the distance to neighborhood *i*. The weighted average is denoted as *AvgP*. Then we define ln*AvgP* as follows:

$$\ln AvgP = \log(1 + AvgP) \qquad (1)$$

ln*AvgP* is our IV for *Grow*. For a given neighborhood, ln*AvgP* should not directly affect the prices of houses in it, because we exclude its own *Parking* when calculating ln*AvgP*. Nevertheless, ln*AvgP* affects house prices through *Grow*. The logic is as follows. Bike sharing is featured by economics of scale. If a neighborhood is surrounded by communities with high car ownership, then residents in this neighborhood faces a low density of sharing bikes in nearby areas. This leads to a low value of *Grow* around this neighborhood, regardless of the demand for bike sharing from itself.

IV. Hypothesis development

Change in house listing prices reflects the utility gain of local residents from sharing bikes. The utility gain involves three elements:

a. The value of sharing bikes as a substitute to driving, walking, and travelling by public transportation:
   $Value^s$ = Original travelling cost to destination - Sharing bike fee
b. The value of sharing bikes as a complement to the public transportation network:
   $Value^c$ = (Original travelling cost to destination - Sharing bike fee) + (Public transportation benefit - public transportation fee)
c. The negative externality of sharing bikes' misuse of public space: *M*

The net benefit from sharing bikes can be calculated as follows. In expression (2) below, parameter *A* is the density of sharing bikes, and parameter *p* is the possibility that a shared bike is used as a complement to public transportation, conditional on its being used:

[8] Relative to circles, rectangles can simplify the data collection process.

$$Benefit = A \times [(1-p) \times Value^s + p \times Value^c + M] \quad (2)$$

where $Value^s$ depends on the pricing of shared bikes. The fee of Mobike was 1 yuan per 15 minutes in May 2019. If there is no arbitrage opportunities between the original travelling cost and Mobike fees, then $Value^s$=0.[9] Then expression (2) is simplified:

$$Benefit = A \times [p \times Value^c + M] \quad (3)$$

Note that $Value^c$ is positive, because the benefit of public transportation usually outweighs the fees. The public transportation system receives government subsidy. In 2017, for example, the public transportation system of Shanghai received 3.04 billion yuan from the government, and the system served 5.74 billion passengers. This results in a subsidy of 0.53 yuan per passenger. If we take into account the high construction cost of the system, then the net benefit of passengers is even larger. For example, the Shanghai government invested nearly 30 billion in the fixed assets of the subway system in 2017. Subway passengers directly benefit from such investments.[10]

The value of *p* depends on the distance from one's home to subway/bus stations. When the distance is too short or too long for riding, bike sharing becomes irrelevant, and *p* is virtually 0. Then *Benefit* equals *A***M*. In our empirical work, *Grow* is regarded as a measure of *A*. We assume that a higher growth rate of Mobike usage after its launch indicates a high density in steady state. So we have our first hypothesis:

H1: Bike sharing negatively affects prices of houses that are too close or too far from subway stations.

When one's home has a medium distance from subway stations, then bike riding becomes a means to reach these stations, so *p* becomes positive. This results in a positive $A*p*Value^c$, the value of which increases with *p*. Parameter *p* increases with the number of medium-distance stations. When this number is large enough, the positive effect can even dominates the negative externality caused by the misuse of public space. Our second hypothesis is then as follows:

H2: The interaction between *Grow* and the number of stations with a medium distance from one's home positively affects the house price.

V. Empirical results

We first conduct micro-level analysis. Then we document aggregate-level results.

V.1. Mobike, subway stations, and house prices

We first run the baseline OLS regression. Then we adopt the IV approach. Finally, we distinguish between shopping-mall stations and non-shopping-mall stations.

V.1.1. OLS regression

We use the hedonic approach to test whether Mobike and its interaction with subway stations increase house value. In regression (4) below, the dependent variable is the natural logarithm of the listing price of house *i*, which is listed in month *t* and

[9] We consider a positive $Value^s$ in Section 6.6.

[10] The summary statistics in this paragraph is from Wind database.

located at neighborhood n of zone z:

$$\begin{aligned} \ln prc_{i,t,n,z} &= c+\beta_1 Grow_n+\beta_2 Grow_n*ClsSub_n+\beta_3 Grow_n*MidSub_n+\beta_4 ClsSub+\beta_5 MidSub \\ &+\beta_6 DisSub_n+\beta_7 DisCenter_n+\beta_8 Size_i+\beta_9 Size_i^2+\beta_{10} Age_i+\beta_{11} Rooms_i+\beta_{12} East_i+\beta_{13} South_i \\ &+\beta_{14} West_i+\beta_{15} North_i+\beta_{16} Floor_i+\beta_{17} Totfloor_i+\beta_{18} Floor_i*Totfloor_i+\beta_{19} Decoration_i \\ &+\beta_{20} Villa_i+\beta_{21} LuxVilla_i+\beta_{22} LiLong_i+\beta_{23} DualHouse_i+\eta_z+\tau_t+\varepsilon_{i,t,n,z} \end{aligned} \quad (4)$$

On the right-hand side (RHS) of (4), *MidSub* is the number of subway stations with a distance of 1 km to 2 km from the neighborhood in which house i is located. *ClsSub* is the number of subway stations that are less than 1 km away from the neighborhood. We also control for *DisSub*, which is the distance to the nearest subway station. *DisCenter* is the distance to the city center, i.e. People's Square in Shanghai. Furthermore, we control for house size, house age, the number of rooms, the direction that a house faces, the house level in a building, the total number of levels in the building, extent of interior decoration, type of house, etc.[11] Finally, we control for zone-fixed effects and month-fixed effects by dummies. In **Appendix C**, we summarize the definitions of these variables; in **Table B1** of **Appendix B**, we provide their summary statistics.

Table 2 Regression of house listing prices: OLS

	Pre-launch		Post-launch	
	Coeff.	**p-value**	**Coeff.**	**p-value**
c	5.4819***	<.0001	5.4293***	<.0001
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
DisSub	-0.0484*	0.0665	-0.0610***	0.0039
DisCenter	-0.0327***	0.0048	-0.0140	0.1479
Size	0.0053***	<.0001	0.0068***	<.0001
Size^2	0.0000***	<.0001	0.0000***	<.0001
Age	-0.0019***	<.0001	-0.0036***	<.0001
Room	0.1607***	<.0001	0.1257***	<.0001
East	0.0296	0.1672	0.0025	0.8810
South	0.1501***	<.0001	0.1342***	<.0001
West	0.0292	0.1869	-0.0286	0.1193
North	0.0769***	<.0001	0.0602***	<.0001
Floor	-0.1933***	<.0001	-0.1210***	<.0001
Totfloor	0.0035**	0.0171	0.0054***	<.0001

[11] As some houses face south-east, south-west, north-east, or north-west, we include four direction dummies in regression (4). Regarding type of houses, the default type is apartment, the most common type. The dummy *LuxVilla* equals 1 for luxury villa, and 0 otherwise. The dummy *LiLong* equals 1 for renovated "lilong", and 0 otherwise. "Lilong" is a traditional type of residential house: Shanghai keeps a small number of "Lilong", which attracts many tourists. *DualHouse* is a dummy that equals 1 for houses with dual-purposes, and 0 otherwise. This special type of houses are allowed to be used as offices; they are usually cheaper than pure residential houses.

Floor*Totfloor	0.0100***	<.0001	0.0067***	<.0001
Decolevel	0.0448***	<.0001	0.0335***	<.0001
Villa	0.2747***	0.0013	0.2343***	0.0011
LuxVilla	0.1995***	0.0008	0.2060**	0.0280
Dual	-0.5505***	<.0001	-0.4637***	<.0001
Lilong	0.0969***	0.0057	0.1405***	0.0012
Zone FE	Y		Y	
Month FE	Y		Y	
Obs	12423		28480	
R^2	80.37%		76.00%	

Note. We run regression (4) for each period. The dependent variable is the natural logarithm of house listing prices. Coefficients of other controlling variables are not reported. Standard errors are clustered by neighborhood. Numbers in italics are p-values. Significant levels of 10%, 5%, and 1% are marked by *, **, and ***, respectively.

