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

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Abstract

Dockless bike sharing provides a convenient and affordable means of transport for urban residents. It solves the "last-mile problem" in public transport by reducing the travel cost between home and subway stations and thus increasing the attractiveness of distant apartments. This may affect the relationship between housing price and distance to subway and reduce the price premium enjoyed by proximate apartments. Using resale apartment data in 10 major cities in China, a difference-in-differences approach at the apartment level, and a two-step estimator at the city-month level, we find that the entry of bike sharing reduces the housing price premium by 29% per km away from a subway station. The effect is equivalent to a reduction of 1,893–2,127 CNY (282–317 USD) in commuting costs per household per annum over 30 years. The effect is driven by a *relative* increase in the listing price of, and in the demand for, apartments distant from vis-à-vis proximate to subway stations.

Keywords: Sharing economy, dockless bike sharing, last-mile problem, urban economics.

1. Introduction

In recent years, 1,608 cities in the world have embraced shared bikes as an innovative and economical alternative for urban commuting. From 2013 to 2018, the number of shared bikes worldwide increased from 700,000 to 18 million, most of which are dockless bikes that are operated without docking stations, and hence can be parked anywhere. Ofo and Mobike, two bike sharing start-ups in China, have jointly introduced 17 million dockless bikes to more than 200 cities globally, and each has acquired over 200

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million users since 2015.[1]

Several technological advances and economic benefits of dockless shared bikes may have contributed to their fast expansion and wide adoption. GPS sensors, smart locks, mobile payments, and the docklessness feature offer great flexibility and convenience, and the lower price and various promotions have vastly enhanced affordability. Studies have found that docked shared bikes can reduce commuting costs, traffic congestion, and air pollution, and have positive health effects (Woodcock et al. 2014; Pelechrinis, Li and Qian 2016). Dockless shared bikes are likely to have similar benefits.

One notable benefit of dockless bike sharing is that it is an effective solution for the "last-mile problem" that has hindered public transit systems. In metropolitan areas worldwide, despite affordable means of station-to-station commuting such as subways, buses, and trains, commuting remains disproportionally costly in terms of both money and time to travel between home and a public transit station. To alleviate such costs, people choose to live near subway stations, which drives up the demand for and the price of proximate apartments. Apartments close to subway stations tend to be priced higher than, or enjoy a price premium over, identical but distant ones, which is dubbed "subway housing price premium" (Dewees 1976; Coulson and Engle 1987; Baum-Snow and Kahn 2000; Bowes and Ihlanfeldt 2001; Gibbons and Machin 2005; Bajic 1983; Yiu and Wong 2005; Fesselmeyer and Liu 2017).

Free from docking stations and available almost everywhere, dockless bike sharing is a convenient, reliable, and affordable means of door-to-door commuting and a complement to public transit. It is also considered to be an effective solution to the last-mile problem (United Nations Department of Economic and Social Affairs, 2011)[2] because it allows people to live farther from a subway but still easily access subway services. This may drive up the demand for and the price of distant apartments relative to proximate ones, reduce the price premium enjoyed by proximate apartments, and narrow the price gap between apartments at different distances from subway stations.

In this paper, we study how the presence of dockless bike sharing moderates the relationship between housing price and distance to subway (termed the "housing price gradient" in the literature; e.g., Dewees 1976) and quantify the monetary value of dockless bike sharing in solving the last-mile problem. We can recover people's willingness to pay for the reduction in commuting costs by measuring the change in the

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1 See https://www.bbc.com/news/business-44066083 and https://mobike.com/cn, http://www.ofo.com.

2 Previous surveys and research show that many shared bike users ride from or to public transit hubs. For example, a survey of 1,255 shared bike riders in China reports that 68% of the respondents ride from and to public transit hubs, and over 90% of trips cover a distance under 3 km. A U.S. bike sharing company, LimeBike, reports that 40% of its rides serve the same purpose, and an average ride in U.S. metropolitan areas is around 1 mile. Another report from China finds that over half of the rides are within 0.5-2 km or 6-20 minutes. See https://www.cbinsights.com/research/bike-sharing-boom, http://report.iresearch.cn/wx/report.aspx?id=2961, and http://www.chinadaily.com.cn/a/201801/10/WS5a557e01a3102e5b17371d1b.html,.

housing price gradient against distance to subway and using the hedonic price method (Rosen 1974; Roback 1982).

Our empirical analysis exploits a novel dataset comprising detailed information on nearly 400,000 resale apartments near subway stations. To identify the causal effect of dockless bike sharing on the subway housing price premium, we use the staggered entry of Ofo and Mobike into 10 major Chinese cities at different time points as a quasi-natural experiment to conduct (1) difference-in-differences (DID) analysis at the apartment level and (2) two-stage estimation at the city-month level. In the DID approach, the effect is identified from the spatial variation in prices of apartments at different distances to the same subway station before and after the entry; in the two-stage approach, we directly estimate the housing price gradients in each city at different time points and identify the effect by comparing the gradients before and after the entry. Both approaches yield a consistent finding: The entry of bike sharing significantly attenuates the housing price gradient by 29%, from 4.2% to 3.0% per km, which is equivalent to an urban resident's 1-year disposable income. The implied reduction in commuting costs is 1,893–2,127 CNY (282–317 USD) per household per annum over 30 years—an economically significant figure. Further analysis reveals that the effect is driven by a *relative* increase in the attractiveness to potential buyers, as well as a *relative* rise in initial listing prices of apartments distant from vis-à-vis proximate to subway stations. In addition, the effects are heterogeneous across apartments, communities, and cities, and robust to the selection of time windows around entry, selection of samples, measures of distance, and alternative explanations.