Standard errors are clustered by neighborhood because listing prices in the same neighborhood could be correlated for non-fundamental reasons. For example, Bailey, Cao, Kuchler, and Stroebel (2018) find that social interactions affect individuals' housing market expectations. Guren (2018) emphasizes that the optimal listing price is increasing in the listing price of other sellers because of the strategic complementarity in the price setting behavior.

The regression is run separately for the pre-launch period and the post-launch period. The former spans from 17 March 2016 to 21 April 2016, whereas the latter spans from 1 July 2016 to 31 October 2016.[12] For data reasons, the length of our pre-launch period is relatively short and close to the launch. Therefore, we should be careful when interpreting the results of our pre-launch period, because they may reflect the expectation effect concerning Mobike.[13] It is also worth noting that the housing market return was unusually high in 2016 Q3, as shown in **Fig. A13** of **Appendix A**. This is why we run the regression separately for the two periods, which allows for time-varying pricing of house characteristics.

The results are displayed in **Table 2**. The coefficient of *Grow*ClsSub* is significantly negative in both the pre-launch and post-launch periods. That is, even before the launch of Mobike, the market already realized its negative externality on houses close to subway stations. H1 is supported. The coefficient of *Grow*MidSub* is significantly positive in both the pre-launch and post-launch periods. That is, even before the launch of Mobike, the market already realized that houses that have many medium-distance subway stations would benefit from bike sharing. H2 is supported.

We notice that the coefficients of *Grow*ClsSub* and *Grow*MidSub* both have larger magnitude in the pre-launch period than in the post-launch period. This indicate that the market tended to overestimate both the positive externality and the negative

[12] The post-launch period ends in October 2016 because house characteristics like *Decoration* and house type dummies (i.e. *Villa*, *LuxVilla*, *LiLong*, *Commhouse*) are unavailable since November 2016. We skip May and June, because we use the data Mobike usage during these two months to calculate *Grow*.

[13] **Figure A12** shows the Baidu Index of the keyword "Mobike" in the prior-launch period. The index was highest in Shanghai, which is consistent with the fact that Shanghai is the first city entered by Mobike.

externality of Mobike before its launch.

To obtain a straightforward and quantitative picture of the Mobike effect, we consider the net house price premium of an average house. For houses listed in the pre-launch period, the average *Grow* is 3.29, the average *ClsSub* is 2, and the average *MidSub* is 6. These translate into an appreciation of -0.46%, i.e. 3.29*(0.0010*6-0.0037*2). For houses listed in the post-launch period, the average *Grow* is 3.72, the average *ClsSub* is 2, and the average *MidSub* is 5. These translate into an appreciation of -0.48%, i.e. 3.72*(0.0007*5-0.0024*2).

Figures 6A and **6B** show the distribution of house price appreciation associated with bike sharing. For both the pre-launch period and the post-launch period, the appreciation is negatively correlated with *DisCenter* when the latter is 10 km or greater. This is consistent with the fact that many suburb houses are so far away from subway stations that bike sharing rarely helps.

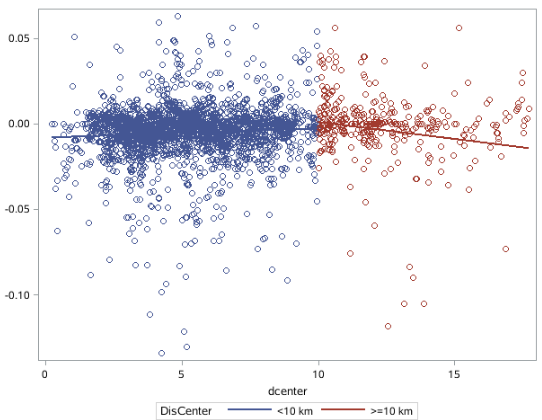

Figure 6A Pre-launch **Figure 6B Post-launch**

Note. The y-axis corresponds to house price appreciation associated with bike sharing. The x-axis corresponds to the distance to the city center (in km). The blue (red, respectively) circles mark the appreciation of houses that are less than 10 km (at least 10 km, respectively) away from the city center. **Figure 6A** corresponds to the pre-launch period; the appreciation is calculated as *Grow**(0.0010**MidSub*-0.0037**ClsSub*). **Figure 6B** corresponds to the post-launch period; the appreciation is calculated as *Grow**(0.0007**MidSub*-0.0024**ClsSub*). We truncate the appreciation at 1% and 99% level.

V.1.2. The IV approach

As we explained in Section 3.2.3, *Grow* is correlated with neighborhood characteristics and may be endogenous. So we use ln*AvgP* as an instrument variable for *Grow*. In the first stage, we regress *Grow* on ln*AvgP* and other controlling variables, as illustrated by equation (5). We cluster standard errors by neighborhood. According to the (untabulated) results, the coefficient of ln*AvgP* is -0.80. The *t*-value is -4.16, and R^2 is 6.18%.

$$\begin{aligned} Grow_{i,n,z} &= c + \beta_1 \ln AvgP_n + \beta_2 Age_i + \beta_3 Totfloor_i + \beta_4 NClsSub + \beta_5 NMidSub \\ &+ \beta_6 Villa_i + \beta_7 LuxVilla_i + \beta_8 DualHouse_i + \beta_9 LiLong_i + \varepsilon_{i,n,z} \end{aligned} \quad (5)$$

In the second stage, we replace *Grow* by its predicted value from regression (5), and rerun regression (4). As displayed in **Table 3**, the results are similar to those in **Table 2**. In particular, the coefficient of *Grow***ClsSub* is significantly negative, whereas the coefficient of *Grow***MidSub* is significantly positive. Regarding houses listed in the pre-launch period, the average of predicted *Grow* is 3.39, which translates into an appreciation of 5.22%, i.e. 3.39*(0.0069*6-0.0130*2). Regarding houses listed in the post-launch period, the average *Grow* is 3.68, which translates into an appreciation of -0.88%, i.e. 3.68*(0.0046*5-0.0103*2).

Table 3 Regression of house listing prices: The 2nd stage of IV regressions

	Pre-launch		**Post-launch**	
	Coeff.	**p-value**	**Coeff.**	**p-value**
c	5.5583***	<.0001	5.6060***	<.0001
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
DisSub	-0.0584**	0.0352	-0.0711***	0.0029
DisCenter	-0.0311***	0.0087	-0.0120	0.2178
Size	0.0053***	<.0001	0.0068***	<.0001
Size^2	0.0000***	<.0001	0.0000***	<.0001
Age	-0.0019***	0.0010	-0.0039***	<.0001
Room	0.1606***	<.0001	0.1259***	<.0001
East	0.0271	0.1993	0.0010	0.9543
South	0.1514***	<.0001	0.1360***	<.0001
West	0.0289	0.1903	-0.0274	0.1331
North	0.0776***	<.0001	0.0602***	<.0001
Floor	-0.1913***	<.0001	-0.1211***	<.0001
Totfloor	0.0036**	0.0155	0.0050***	<.0001
Floor*Totfloor	0.0100***	<.0001	0.0067***	<.0001
Decolevel	0.0449***	<.0001	0.0332***	<.0001
Villa	0.2630***	0.0049	0.1680**	0.0308
LuxVilla	0.1925***	0.0025	0.1885**	0.0431
Dual	-0.5456***	<.0001	-0.4492***	<.0001
LiLong	0.0962**	0.0363	0.1165**	0.0193
Zone FE	Y		Y	
Month FE	Y		Y	
Obs	12423		28480	
R^2	80.38%		76.02%	

Note. The dependent variable is the natural logarithm of house listing price. This table reports the second stage results of an IV regression. In the first stage, we regress *Grow* on an instrument variable (i.e. ln*AvgP*) and other variables, as illustrated by equation (5). For a neighborhood, ln*AvgP* is the weighted average of the number of parking plots around other neighborhoods that are located in the same zone. Then we replace *Grow* with its predicted value from the first stage regression and rerun regression (4). Standard errors are clustered by neighborhood. Numbers in italics are p-values. Significant levels of 10%, 5%, and 1% are marked by *, **, and ***, respectively.

V.1.3. Shopping-mall vs. non-shopping-mall stations

So far, we have considered all types of subway stations when computing *ClsSub* and *MidSub*. However, many subway stations are located near shopping malls. The difference between shopping-mall stations and non-shopping-mall stations is relevant for two reasons. First, the negative externality of bike sharing on residents living near subway stations depends on the station type. We expect that this negative effect is weaker if the stations coincide with shopping malls, because shopping malls often have staffs who must keep the surrounding area clean and tidy. Second, the "last mile" problem also depends on the station type. We expect that the value of bike sharing as a solution to the last-mile problem is weaker for shopping-mall stations, because there are often bus lines that connect neighborhoods with major shopping malls nearby.

Table 4 Shopping mall vs. non-shopping mall stations

	Pre-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
DisSub	-0.0405	0.1139	-0.0546***	0.0087
DisCenter	-0.0194	0.1631	-0.0021	0.8456
Size	0.0053***	<.0001	0.0068***	<.0001
Size^2	0.0000***	<.0001	0.0000***	<.0001
Age	-0.0019***	<.0001	-0.0036***	<.0001
Room	0.1612***	<.0001	0.1262***	<.0001
East	0.0313	0.1425	0.0031	0.8535
South	0.1492***	<.0001	0.1340***	<.0001
West	0.0285	0.2016	-0.0283	0.1213
North	0.0759***	<.0001	0.0600***	<.0001
Floor	-0.1932***	<.0001	-0.1209***	<.0001
Totfloor	0.0034**	0.0223	0.0054***	<.0001
Floor*Totfloor	0.0101***	<.0001	0.0067***	<.0001
Decolevel	0.0448***	<.0001	0.0333***	<.0001
Villa	0.2726***	0.0014	0.2264***	0.0023

LuxVilla	0.2017***	0.0007	0.2098**	0.0259
Dual	-0.5516***	<.0001	-0.4636***	<.0001
Lilong	0.0961***	0.0064	0.1387***	0.0013
Zone FE	Y		Y	
Month FE	Y		Y	
Obs	12423		28480	
R^2	80.41%		76.03%	

Note. The dependent variable is the natural logarithm of house listing prices. We split *MidSub* into *SMidSub* and *NSMidSub*. They are, respectively, the numbers of shopping-mall stations and non-shopping-mall stations that are 1 km to 2 km away from the neighborhood of a house. Similarly, we split *ClsSub* into *SClsSub* and *NSClsSub*. Then we replace *MidSub* with *SMidSub* and *NSMidSub*, replace *ClsSub* with *SClsSub* and *NSClsSub*, and repeat the analysis in **Table 3**. The table shows the second stage results. We control for zone-fixed effects. Standard errors are clustered by neighborhood. Numbers in italics are p-values. Significant levels of 10%, 5%, and 1% are marked by *, **, and ***, respectively.

We are interesting in examining these two conjectures, because any supportive evidence helps confirm the mechanism(s) through which bike sharing affects house prices. To test the conjectures, we make use of the POI data from Baidu Map. We define shopping-mall stations as the subway stations with shopping malls that are less than 0.2 km away. Other subway stations are non-shopping-mall stations. Then we define *SClsSub* as the number of shopping-mall stations that are less than 1 km away from a neighborhood. *NSMidSub* equals *MidSub* minus *SMidSub*. Similarly, *MidSub* is split into the number of shopping-mall stations (i.e. *SMidSub*) and the number of non-shopping-mall stations (i.e. *NSMidSub*).

We replace *ClsSub* with *SClsSub* and *NSClsSub*, and replace *MidSub* with *SMidSub* and *NSMidSub*. Then we repeat regression (4). The results are displayed in **Table 4**. As expected, the negative effect of the interaction between *Grow* and *ClsSub* concentrates on non-shopping-mall stations. So does the positive effect of the interaction between *Grow* and *MidSub*. Therefore, the two conjectures are supported, which confirms that the misuse of public space and solution to the last-mile problem are two important channels through which bike sharing affects home value.

V.2. Mobike, bus stations, and house prices

Now we investigate the house-price impact of Mobike that works through the interaction with buses. For a neighborhood, we define *ClsBus* as the number of bus stations that are less than 0.5 km away; *MidBus* is the number of bus stations that are 0.5 km to 1 km away. Unlike the case of subway stations, we only consider bus stations that are less than 1 km away because people are willing to go through a longer distance to take a subway than to take a bus (El-Geneidy, Grimsrud, Wasfi, Tétreault, and Surprenant-Legault, 2014).

We replace *ClsSub* with *ClsBus*, replace *MidSub* with *MidBus*, and repeat the baseline regression (4). As shown in **Table 5**, the coefficients of *Grow**ClsBus* and *Grow**MidBus* are insignificant in both the pre-launch period and the post-launch period. That is, the interaction of Mobike with bus stations delivers neither benefits nor harms. This result is unsurprising, because bus stations have much smaller passenger flows than subway stations and are usually located much closer to people's homes than subway stations.

Table 5 Interaction between Mobike and Bus station

	Pre-launch		Post-launch	
	Coeff.	**p-value**	**Coeff.**	**p-value**
c	5.4583***	<.0001	5.4345***	<.0001
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
DisSub	-0.0420	0.1017	-0.0509**	0.0128
DisCenter	-0.0309***	0.0036	-0.0140*	0.0975
Size	0.0053***	<.0001	0.0068***	<.0001
Size^2	0.0000***	<.0001	0.0000***	<.0001
Age	-0.0019***	<.0001	-0.0037***	<.0001
Room	0.1607***	<.0001	0.1261***	<.0001
East	0.0299	0.1554	0.0025	0.8787
South	0.1495***	<.0001	0.1348***	<.0001
West	0.0253	0.2538	-0.0294	0.1149
North	0.0781***	<.0001	0.0608***	<.0001
Floor	-0.1918***	<.0001	-0.1222***	<.0001
Totfloor	0.0035***	0.0186	0.0054***	<.0001
Floor*Totfloor	0.0100***	<.0001	0.0067***	<.0001
Decolevel	0.0441***	<.0001	0.0329***	<.0001
Villa	0.2735***	0.0015	0.2358***	0.0015
LuxVilla	0.2069***	0.0005	0.2109**	0.0243
Dual	-0.5485***	<.0001	-0.4610***	<.0001
Lilong	0.0950***	0.0070	0.1401***	0.0013
Zone FE	Y		Y	
Month FE	Y		Y	
Obs	12423		28480	
R^2	80.34%		75.99%	

Note. The dependent variable is the natural logarithm of house listing price. *ClsBus* is the number of bus stations within 0.5 km from a given neighborhood; *MidSub* is the number of bus stations that is 0.5 km to 1 km away from a given neighborhood. Standard errors are clustered by neighborhood. Numbers in italics are p-values. Significant levels of 10%, 5%, and 1% are marked by *, **, and ***, respectively.

V.3. Aggregate-level analysis

In Sections 5.1 and 5.2, we control for zone-fixed effects when investigating the impact of Mobike on house prices. By doing so, we focus on within-zone differences. Now we conduct an aggregate-level analysis and focus on cross-zone differences.

Using house listing data, we construct a house price index for each of the 80 zones involved in the five regions covered by our Mobike data. We adopt the hybrid approach of Fang, Gu, Xiong, and Zhou (2016) by running regression (6a) below. The dependent variable is the natural logarithm of the unit listing price (yuan/m^2) of house *i*, which is located in neighborhood n of zone *z*, and first listed in month *t*. We control for neighborhood fixed effects by dummies; we do not control for decoration level or house type, because they are unavailable after October 2016. Then the coefficients of the time dummies are used to construct the indexes (i.e. *HPI*), as illustrated by formula (6b).