Our paper's main contributions are as follows. First, we use different approaches to convincingly establish the causal effect of dockless bike sharing on subway housing price premium. In addition to the DID approach and two-step estimation, which rely on different identification strategies, we conduct falsification tests to rule out the effect of anticipated entry and implement various robustness checks to unobserved apartment characteristics and time-varying community characteristics, the selection of time windows around entry, selection of samples, measures of distance, omitted variables, measurement errors, and alternative explanations. We thus rule out potential endogeneity concerns to a great extent. Second, we explore the mechanism of the effect from the supply side, the demand side, and the market equilibrium. We find that both property owners and buyers respond to the entry of dockless bike sharing, which jointly leads to a reduction in the housing price gradient. We also find that the gradient reduction arises from a reduction in commuting costs. Third, we quantify the monetary value of the commuting cost reduction brought forward by dockless shared bikes and indirectly demonstrate the benefits of solving the last-mile problem in urban commuting. Hence, our findings have significant implications for bike sharing firms, property developers, policymakers, and bike riders.

The reminder of the paper proceeds as follows. Section 2 reviews related literature. Section 3 presents the data, Section 4 introduces our empirical strategy, and Section 5 reports findings. Section 6 conducts validation and robustness tests, and Section 7 concludes.

2. Literature Review

Our research is related to the burgeoning literature on the sharing economy. Pioneered by Uber, Airbnb, and other gig companies, the sharing economy has brought about fundamental changes to the traditional economy. Airbnb has been found to reduce the prices of low-end hotels (Zervas, Proserpio, and Byers 2017) but raise the prices of rentable properties (Barron, Kung, and Proserpio 2018). Uber has been shown to promote self-employment among taxi drivers (Berger, Chen, and Frey 2017) and complement public transit and taxis (Hall, Palsson, and Price 2017; Mammen and Shim 2017), but also reduce taxi drivers' wage earnings (Berger, Chen, and Frey 2017). The traditional economy, on the other hand, has also implemented various changes to respond to threats from the sharing economy. Uber's entry in New York City and Chicago reduces consumer complaints about taxi services, which implies that competition from Uber improves the service quality of taxis (Wallsten 2015). In Singapore, taxi companies introduced a flat-fare option to mitigate competition from ride-hailing platforms (Miao and Chu 2019).

The sharing economy boom has important welfare implications. Fraiberger and Sundararajan (2017) find that a peer-to-peer rental market for used goods raises consumer surplus by accelerating the replacement of used goods and offering lower prices. Ride-hailing platforms are found to improve rider welfare by matching drivers to riders who value the ride the most (Cohen et al. 2016) and serving areas that are underserved by taxis (Lam and Liu 2017). They also benefit drivers by offering more flexible working hours (Chen et al. forthcoming), proportional commission fees to share the risk of demand uncertainty (Angrist, Caldwell and Hall 2017), and higher capacity utilization rates of vehicles (Cramer and Krueger 2016). In terms of nonpecuniary benefits, Uber is found to relieve traffic congestion (Li, Hong and Zhang 2016) and reduce traffic accidents related to drunk driving (Greenwood and Wattal 2017). Docked bike sharing is found to reduce traffic congestion (Wang and Zhou 2017) and CO_2 emissions (Pelechrinis, Li and Qian 2016). For a comprehensive review of the literature, we refer the reader to Proserpio and Tellis (2017).

Our paper extends the literature in several important ways. To the best of our knowledge, we are the first to study the economic impact of dockless bike sharing. In contrast to Uber, which seeks to disrupt the traditional business, bike sharing serves more as a complement to public transit, and the complementarity effect could be more salient for dockless bikes because they offer greater flexibility in riding routes than docked bikes. Further, instead of studying closely related industries such as taxis and public transit, we investigate how dockless bike sharing affects subway housing price premium and quantify the monetary value of dockless bike sharing in reducing commuting costs.

Our research is mostly related to that of Pelechrinis et al. (2017), who study the effect of docked bike sharing in Pittsburgh on housing prices around docking stations and find that the presence of 50 shared bike stations in 12 Zip codes with a total of 500 bikes led to a 2.5% increase in real estate value. However, their study does not provide sufficient evidence to justify the parallel pre-trend assumption and the exogeneity of docking stations, and thus cannot establish a causal relationship. By contrast, we use two approaches and various robustness checks to demonstrate the causal effect of dockless bike sharing on the subway housing price premium. We further show that the effect depends on an apartment's distance to a subway station, i.e., dockless bike sharing reduces the negative effect of distance on housing price, while Pelechrinis et al. do not investigate how the distance between docking stations and other public transit options affects housing price. Also in contrast to Pelechrinis et al.'s study, we take two further steps to explore the mechanism underlying the change from both the demand side and the supply side, and quantify the savings in commuting costs brought forward by bike sharing.

Another related study is by Cao, Jin, and Zhou (2018), who examine the competition between dockless bike sharing companies in China. Although we study the same market, we focus on a different aspect: How dockless bike sharing reduces commuting costs, and thus moderates the relationship between housing price and distance to subway.

Beyond the sharing economy literature, our paper is also related to the urban economics literature on China's housing market (e.g., Chen and Wen 2017; Deng et al. 2015; Fang et al. 2016; Wei, Zhang, and Liu forthcoming) and the influence of transportation condition on housing price (e.g., Bajic 1983; Baum-Snow and Kahn 2000; Bowes and Ihlanfeldt 2001; Coulson and Engle 1987; Dewees 1976; Fesselmeyer and Liu 2018; Gibbons and Machin 2005; Yiu and Wong 2005). In particular, our result is consistent with existing findings that housing prices are higher nearer subway stations because residents enjoy more convenient public transport services. Furthermore, we validate the theory that households make a trade-off between lower commuting cost and higher housing prices. Our estimates show that as commuting costs fall due to the entry of dockless bike sharing, the housing price premium near subway stations also falls and the price difference between houses of different distances to subway shrinks.