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

$$HPI_{z,t} = \begin{cases} 1 & \text{if } t=0 \\ \exp(\lambda_{t,z}) & \text{for } t=1,2,\ldots \end{cases} \tag{6b}$$

Using the above approach, we obtain the house price indexes for the 80 zones. The sample period spans from 17 March 2016 to 14 November 2017. We further calculate the average of the 80 indexes, weighted by the number of observations in each zone. Then we obtain a general house price index (i.e. *GHPI*). We compare *GHPI* with the Shanghai house price index disclosed by Wind. The correlation is 0.59.[14]

Then we investigate whether a larger *Grow* is associated with higher growth of house price indexes during a period that straddles the launch of Mobike. To this end, we need a zone-level measure of *Grow*. For May and June 2016, we calculate the distance from the starting points of the rides to the center of the 80 zones. Here the location of the center of a zone is determined by the median longitude and latitude of houses listed in the zone during the period from 17 March 2016 to 14 November 2017. We match each ride to the zone the center of which is closest to the starting point. By comparing the number of rides in May and June 2016, we calculate zone-level *Grow*.

When investigating the aggregate-level impact of *Grow* on house listing prices, we also consider its interaction with the distance to the city center. Our micro-level evidence above indicates that the house-price impact of *Grow* varies with this distance, as shown in **Figures 6A** and **6B**.

Ideally, we shall regress *HPI* on *Grow*, *DisCenter*, and the interaction between the latter two. However, at zone-level, the correlation between *Grow* and *DisCenter* is 0.45.[15] To deal with the collinearity problem, we regress *Grow* on *DisCenter*, and denote the residual as *GrowR*. Then we run the following regression separately for each month. The dependent variable is house price index of zone *z* in month *t*, which

[14] If we use the natural logarithm of the total price rather than the unit price as the dependent variable in regression (6a), this correlation drops to 0.38. So we use the natural logarithm of the unit price.

[15] One possible reason for the positive correlation is that the regulation of public space usage is stricter in downtown than in suburb. According to the Survey of Sharing Bikes in Shanghai, 75.4% of the respondents regard the misuse of public space as the most serious problem of dockless bike sharing. **Fig. A14** in **Appendix A** shows the location of "City Management" (i.e. "Chengguan" in Chinese) POIs. Such POIs obviously concentrate in downtown. It is the responsibility of city management teams to relocate dockless shared bikes so that the public space is not misused. In some downtown areas, sharing bikes are not allowed to be parked, which limits the growth of Mobike usage.

measures the cumulative growth of house listing price from March 2016 to month *t*. We exclude a zone if its *HPI* is the highest or lowest among the 80 zones.

$$HPI_{z,t} = c_t + \beta_{1,t} GrowR_z + \beta_{2,t} GrowR_z * DisCenter_z + \beta_{3,t} DisCenter_z + \varepsilon_{z,t} \quad (7)$$

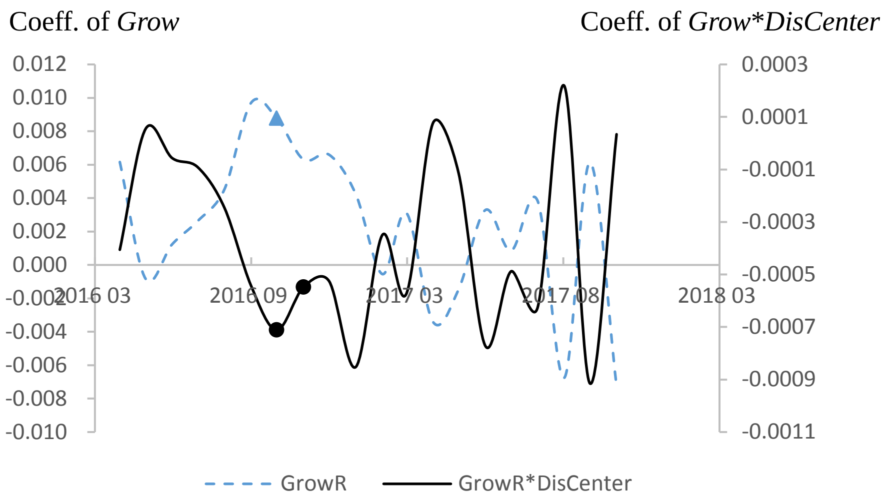

Figure 7 Zone-level analysis

Note. This table reports the coefficients of *GrowR* and *GrowR*DisCenter* in regression (7), which is run separately for each month during the period from April 2016 to November 2017. The dash line shows the coefficient of *GrowR*, which corresponds to the left axis; a coefficient that is significant at the 10% level is marked with a dot. The solid line shows the coefficient of *GrowR*DisCenter*, which corresponds to the right axis; a coefficient that is significant at the 10% level is marked with a triangle.

As can be seen from **Figure 7**, the coefficient of *GrowR* is significantly positive in October 2016. That is, a high *Grow* is associated with a higher growth rate of house listing prices in the first six months after Mobike's launch. Moreover, the coefficient of *Grow*DisCenter* is significantly negative in October and November of 2016. So the positive effect of *Grow* is weaker in areas that are farther away from the city center. When *DisCenter* is greater than 12.3 km, the net impact of Mobike is negative.

In general, the above analysis shows that the externality of Mobike tends to be positive (negative) in zones close to (far from) the city center, which have denser (sparser) subway network. This is consistent with **Figures 6A** and **6B**. More importantly, the aggregate-level result is consistent with the negative effect highlighted by H1 and the positive effect highlighted by H2.

VI. Robustness checks and additional tests

First, we test whether our aggregate-level results are robust when more controlling variables are included in the construction of house price indexes. Second, we discuss about a weakness in our house listing data and its potential effect on our results. Third, to make our micro-level findings and aggregate-level findings more integrated, we directly show that Mobike is more likely to serve as a complement to subways in regions closer to the city center. Fourth, we show that *Grow* is a good predictor of the long-term growth of Mobike usage. Fifth, we do a sensitivity test regarding the bandwidth of *ClsSub* and *MidSub*. Sixth, we discuss about the constraint $Value^s$=0.

VI.1. More controlling variables in the construction of house price indexes

In regression (6a) of Section 5.3, we do not control for decoration level and house type dummies, because these variables are unavailable after October 2016. We now add these variable into the RHS of regression (6a) and repeat the analysis of Section 5.3.

The results are displayed by **Figure 8**. It is a counterpart of **Figure 7**, but has a shorter horizon for data reasons. Though the significant level is low, it is still true that the coefficient of *Grow* is positive and the coefficient of *Grow**DisCenter* is mostly negative. These patterns are consistent with the results in Section 5.3.

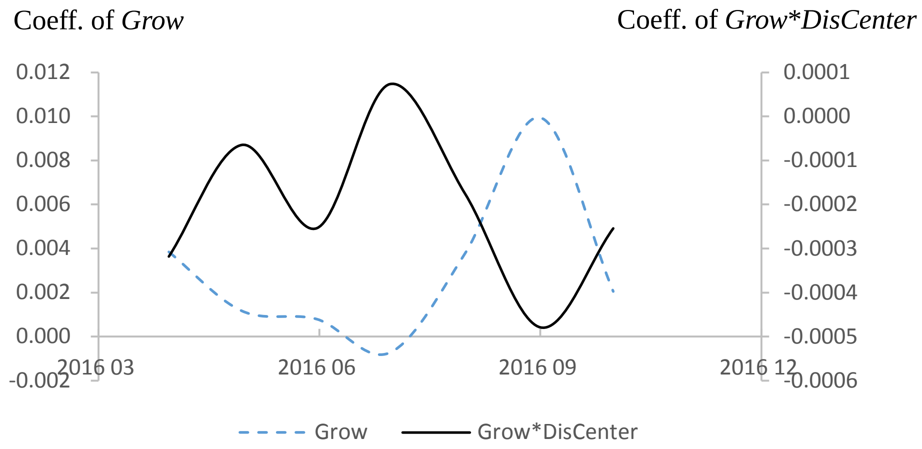

Figure 7 Zone-level analysis: More controlling variables

Note. This figure is a counterpart of **Figure 6**. We control for decoration level and house type dummies when constructing the house listing price indexes. For data reasons, the indexes end in October 2016.

VI.2. Concerns related to listing prices

Our house listing data is imperfect. Although we have the first listing date, we do not have the first listing price. The listing price that we observe is the last revision by 14 November 2017. The revision process may introduce biases to analysis.

However, we argue that the revision process is unlikely to affect our results. There are two pieces of supportive evidence. First, Chu, Duan, Yang, and Wang (2018) also use house listing data from Lianjia. They find that there is no significant difference in price negotiation and adjustment process between apartments close to and farther from subway stations, either before or after the entry of bike sharing.

Second, using our data, we reach results similar to those of Chu, Duan, Yang, and Wang (2018). With 10 sample cities (including Shanghai), they find that the entry of bike sharing reduces the housing price premium. We do a similar analysis by running regression (8). The dummy *Post* equals 1 for houses listed after 21 April 2016, and 0 otherwise.

$$\begin{aligned}\ln prc_{i,t,n,z} &= c+\beta_1 DisSub_n+\beta_2 Post*DisSub+\beta_3 DisCenter_n+\beta_4 Size_i+\beta_5 Size_i^2+\beta_6 Age_i+\beta_7 Rooms_i \\ &+\beta_8 East_i+\beta_9 South_i+\beta_{10} West_i+\beta_{11} North_i+\beta_{12} Floor_i+\beta_{13} Totfloor_i+\beta_{14} Floor_i*Totfloor_i \\ &+\beta_{15} Decoration_i+\beta_{16} Villa_i+\beta_{17} LuxVilla_i+\beta_{18} LiLong_i+\beta_{19} DualHouse_i+\eta_z+\tau_t+\varepsilon_{i,t,n,z}\end{aligned} \tag{8}$$

According to the (untabulated) results, the coefficients of *DisSub* and *Post***DisSub* are -0.0582 (p=0.0002) and 0.0112 (p=0.0823), respectively. That is, bike sharing reduces the subway station gradient. This is consistent with Chu, Duan, Yang, and Wang (2018), which further indicates that the bias in our data is quite limited.

Another possible concern related to our data is that listing prices are not transaction prices. Listing prices involve the strategic behavior of sellers. However, transaction prices also have problems. On the one hand, financially constrained home buyers artificially inflate transaction prices in order to draw larger mortgages (Ben-David, 2011). On the other hand, unconstrained home buyers use dual contracts to artificially deflate transaction prices and evade taxes. In contrast, listing prices are not subject to such measurement error.

VI.3. Distance to city center and the last-mile problem

According to Section 5.3, house listing price grows faster in zones that are closer to the city center after Mobike's launch. 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.

We define *Firstmile* (*Lastmile*) as a dummy that equals 1 if a riding ends (starts) in a place that are less than 0.2 km away from a subway station. Then we run the following OLS regressions. The sample period spans from May 2016 to June 2016. *DisCenter* is the distance from the starting point of a ride to the city center. Standard errors are clustered by user ID.

$$Firstmile_i = c + \beta DisCenter_i + \varepsilon_i \tag{8}$$

$$Lastmile_i = c + \beta DisCenter_i + \varepsilon_i \tag{9}$$

In regression (8), the coefficient of *DisCenter* is -0.0086 (p<0.0001). As the distance to city center increases by 1 km, the probability that sharing bikes solve the first mile problem decreases by 0.86%. In regression (9), the coefficient is -0.0074 (p<0.0001). As the distance to city center increases by 1 km, the probability that sharing bikes solve the last mile problem decreases by 0.74%.

The above results confirm that sharing bikes are more likely to complement the subway network in regions that are closer to the city center. In suburb zones, sharing bikes are just transportation tools, so the positive externality is smaller. The results here support our argument in Section 5.3 that the positive externality of bike sharing decreases with the distance to the city center because sharing bikes are less likely to complement the sparse subway network in suburb areas.

VI.4. Mobike usage growth at longer horizon

So far, we have assumed that the growth of Mobike usage from May to June, 2016, is a good measurement for Mobike density at steady state. To see if this assumption is reliable, we look at Mobike usage on 9 October 2017, which was a cloudy Monday. In May and June 2016, the total number of rides was 177,705. On 9 October 2017, the number of rides reached 764,802. In **Fig. A15** of **Appendix A**, we plot the spatial distribution of the ridings.

We match each riding to a zone according to the starting point of the ridings and the center of the zones. Then we calculate zone-level Num_{171009}, which is the number of ridings on 9 October 2017. Recall that Num_{1605} the number of rides in May 2016. We define $Grow^{long}$ as Num_{171009}/Num_{1605}-1.

The correlation between *Grow* and $Grow^{long}$ is 0.4280 ($p<0.0001$). That is, the growth of Mobike usage in the first two months helps predict the total growth in the first 18 months. This support our usage of *Grow* as a measurement for Mobike density at steady state.

VI.5. Sensitivity test regarding band width

In **Table 3**, we define *MidSub* as the number of subway stations that is 1 km to 2 km away from a neighborhood. A potential concern is that 1 km is too long for walking and 2 km is too short as the ceiling of riding distance. El-Geneidy, Grimsrud, Wasfi, Tétreault, and Surprenant-Legault (2014) mention that 800 m (0.5 miles) around rail stations are commonly used to identify the area from which most transit users will access the system by foot. So we redefine *ClsSub* as the number of stations that are less than 0.8 km away. Considering that riding speed is roughly 3 times that of waling according to Baidu Map, we redefine *MidSub* as the number of stations with a distance between 0.8 km and 2.4 km. Then we repeat regression (4).

As shown in Panel 1 of **Table 6**, for the pre-launch period, the results are quite similar to those in **Table 2**. For the post-launch period, the coefficient of *Grow***MidSub* remains significantly negative. Moreover, the coefficient of *Grow* becomes significantly negative, whereas that of *Grow***ClsSub* becomes insignificant. This means the negative externality of bike sharing is not limited to places that are close to subway stations. In general, H1 are H2 are robust to alternative band width.

We also conduct the analysis using alternative bands. For example, instead of the breakpoint combinations of (1 km, 2km) and (0.8 km, 2.4 km), we also try the combinations (1 km, 2.5 km) and (1 km, 3 km). The results are displayed in Panels 2 and 3, which are consistent with those in **Table 2**.

VI.6. Value of bike sharing as an alternative transportation mode

In Section IV, we assume that bike-sharing fees leave zero surplus to riders who simply regard bike sharing as an alternative transportation mode, i.e. $Value^s=0$. Now we consider the possibility that $Value^s>0$.

Table 6 Alternative band width

	Panel 1: (0.8 km, 2.4 km)				Panel 2: (1 km, 2.5 km)				Panel 3: (1 km, 3 km)			
	Pre-launch		Post-launch		Pre-launch		Post-launch		Pre-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%	

Note. The dependent variable is the natural logarithm of house listing prices. In Panel 1, we redefine *ClsSub* as the number of subway stations that are less than 0.8 km away. *MidSub* is redefined as the number of subway stations with a distance between 0.8 km and 2.4 km. Then we rerun regression (4). The controlling variables are the same as in **Table 2**; their coefficients are not reported here. In Panel 2, we redefine *ClsSub* as the number of subway stations that are less than 1 km away. *MidSub* is redefined as the number of subway stations with a distance between 1 km and 2.5 km. In Panel 3, we redefine *ClsSub* as the number of subway stations that are less than 1 km away. *MidSub* is redefined as the number of subway stations with a distance between 1 km and 3 km. Standard errors are clustered by neighborhood. Numbers in italics are p-values. Significant levels of 10%, 5%, and 1% are marked by *, **, and ***, respectively.