3. Data

3.1. Housing prices and characteristics

We exploit a novel administrative dataset of resale apartments provided by a Chinese real estate agency, which has the largest market shares in all 10 cities. The dataset comprises 507,975 apartments initially listed for resale between July 1, 2015 and December 31, 2017 and tracks all unsold apartments until March 12, 2018, when the dataset was compiled. Thus, each apartment in our dataset is observed for at least 2.5 months. The data contain detailed characteristics of each apartment, including size, number of rooms, floor number, age of the building, decoration status, window directions, geo-coordinates, and whether it is proximate to a good public school (referred to as school-district apartment hereafter). It also tracks each apartment's historical and current prices, transaction status (sold out or not), and number of visits by potential buyers.

We distinguish an apartment's initial price, adjusted price, and last/transaction price as follows. When a seller decides to list their apartment on the agency's website, they set an initial price for the apartment at will. Before the apartment is sold, the seller can overwrite the previous price with an adjusted price, which can be lower or higher. The dataset records all price adjustments and the time of adjustments. If the apartment is sold via the agency, the dataset will record the transaction date and actual transaction price; otherwise, it will keep tracking the price until the latest one. Thus, an apartment will have multiple observations if there are price adjustments or updates on the sales status. If a listed apartment is transacted between buyer and seller directly without notifying the agency (usually to avoid paying sales commissions), the last price is likely the actual transaction price, but the price and transaction status of the apartment are not updated.

When an apartment is available for resale, interested buyers may contact the agency to arrange a visit to check the status of the apartment, and likely bargain with the seller for a lower price. The sale of an apartment typically involves many rounds of visits and bargaining between buyers and sellers. For all apartments, we have the total number of visits by interested buyers up to March 12, 2018; for apartments in Beijing, we also have a detailed viewing history with viewer identifiers.

3.2. Distance to subway station

To complement the housing data, we manually collect information on each city's subway network and each station's geo-coordinates and start date of operation. Then we match each apartment to its nearest subway station by geodesic distance and keep apartments within 3 km of their respective nearest stations. Apartments beyond 3 km (12%) are excluded, because we believe buyers of these apartments are less likely to use dockless shared bikes to commute between home and subway (see footnote 2). Online Appendix A illustrates in detail how distances to subway are calculated and updated, and Figure A1 shows the distribution of apartments before and after the entry. For apartments with single observations, their distances to the respective nearest subway station are calculated only once and do not change over time. For apartments with multiple records, their distances may decrease over time if new and closer subway stations are built. In the end, we have 399,840 apartments matched to 1,422 stations.

The geodesic distance to subway is intuitive for illustrating the housing price gradient. In reality, however, commuters only consider walking distance to a subway station. Therefore, we manually determine the walking distance from each apartment to the nearest subway station identified by geodesic distance. In this process, we might occasionally match an apartment to a non-nearest station because of the potential discrepancy between geodesic and walking distance, and lose 3.8% observations. Fortunately, and as expected, the two measures of distance are highly consistent, with a correlation coefficient of 0.89.

3.3. Entry of bike sharing

In online Appendix B, Table B1, we report the entry dates of Ofo and Mobike to each city, which are collected from each company's corporate website and public internet sites, and cross-validated with the dates in Cao, Jin, and Zhou (2018). The earlier of Ofo's and Mobike's entry dates is defined as the entry date of dockless bike sharing. Figure B1 presents some photos of shared dockless bikes in the 10 cities. Inspired by Hall, Palsson, and Price (2017), who use Google Trend to proxy Uber's penetration in the U.S., we also use the daily Baidu search index[3] on the keyword "bike sharing" to proxy bike sharing's penetration in each city. As Figure B2 shows, in many cities the index peaks around the entry dates of Ofo and Mobike.

3.4. Summary statistics

Table 1 presents summary statistics of our data. The top panel reports prices, price adjustments, and viewing visits; the middle panel reports housing characteristics; and the bottom panel reports bike sharing and distance to nearest subway station. In total, we have 617,271 price records from 399,840 apartments. The average of all prices is 31,536 CNY/m^2 (437 USD/ft^2); the average price adjustment over the previous price is 7.4% with a standard deviation of 5.6%; and each apartment is visited 6.3 times with a standard deviation of 17.1.

[Insert Table 1 Here]

An average apartment is 90.5 m^2 (974 ft^2) in size, has 2.2 bedrooms, and is located on the ninth floor of a 14-year-old building[4]. One-half are school-district apartments; 13% of apartments have basic decoration, 20% have intensive decoration, and the remaining have no decoration or missing decoration information. The apartments have windows that face different directions, with the most common direction being south (77%) and the least common being west (12%). The average geodesic and walking distances to subway are 1.08 km and 1.62 km, respectively, and the maximums are 3 km and 5.2 km. Finally, 55% of apartments are listed before the entry of bike sharing and 45% after.

4. Empirical Strategy

Our objective is to investigate how the presence of dockless bike sharing moderates the relationship between housing prices and distance to subway and quantify its impact on commuting costs from and to subway stations. We can directly estimate the effect on housing price premium, but since commuting costs are not observed in our data, we instead indirectly infer the impact on commuting costs from the change in

[3] The Baidu search index is the Chinese analog of Google Trend developed by Baidu, the largest search engine in China. It counts how many times a keyword is searched on Baidu.com every day from IPs in each city.

[4] About 37% of observations lack building age. To avoid losing these observations, we create an indicator for apartments with missing data on age and replace the missing data with the mean of reported ages. In Table 8, column (e), we report estimates without controlling for building age as a robustness check.

the housing price gradient. The idea is that households trade off between housing prices and commuting costs: They choose to either live closer to a subway station to enjoy lower commuting costs but pay higher housing prices, or live farther from a subway station to enjoy lower housing prices but pay higher commuting costs. Hence, in equilibrium, housing price and distance to subway are negatively correlated, and the price difference between proximate and distant (otherwise identical) apartments will capitalize the difference in commuting costs. As dockless bike sharing reduces commuting costs, the price gap will also shrink, resulting in a flatter gradient between housing prices vis-a-vis distance to subway.

Absent randomized controlled trial or other better identification strategies like regression discontinuity (e.g., Chu, Liu and Png, 2019), we take two approaches to establish the causal impact of dockless bike sharing on the relationship between housing price and distance to subway: A DID approach at the apartment level and a two-step estimator at the city-month level.

4.1. Difference-in-differences estimation at apartment level

Our DID specification is similar to that of Archibong and Annan (2017), who perform a DID estimation on cross-sectional data with some observations entering the sample before the treatment and others after the treatment. In our study, we estimate the following model using DID, in which one difference is before and after the entry of bike sharing and the other is the price difference between apartments at different distances to the same subway station.

$$ln(P_{ict}) = \beta_0 + \beta_1\, Dist_{ist} + \beta_2\, Bike_{ct} + \beta_3\, Dist_{ist} \times Bike_{ct} + \boldsymbol{X_{it}\beta} + \delta_s + \theta_{cym} + \varepsilon_{ict}\ . \tag{1}$$

Here, i, c, and t represent apartment, city, and time, respectively; P_{ict} is apartment i's price per m^2; $Dist_{ist}$ is apartment i's distance to the nearest subway station s at time t; $Bike_{ct}$ is an indicator for the entry of and presence of bike sharing in city c in time t; and $\boldsymbol{X_{it}}$ represents apartment characteristics, including size, floor number, building age, number of bedrooms, decoration status, window direction, school district, apartment density (measured as the number of apartments within a 3-km radius of the closest subway station in each month); and indicators of initial and last prices. δ_s and θ_{cym} are subway station and city-year-month fixed effects, and ε_{ict} is the error term.

In particular, the inclusion of subway station fixed effects not only accounts for neighborhood conditions that might affect the suitability of bike riding (e.g., ambiance, terrain, weather), but also addresses the uneven supply of and demand for shared bikes around each subway station. Even if the initial geographical supply of dockless shared bikes is endogenous, because people ride the bikes from place to place, the distribution will soon be randomized. City-year-month fixed effects control for any city-wide policy impacts, such as regulations on the housing market or bike sharing companies. Since dockless bike sharing may enter a city in the middle of a month, θ_{cym} does not completely absorb $Bike_{ct}$. Moreover, controlling for apartment characteristics allows us to compare the prices of similar apartments.

The economic intuition of model (1) is as follows. Before the entry of bike sharing ($Bike_{ct}$ = 0), the housing price gradient with respect to distance to a subway station is β_1, which is expected to be negative: Ceteris paribus, for each km away from a station, average housing price drops by -100β_1%[5]. After the entry of bike sharing, however, the gradient becomes $\beta_1+\beta_3$: Ceteris paribus, for each km away from a station, average housing price drops by -100($\beta_1+\beta_3$)%. Therefore, β_3 identifies the impact of bike sharing on the gradient. A positive β_3 implies that dockless bike sharing flattens the gradient, reduces the price premium of apartments near a subway station, and narrows the price gap.

To identify the causal impact of dockless bike sharing on subway housing price premium, we exploit the staggered entry of Ofo and Mobike into the 10 Chinese cities as a quasi-natural experiment. Ofo and Mobike are the two largest dockless bike sharing companies, with a combined market share of over 90%. Between 2016 and 2018, they expanded to hundreds of cities in China and many others around the world. All 10 cities, with a total population of 152 million, have mature subway networks that play important roles in everyday commuting (online Appendix B, Table B1). This allows us to focus on the housing price gradient around subway stations. As we will show later, the entry of Ofo and Mobike to these 10 cities is ideal for our study, because it is fast enough to be considered exogenous but slow enough to generate sufficient variation for DID analysis. Also, they are always the first entrant in the 10 cities.

Essentially, our DID identification relies on the within-station, within-month spatial variation in the prices of similar apartments at different distances to the *same* subway station. Thus, our estimates are robust to a wide range of confounders, with one exception: those that affect apartments matched to the same station differently depending on their distances. In Section 6.2, we show that such confounders are unlikely to bias our estimates.

4.2. Two-step estimation at city-month level

In the DID specification, we do not include apartment fixed effects because many apartments have only one observation. The presence of unobserved apartment characteristics or other macro-socioeconomic factors may bias the estimates if they affect apartments at different distances from the same subway station differently. As our main focus is to study how the entry of dockless bike sharing in a city attenuates the housing price gradient, a more appropriate unit of analysis is city-month. Therefore, we conduct another analysis at the city-month level via a two-step approach[6]. In the first step, we estimate a housing price gradient for each of the 329 city-month subsamples by Equation (2a); in the second step, we compare the

[5] In continuous form, β_1 can be interpreted as semi-elasticity, which is the percent change in P_{ict} when $Dist_{ist}$ changes by 1 unit (Wooldridge 2016); in discrete form, exp(β_1)-1 represents the percent change in P_{ict} when $Dist_{ist}$ changes by 1 unit. When β_1 is small (-0.05–0.05), exp(β_1)-1≈β_1.