Table 7 Growth of rush hour usage and house prices

	Pre-launch		Post-launch	
	Coeff.	**p-value**	**Coeff.**	**p-value**
GrowRush	-0.0098**	0.0381	-0.0052*	0.0638
GrowRush*ClsSub	-0.0021	0.4226	-0.0013	0.5583
GrowRush*MidSub	0.0021**	0.0422	0.0013*	0.0809
Controls	Y		Y	
Zone FE	Y		Y	
Month FE	Y		Y	
Obs	8470		19221	
R^2	80.14%		78.71%	

Note. The dependent variable is the natural logarithm of house listing prices. We replace *Grow* with *GrowRush* and rerun regression (4); the latter is the growth rate of Mobike usage during morning rush hours from May 2016 to June 2016. The controlling variables are the same as in **Table 2**; their coefficients are not reported here. The number of observations is smaller than that in **Table 2**, because some neighborhoods have zero rides nearby in May 2016. Standard errors are clustered by neighborhood. Numbers in italics are p-values. Significant levels of 10%, 5%, and 1% are marked by *, **, and ***, respectively.

Other things equal, a positive *Value*^{s} means larger benefit brought by bike sharing. This should lead to a larger coefficient of *Grow* in **Table 2**. To empirically examine the value of bike sharing as an alternative transportation mode, we define *GrowRush* as the growth rate of Mobike usage during morning rush hours from May to June 2016.[16] The logic is as follows. Rides happening in rush hours are more likely to serve commuting purposes than other purposes. For commuters, sharing bikes are less likely to simply serve as an alternative transportation mode, because commuters who ride to office usually have their own bikes. Therefore, *GrowRush* is positively correlated with the tendency that local residents complement public transportation by bike sharing. Compared with *Grow*, *GrowRush* is less related to *Value*^{s}. Replacing *Grow* with *GrowRush*, we repeat regression (4). If the coefficient of *GrowRush* becomes more negative than that of *Grow* in **Table 2**, then it means the general benefit brought by bike sharing becomes lower without *Value*^{s}. This, in turn, means that *Value*^{s} is positive.

As shown in **Table 7**, the coefficient of *GrowRush* becomes significantly negative for both periods. According to the logic described above, this result indicates that *Value*^{s} is positive. Therefore, the true magnitude of the negative externality associated with bike sharing seems to be larger than the one reflected by **Table 2**.

VII. Discussion and Conclusion

In this paper, we have combined three micro-level datasets to study the impact of bike sharing on house prices. We found that bike sharing has a negative effect on house

[16] Morning rush hours span from 7:30 a.m. to 9:30 a.m. We use morning rush hours rather than evening rush hours because most recreation facilities, such as shopping malls, are not opened yet in the morning. This helps us focus on the rides for commuting purposes.

prices. In the post-launch period, the net price appreciation of an average house is -0.48%. Nevertheless, the interaction between bike sharing and medium-distance subway stations leads to an offsetting and positive externality. Bike sharing provides a good solution to the “last mile” problem of subway stations. In contrast, bike sharing does not generate positive externality by improving residents’ access to bus stations. At aggregate level, a higher ride intensity of sharing bikes is associated with higher (lower, respectively) post-launch house price growth in zones that are close to (far from, respectively) the city center. This is consistent with our micro-level finding, because the subway network in suburb is too sparse for sharing bikes to solve the last-mile problem.

We shall notice that the externalities of sharing bikes, no matter positive or negative, have different meaning for renters versus homeowners. In downtown, easier access to subway stations are capitalized into house prices, from which homeowners benefit. In suburbs, sharing bikes’ negative externality decreases the wealth of homeowners. But for renters, the net utility change is virtually zero, because any sharing bike externality can be offset by changes in the rents.

Most studies about transportation infrastructure provide land financing implications. However, the land financing implication of dockless bike sharing is somehow tricky. Prior to the launch, it is hard to predict the density of dockless sharing bikes in a place, which makes it difficult to form an expectation of net externality. However, it is likely that bike sharing results in a larger passenger flow to subways by solving the last-mile problem. This helps justify dockless sharing bikes’ free use of public space, given that subways are run by state-owned enterprises.

There are several possible extensions from the present study. For example, we can study the different forces that affect the externality of bike sharing. In this paper, the tests involving subway stations provide direct evidence that the positive externality is generated by serving as a complement to the subway system. However, we lack direct evidence for the channel through which that the negative externality is generated. The finding that the negative externality concentrates on houses near non-shopping-mall stations only provides suggestive evidence that the misuse of public space is a probable channel. With proper data about the parking of sharing bikes, we can look into the channels behind the negative externality.

Another potential extension involves the labor market. It has been found that population mobility is an important issue in the labor market (e.g. Head, and Lloyd-Ellis, 2012; Ahlfeldt, Redding, Sturm, and Wolf, 2015). Bike sharing improves labor mobility, and its effect on labor cost varies across regions. Baum-Snow, Henderson, Turner, Zhang, and Brandt (2018) find that investment in national highways hurt hinterland city growth. With bike sharing, it is possible that downtown firms find it easier to attract workers from suburbs. On one hand, this may hurt suburb development because of reduced labor supply. On the other hand, this may stimulate development because of higher household income and consumption. Increased labor mobility may also facilitate suburb development by supporting the formation and expansion of suburb employment centers with initially poor accessibility.

Finally, we can look at house supply issues in the future. Baum-Snow, Brandt, Henderson, Turner, and Zhang (2017) show that roads and railroads lead to the decentralization of Chinese cities. In the context of bike sharing, we may investigate whether it leads to an increased supply of new houses in areas that are far from subway stations. This, in the long term, may offset the reduction in subway gradient documented by Chu, Duan, Yang, and Wang (2018).