[6] We thank the Associate Editor for suggesting this approach.

gradients before and after the entry using Equation (2b).

$$\text{(2a)} \qquad \ln(P_{ict}) = \beta_0 + \beta_{cym} Dist_{ist} + X_{it}\beta + \delta_s + \theta_{cym} + \varepsilon_{ict}$$

$$\text{(2b)} \qquad \hat{\beta}_{cym} = \gamma_0 + \gamma_1 Bike_{cm} + \delta_c + \xi_{cym}$$

where β_{cym} is the housing price gradient for city c, year y, and month m, and δ_c is city fixed effects.

5. Results

5.1. Main results

We estimate model (1) by OLS and report robust standard errors clustered by subway station[7]. In the baseline estimates, we define $Dist_{ist}$ as the geodesic distance and $Bike_{ct}$ as the indicator of the earlier entry of Ofo and Mobike, and let P_{ict} include all prices. If an apartment ever has its price adjusted, it will have multiple observations, and we include two indicators for the initial and last price. The results are presented in Table 2.

[Insert Table 2 Here]

Table 2, column (a) presents the average effect of the entry of dockless bike sharing on housing price close to subway stations. The coefficient of *distance to subway*, -0.042 (s.e. 0.003), indicates that before the entry of bike sharing, apartments near subway stations enjoy a price premium. For every km away from a subway station, housing price on average falls by 4.2%. The coefficient of *distance x bike sharing*, 0.012 (s.e. 0.003), implies that the entry of bike sharing reduces the premium and flattens the gradient by 1.2 percentage points (ppts) or 29% (= 0.012/0.042). As a result, apartments near subway stations still enjoy a price premium after entry, but the magnitude is 71% of the premium before entry.

At the average housing price of 31,536 CNY/m^2 and average size of 90.5 m^2, the estimated price gradient for an average apartment before entry is equivalent to 119,868 CNY (17,890 USD) per km. In other words, an average apartment 1 km closer to a subway enjoys an 119,868 CNY price premium. The premium can be interpreted as a household's willingness to pay to live 1 km closer to a subway or total compensation for the commuting costs of living 1 km farther from a subway during its tenure in the apartment. After entry, the reduction in the gradient is equivalent to 34,248 CNY (5,112 USD). The effect is both statistically and economically significant: To put this in context, in 2016 the average disposable income of an urban resident in China was 33,616 CNY, so the reduction is approximately 1 year of disposable income.

Columns (b) and (c) examine the entry of Ofo and Mobike, respectively. Ofo's entry attenuates the gradient by 1.3 ppts per km and Mobike's entry by 1.1 ppts per km, both of which are close to the estimate in column (a). Column (d) uses the Baidu search index to measure entry. For every increase of 1,000 in the

[7] We also cluster standard errors by city and obtain similar results. See Table 8, column (f).

search index, the gradient will be flattened by 1.0 ppt per km.

Since many apartments have only one observation, we cannot include apartment fixed effects in model (1), unlike in the conventional DID approach. This raises the question of whether any unobserved heterogeneity of apartments matched to the *same* subway station before and after entry might bias our estimate. To address this, we estimate a model with grid fixed effects. Specifically, we use the geo-coordinates of the apartments to partition the sample into 173,175 10m x 10m grids with an average of 2.3 apartments within each grid. The grid size is roughly the size of an average apartment, and multiple apartments within the same grid are typically different floors of the same building, for which we use floor number to control. The estimated effect (Table 2, column (e)) of bike sharing on subway housing gradient, 0.012 (s.e. 0.003), is similar to that using subway station fixed effects. Hence we are confident that unobserved characteristics of apartments within each grid are unlikely to bias our results.

To further investigate the effect dynamics, Table 2, column (f) reports the estimated effect of bike sharing by month. We find that the housing price gradient starts to respond 1 month after entry, and the effect gets larger as time goes by. In the longer term, dockless bike sharing reduces the housing price gradient by 1.3 ppts, which is in line with the estimated average effect in column (a).

Table 2, column (g) reports two-step estimates at the city-month level. After the entry of bike sharing, the housing price gradient becomes flatter by 1.4 ppts, which is not statistically different from the estimate using the DID model that controls for station fixed effects and city-year-month fixed effects. Given that both approaches yield statistically identical results, we will use model (1) in the remaining analyses.

5.2. Nonlinear estimates

The above estimates assume that the housing price gradient is constant over all distances to subway. However, as shown in online Appendix B, Figure B3, the nonparametrically estimated housing price gradients are nonlinear both before and after the entry of dockless bike sharing. To capture the nonuniform pattern, we re-estimate model (1) but replace the continuous variable $Dist_{ist}$ with indicators that an apartment falls within 0-0.5 km, 0.5-1 km, 1.0-1.5 km, 1.5-2.0 km, or 2.0-3.0 km of the nearest station, with the last segment as the reference group; this allows the gradients to vary by distance. In Figure 1, the blue dots and line depict coefficient estimates before entry, the red ones estimates after entry, and the bars denote the corresponding 95% confidence intervals.

[Insert Figure 1 here]

Consistent with the findings in Table 2, the estimated housing price gradients are negative and become flatter after the entry of bike sharing. However, neither the slope nor its change (the gap between the two lines) is uniform: The slope is the steepest between 0.5–2.0 km of subway station both before and after entry; the entry of bike sharing “rotates” the gradient curve, which implies that the reduction in housing price premium is stronger for apartments closer to a subway (i.e., the more expensive ones).

5.3. Effect heterogeneity

The effect of bike sharing on subway housing price premium may vary across apartments, communities, and cities. In Table 3, we examine the within-city heterogeneities by introducing three-way interactions between distance to subway, entry of bike sharing, and apartment- or community-level moderators.

[Insert Table 3 Here]

Table 3, columns (a) and (b) report, respectively, the effect of bike sharing by apartment size and floor number. The coefficient of *distance x bike sharing* represents the *average* effect size across all apartments, while the coefficient of *distance x bike sharing x moderator* represents the *change* in the effect size as the moderator increases by 1 standard deviation (for continuous moderators, normalized to zero mean and unit standard deviation), or that the moderator possesses that property. We find that the effect of bike sharing is centered on the previously estimated average effect, but is particularly large for larger and higher-level apartments: A 1 standard deviation (42.7 m^2) increase in apartment size is associated with a 63.6% (0.007/0.011) increase in the effect over the average effect; a 1 standard deviation rise in floor number (7.8 stories) is associated with a 30.8% (0.004/0.013) increase over the average effect. Bigger and higher-floor apartments tend to be priced higher. The direction of the effect is consistent with the following: Before the availability of dockless bike sharing, people did not want to live in bigger or higher-floor—but distant—apartments due to higher commuting costs and higher housing prices. After the entry of bike sharing, however, they could afford to do so. Dockless bike sharing renders these types of apartments more attractive and drives higher demand for them.

Table 3, column (c) reports the effect of bike sharing by whether an apartment falls within a school district. The coefficient of *distance x bike sharing x moderator* stands for the difference in effect size between apartments within and those outside a school district. The coefficient is statistically insignificant, which means that the effect of bike sharing is not contingent on whether an apartment is within a school district. This might be due to the balance of two conflicting considerations: On the one hand, dockless bike sharing offers a convenient means of commuting to the subway for parents. On the other hand, children under age 12 are not allowed to ride dockless shared bikes—and given the competitiveness of all kinds of exams in China, parents may still prefer to live closer to subway stations to save their children's commuting time.

Next, we show how the effect of dockless bike sharing is moderated by local commuting conditions. We measure commuting conditions in two ways to capture accessibility to a subway: Whether an apartment's closest subway station is a transit station—i.e., a station that connects several subway lines—and the number of subway stations within a 3 km radius of an apartment. Columns (d)-(e) report estimates using each of the two measures. As before, the coefficients of *distance x bike sharing* are all positive, significant, and close to that in Table 2, column (a). The coefficients of the three-way interactions are significantly positive, which indicates that the effect of bike sharing on subway housing premium is stronger for apartments that have advantageous commuting conditions, are i.e., near a transit station or have more stations within 3 km. This further testifies to the complementarity of dockless bike sharing to subway commuting.

We take two approaches to examine how the effect of dockless bike sharing varies across cities. First, we estimate model (1) with city-specific coefficients for distance and the interaction between distance and bike sharing. Second, we estimate model (1) separately for each city. The results are in online Appendix B, Tables B2 and B3. We find downward-sloping housing price gradients in all cities, which reflects higher housing prices near subway stations, but the magnitude differs substantially across cities. Tianjin has the steepest housing price gradient of 6.9% per km, followed by Shanghai (6.5%), Dalian (5.7%), Beijing (5.5%), and Wuhan (4.7%). The gradients are smaller in Chengdu (3.9%), Shenzhen (2.3%), Nanjing (2.5%), Hangzhou (3.7%), and Chongqing (0.8%, not significant). The gradient is significantly attenuated by the entry of dockless bike sharing: by 3.7 ppts in Shanghai, 2.9 ppts in Beijing, 2.1 ppts in Shenzhen, 2.0 ppts in Wuhan, and 1.5 ppts in Chongqing, all of which have large populations and extensive subway networks. The attenuation in other cities is not statistically significant.

In reference to housing prices and disposable income, the impact of dockless bike sharing on housing price gradients is huge. In Beijing, the housing price gradient drops by 52.7%, which is equivalent to 2.98 times the city's per capita disposable income in 2016; the reduction amounts to 2.96 times the per capita disposable income in Shanghai, 2.03 times in Shenzhen, and 0.81 times in Wuhan. In Chongqing, dockless bike sharing completely flattens the housing price gradient.

5.4. Mechanisms

The above estimates indicate that the entry of dockless bike sharing is associated with a reduction in the subway housing price gradient around subway stations and a narrower price gap between distant and proximate apartments. In this subsection, we explore the mechanism through which the effect operates. As we have proposed, dockless bike sharing increases the attractiveness of apartments distant from vis-à-vis proximate to subway stations and shifts the former's demand curve outwards. Anticipating this, sellers of distant apartments may raise their listing prices and gain more bargaining power in price negotiations. Using detailed data on housing prices and the transaction process, we empirically test the above mechanism.

We estimate model (1) with five outcome variables: initial listing price, frequency of visits by potential buyers, last price, transaction price, and price adjustments before the transaction completes or by the end of the data period. The initial price reflects the seller's perceived value of the apartment; frequency of visits reflects buyers' interest and purchase intention; the last and transaction prices are the prices in market equilibrium; and the direction of price adjustment reflects the bargaining power of sellers and buyers. Hence, the effect of bike sharing on these variables represents its effect on the supply side, the demand side, and the market equilibrium, respectively.