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Appendix A

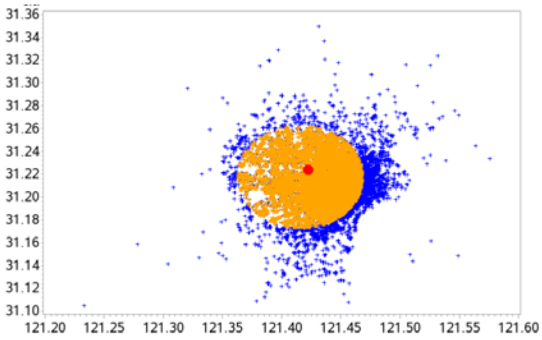


Fig. A1 Region 1, May 2016

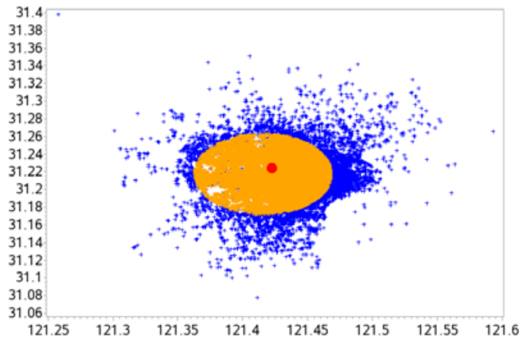


Fig. A2 Region1, June 2016

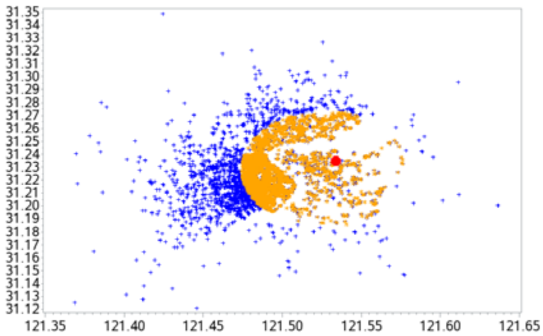


Fig. A3 Region 2, May 2016

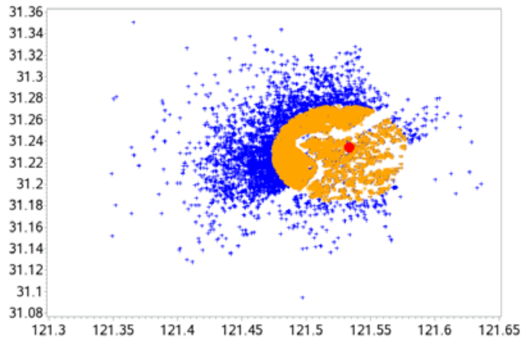


Fig. A4 Region 2, June 2016

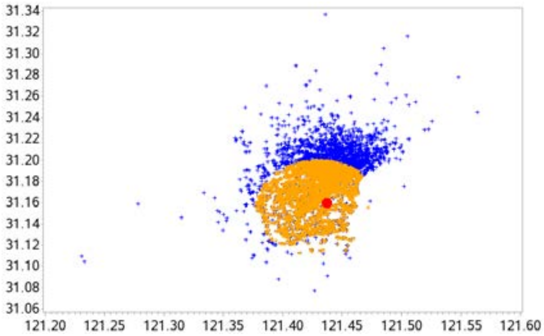


Fig. A5 Region 3, May 2016

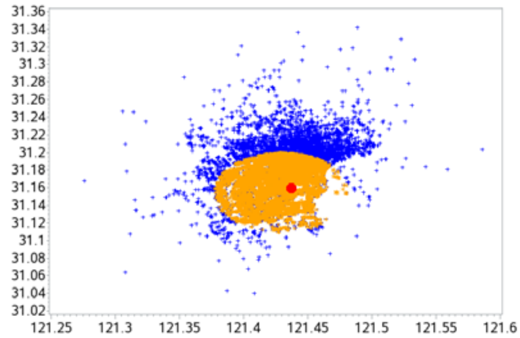


Fig. A6 Region 3, June 2016

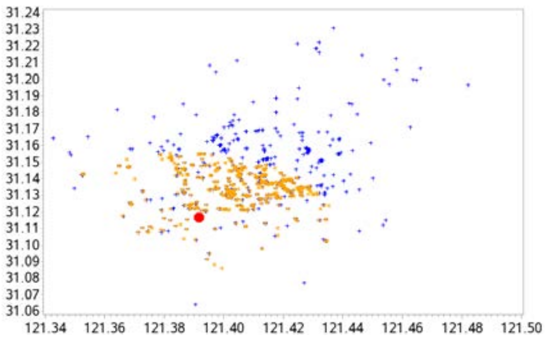


Fig. A7 Region 4, May 2016

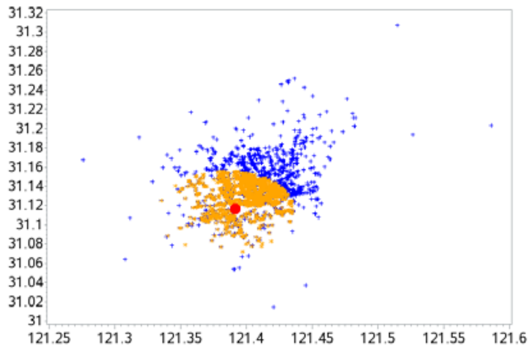
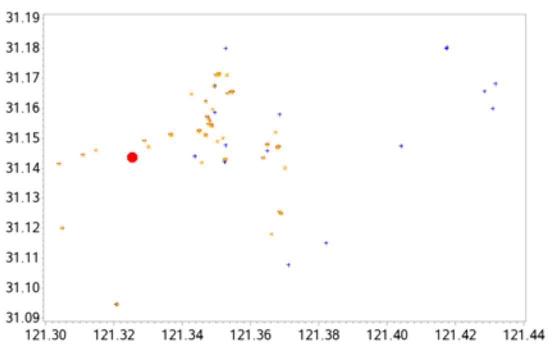


Fig. A8 Region 4, June 2016



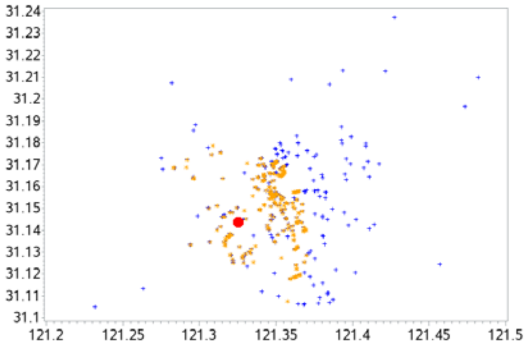


Fig. A9 Region 5, May 2016 **Fig. A10 Region 5, June 2016**

Note. The figures show the starting locations and the ending locations of ridings in each region. The region of a riding is identified by the starting location. The x-axis is longitude, and the y-axis is latitude. We mark the center of each region by a red dot. The orange stars mark the starting locations. The blue pluses mark the ending locations. If the starting location belongs to the overlapping area of two regions, the corresponding points appear in both figures.

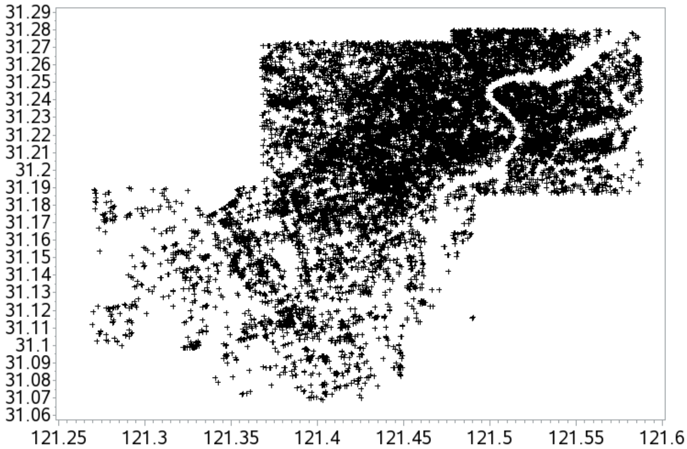


Fig. A11 Locations of parking lot POIs

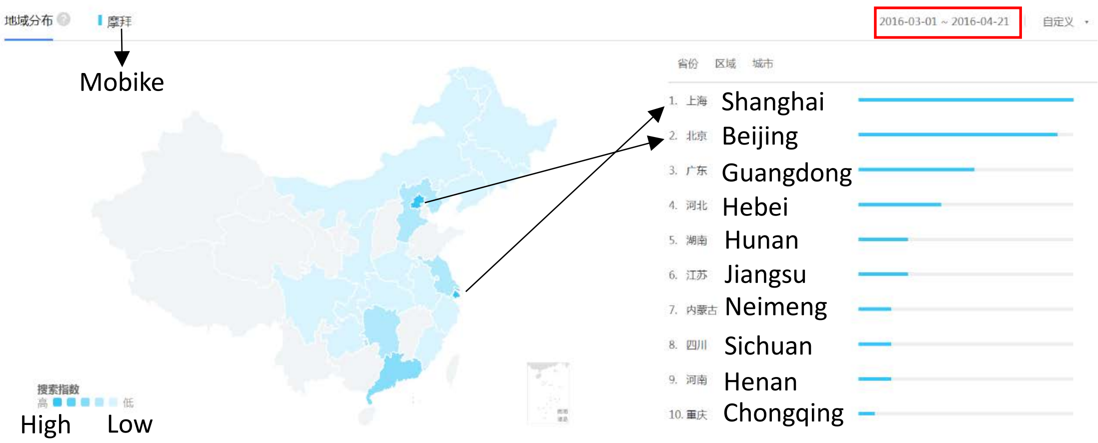


Fig. A12 Baidu Index for the keyword "Mobike": Prior-launch period

Note. The figure shows the distribution of the index value during the period from 1 March 2016 to 21 April 2016. The data source is https://index.baidu.com.

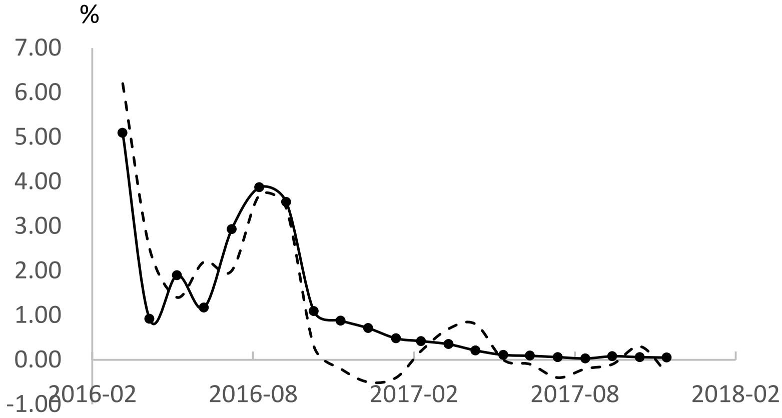


Fig. A13 Monthly growth rate of the house price index of Shanghai

Note. The solid (dash) line shows the house price index of Shanghai, which is one of the cities covered by the 100-city (70-city) house price index series. The 100-city and 70-city series are available in Wind database and National Bureau of Statistics, respectively.