Table 4, column (a) presents the estimates on initial prices. The coefficient of *distance x bike sharing* is positive and significant (0.015, s.e. 0.003), which indicates that the entry of bike sharing reduces the gradient of initial prices by over one-third (0.015/0.043). This suggests that when setting initial listing prices, property owners already take into account the effect of dockless bike sharing on housing price.

[Insert Table 4 Here]

Next, column (b) shows the estimates on frequency of visits. The coefficient of *distance to subway*, -0.018 (s.e. 0.005), implies that apartments proximate to subway stations attract more visits before the entry of dockless bike sharing despite their higher prices: For every 1 km away from a subway, the number of visits declines by 1.8%. The coefficient of *distance x bike sharing*, 0.016 (s.e. 0.006), means that the entry of bike sharing increases visits to apartments farther from subway stations relative to proximate ones, which indicates that potential buyers are more interested in the distant apartments. The post-entry distance coefficient is no longer significant, which means that after the entry of dockless bike sharing, proximate apartments no longer enjoy a significant premium in attracting viewers.

Table 4, columns (c) and (d) report, respectively, estimates on last prices for all apartments and transaction prices for sold apartments. The coefficient of *distance x bike sharing* for last prices is positive and has the same magnitude as that for initial prices; that coefficient for transaction prices, 0.013 (s.e. 0.005), is about 27% of the subway housing price gradient. This implies that in equilibrium, dockless bike sharing narrows the price gap between distant and proximate apartments by 27%.

Column (e) reports the estimates on price adjustment. The coefficients of *distance to subway* and *distance x bike sharing* are both in the right direction, in that distant apartments tend to experience downward price adjustments and the entry of dockless bike sharing causes their prices to adjust upward, but they are not statistically significant. This implies that there is no significant difference in price negotiation and adjustment process between apartments closer to and farther away from subway stations, either before or after the entry of bike sharing.

Combining the effects on initial price, frequency of potential buyers' viewing visits, last price, transaction price, and price adjustments, we conclude that both the supply side and the demand side respond to the entry of dockless bike sharing and jointly flatten the housing price gradient.

5.5. Welfare implications

Our analysis above indicates that dockless bike sharing generates considerable benefit for urban commuters by making subway services more accessible to people living farther from subway stations. From a hedonic price approach, we interpret the housing price gradient as the compensating commuting costs for living in distant apartments. Analogously, the reduction in the gradient can be interpreted as the reduction in commuting costs due to the entry of dockless bike sharing.

In this subsection, we conduct a back-of-the-envelope analysis to recover the reduction in commuting costs from the previously estimated change in housing price gradient. The calculation goes as follows. For each apartment listed after entry (all with $Bike_{ct} = 1$), we use the estimates in Table 2, column (a) to predict its total price (predicted price per m^2 times size) and counterfactual total price as if there were no bike sharing ($Bike_{ct} = 0$). Then we compute the difference between these two prices, which we treat as the reduction in commuting costs during the buyer's entire stay in the apartment. Next, we amortize the total reduction in commuting costs into 30 years of residence[8] to obtain the annual reduction in commuting costs. We use China's latest compound interest rate for 5-year fixed deposits (2.86% per annum) and 5-year treasury bills (3.86% per annum), respectively, as the lower- and upper-bound of discount factors.

With these numbers, we estimate the annual reduction in commuting costs to be 1,893–2,217 CNY (282–317 USD) per apartment, averaged across all apartments. To put this number in context, the starting bus fare in these 10 cities is 2 CNY per ride, so the minimum commuting cost between home and subway by bus will be 1,000 CNY per person and 2,000 CNY per household (assuming two commuters in one household and 250 working days a year). The cost will be higher if households also (and very likely) go out on weekends. In comparison, the cost of using dockless shared bikes is 20 CNY per month, 240 CNY per year per person, and 480 CNY per household. These figures imply that dockless bike sharing considerably reduces commuting costs for urban dwellers relative to the price of using shared bikes. In other words, bike sharing companies do not fully internalize all of the benefits of providing dockless shared bikes; the benefit of solving the last-mile problem is at least partly captured by buyers or sellers in the housing market.

Our identification relies on price differences between distant and proximate apartments matched to the same subway—but what causes the reduction in price premium, the price increase of distant apartments or the price decrease of proximate apartments? Identifying the effect on *absolute* price changes requires that housing prices be stationary in the absence of bike sharing's entry. Unfortunately, since the city-year-month fixed effects for the baseline model are jointly highly significant (F-statistic = 472.70, p-value < 0.001), the stationarity assumption is apparently rejected. Thus, we cannot say more about the driving forces for the entire sample. Instead, we look at a narrower time window (90 days before and after entry) for Beijing and Shanghai—the two largest Chinese cities that experienced the biggest impact of bike sharing on subway

[8] In China, residential buildings become eligible for demolition and reconstruction after 30 years of use. Online Appendix C, Table C1 reports estimates using alternative discounting durations.

housing gradient—and compare the actual price trajectory with the counterfactual trajectory without the entry of bike sharing. As online Appendix C, Figure C1 shows, it seems it is the price increase of distant apartments that narrows the price gap. We caution, however, that this result should not be overinterpreted but rather taken as illustrative. This is because to make the plot, we control for city-year-month fixed effects to detrend the data, but the entry of bike sharing changes the time trend: When we detrend, we also partial out some of the treatment effects.