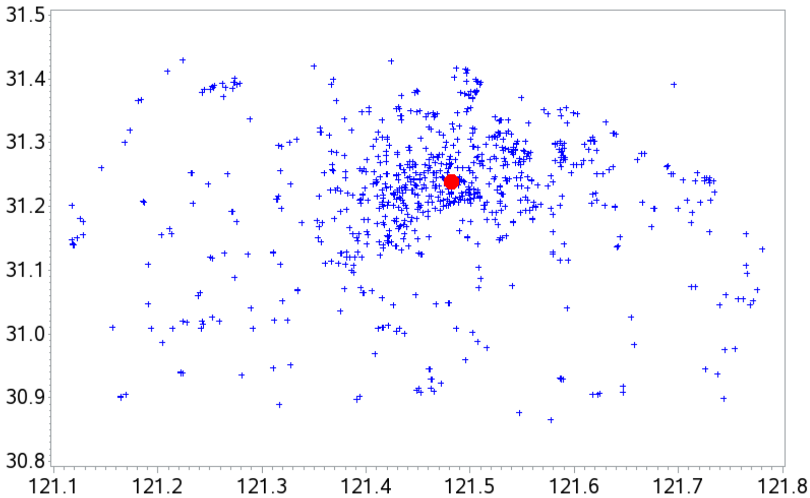


Fig. A14 Location of "City Management" POIs

Note. The figure shows the longitude and latitude of "City Management" (i.e. "chengguan" in Chinese) POIs in Shanghai. The red dot marks the city center, i.e. People's Square.

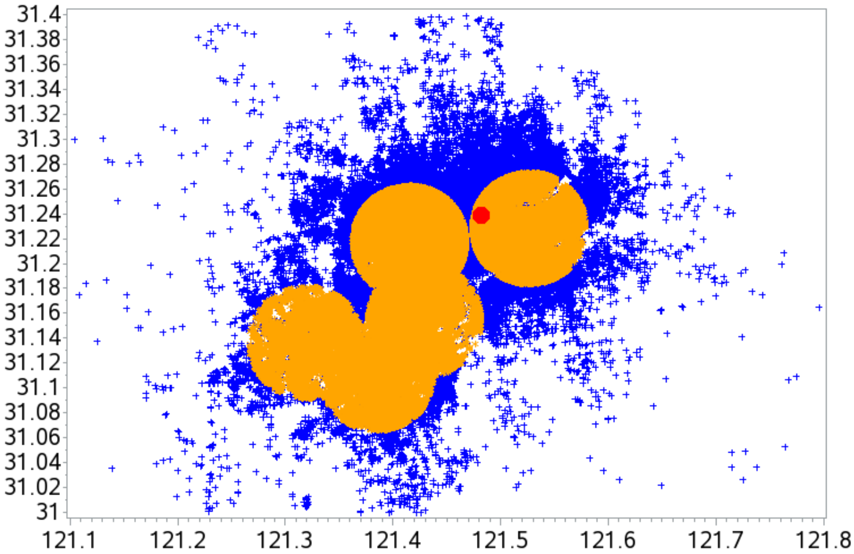


Fig. A15 Spatial distribution of ridings on 9 October 2017

Note. As in **Fig.A1**, the orange points mark the staring points of the ridings in our sample regions. The blue points mark the ending points. The red point marks the city center, i.e. People's Square.

Appendix B

Table B1 Summary statistics of variables used in regression (4)

	Mean	Std	Median
ClsSub	1.9072	1.1496	2
MidSub	5.4056	2.5053	5
lnprc	6.3842	0.7183	6.3421
Grow	3.5931	5.0369	2.2128
DisSub	0.6342	0.3918	0.5720
DCenter	6.7814	3.3937	6.0801
Size	100.0838	88.8564	83
Age	18.6514	14.2251	17
Rooms	2.1678	0.9701	2
East	0.0812	0.2731	0
West	0.0854	0.2794	0
South	0.9067	0.2909	1
North	0.3619	0.4806	0
Floor	0.5255	0.2772	0.5
Totfloor	16.2350	11.9229	12
Decoration	3.5206	0.9020	4
Villa	0.0043	0.0654	0
LuxVilla	0.0046	0.0676	0
Dual	0.0370	0.1888	0
LiLong	0.0147	0.1202	0

Note. The table displays summary statistics of variables involved in regression (4). An average ln*Prc* of 6.3842 translates into an average listing price of 5,924.11 thousand yuan, or $896,871. Here we use the average exchange rate between China yuan and the US dollar during March 2016 to October 2016, i.e. 6.6053 yuan per dollar.

Appendix C

Variable	Definition
***Num*₁₆₀₅**	The number of Mobike ridings in May 2016
***Num*₁₆₀₆**	The number of Mobike ridings in June 2016
Grow	$(Num_{1606}/Num_{1605})-1$
Parking	The number of parking lots with a distance of less than 0.2 km from a point
AvgP	For neighborhood *i*, it is a measure of the average number of parking lots around other neighborhoods in the same zone, weighted by the distance from these neighborhoods to neighborhood *i*
ClsSub	The number of subway stations with a distance of less than 1 km from a point
MidSub	The number of subway stations with a distance of 1 km to 3 km from a point
DisSub	The distance to the nearest subway station
DisCenter	The distance to the city center, i.e. People's Square
Age	Age of a house
Size	Size of a house (m^2)
Rooms	The number of rooms
East	A dummy that equals 1 if a house faces the east
South	A dummy that equals 1 if a house faces the south
West	A dummy that equals 1 if a house faces the west
North	A dummy that equals 1 if a house faces the north
Floor	The floor of a house divided by the total number of floors in a building. In many cases, we only know whether the house is in the highest 1/3, medium 1/3, or the lowest 1/3 of a building, which correspond to three values of *Floor*.
Totfloor	The number of total floors in a building
Decoration	Decoration level. It ranges from 1 to 5, with level 1 (5) being the lowest (highest) one.
Villa	A house type dummy that equals 1 if a house is a villa, and 0 otherwise.
LuxVilla	A house type dummy that equals 1 if a house is a luxury villa ("yangfang" in Chinese), and 0 otherwise.
Commhouse	A house type dummy that equals 1 if a house is a commercial-residential house ("shangzhu" in Chinese), and 0 otherwise.
Xinli	A house type dummy that equals 1 if a house is a new-type alley house ("xinlilong" in Chinese), and 0 otherwise.
SMidSub	The number of shopping-mall subway stations with a distance of 1 km to 3 km from a neighborhood
NSMidSub	The number of non-shopping-mall subway stations with a distance of 1 km to 3 km from a neighborhood
SClsSub	The number of shopping-mall subway stations with a distance of less than 1 km from a neighborhood
NSClsSub	The number of non-shopping-mall subway stations with a distance of less than 1 km from a neighborhood

Totbus	The total number of bus stations with a distance of less than 1 km from a neighborhood
HPI	House price index, which is based on house listing data of Lianjia
GHPI	General house price Index. It is the average HPI across zones, weighted by the number of listed houses in each zone
GrowR	The residual from a regression of Grow on *DisCenter*. It is a zone-level variable.
Firstmile	A dummy that equals 1 if a riding ends at a point that is less than 0.2 km away from a subway station
Lastmile	A dummy that equals 1 if a riding starts at a point that is less than 0.2 km away from a subway station
Num_{171009}	The number of Mobike ridings on 9 October 2017
$Grow^{long}$	$Num_{171009}/Num_{1605}-1$
GrowRush	The growth rate of Mobike usage during morning rush hours (7:30 a.m. to 9:30 a.m.) from May to June, 2016.