Potentially, dockless bike sharing reduces commuting costs via several channels. For people who walk to subway stations, bike sharing offers a faster commuting option and hence saves travel time. For people who first walk to bus stops and then take buses to subway stations, since riding a bike is less likely to be subject to bad traffic during rush hour, dockless bike sharing can reduce their commuting time; this includes waiting time for buses and commuting cost (riding a shared bike is cheaper than taking a bus). For people who ride their own bikes, bike sharing saves not only the cost to purchase, maintain, and park their bikes, but also the risk of having their bikes stolen or damaged. Moreover, with shared bikes, people no longer need to return to the same subway station to pick up their own bikes. For people who do not travel by subway because they live too far from a station, bike sharing provides them with easier access to the subway and encourages them to substitute cheaper public transit for other more expensive commuting methods, such as driving their own car or taking a taxi.

6. Validation

The above estimates indicate that the subway housing price gradient becomes flatter after the entry of bike sharing. To identify this effect as causal, we inspect two critical assumptions underlying the DID approach for causal interpretation: parallel pre-trends and the exogeneity of entry.

6.1. Testing for parallel pre-trends

The assumption of parallel pre-trends implies that absent bike sharing, the average prices of apartments close to and farther from subway would have moved in parallel. In the absence of counterfactual price data after the entry, a common test for this assumption is to check whether the prices of apartments at different distances from a subway moved in parallel before the entry. Therefore, we estimate model (1) including indicators for the first month up to the sixth month before the entry of bike sharing and their interactions with distance to subway. As reported in Table 5, none of the coefficients for the interaction terms is statistically significant. This suggests that the parallel trends assumption is satisfied.

[Insert Table 5 Here]

6.2. Testing for exogenous entry

The second assumption, the exogeneity of entry, refers to (1) the lack of correlation between the citywide entry of bike sharing and city characteristics, and (2) the lack of correlation between within-city distribution of bikes and housing characteristics, especially housing prices. If this assumption is violated, our estimates will capture the effect of confounders on both housing prices and the entry of bike sharing.[9]

We tackle the issue of endogenous entry from various perspectives. At the city level, we have included city-year-month fixed effects to account for both time-invariant and time-varying confounders that may affect the entry of dockless bike sharing. In addition, the institutional background on how local governments regulate the entry of bike-sharing companies further alleviates any concern regarding endogeneity. Before entering a city, a bike sharing company must submit a proposal to the municipal authority for approval. Even if the company endogenously chooses the time to submit the proposal, it is unlikely that the time of approval has any correlation with local socioeconomics, housing prices, or the price gap between apartments at different distances to subway. Further, we conduct three tests on entry exogeneity at the city level, as follows.

6.2.1 The Zervas, Proserpio, and Byers (2017) test

Inspired by Zervas, Proserpio, and Byers (2017), we construct a balanced panel dataset that comprises 240 city-year-month observations for the 10 cities over the period of January 2016 to December 2017. To examine whether pre-entry city characteristics influence the entry decision of bike sharing, we estimate the following regression model:

$$Bike_{ct} = (\boldsymbol{D}_t * \boldsymbol{X}_c)\, \boldsymbol{\theta} + \varepsilon_{ct} \tag{3}$$

where $Bike_{ct}$ is the indicator for the presence of bike sharing in city c, year-month t. $\boldsymbol{D}_t$ represents the year-month dummies, $\boldsymbol{X}_c$ represents pre-entry, time-invariant city characteristics, and ε_{ct} is the error term. Our $\boldsymbol{X}_c$ comprises four city-level variables at the end of 2015: population, annual GDP, annual subway ridership, and annual average housing price. To avoid multicollinearity in the first and last few months when $Bike_{ct}$ equals 0 or 1 for all cities, we do not include city fixed effects.

We plot the estimates of $\boldsymbol{\theta}$ with 95% confidence intervals in Figure 2. For ease of illustration, city characteristics variables are standardized to have zero mean and unit standard deviation. As the figure shows, all but one coefficient is statistically insignificant, which suggests that city characteristics do not predict entry. This finding supports our argument that the entry of bike sharing is exogenous at the city level.

6.2.2 The Bertrand, Duflo, and Mullainathan (2004) test

[9] A common practice in testing this assumption is to run a triple-differences regression that includes cities or apartments that do not have dockless bike sharing, but for which housing prices are equally affected by the confounders. However, by 2017, Ofo and Mobike had entered all Chinese cities with a subway, and in each city, shared bikes could be found in all communities due to the dockless feature and high mobility. Hence, the triple-differences approach is not feasible in our context.

Following the spirit of Bertrand, Duflo, and Mullainathan (2004), we estimate our baseline model using generated random dates of entry. Given the multilevel structure of our empirical context and dataset, we can assume that artificial entry dates differ across cities, subway stations, apartments, and even observations. Allowing for variation in entry date within cities also helps to alleviate the endogeneity concern about the distribution of bikes within each city. As shown in Table 6, the estimates for *distance x bike sharing* are all attenuated toward zero. This is consistent with the fact that the fake entry dates can be viewed as classical measurement errors.

[Insert Table 6 here]

6.2.3 The Seamans and Zhu (2013) test

We conduct a hazard rate test similar to that in Seamans and Zhu (2013) using the four city characteristics, as in subsection 6.2.1. Estimates of the test are reported in online Appendix B, Table B4. Since none of the estimates is statistically significant at the 5% level, it is reasonable to believe that pre-entry city characteristics do not predict the entry of bike sharing, and thus the entry is exogenous at the city level.

At the community level, the placement of shared bikes may not be random. Although subway station fixed effects have controlled for confounders that vary across subway stations, it remains a concern that shared bikes are more likely to concentrate in areas within a subway station that have higher demand. The high mobility and park-anywhere feature of dockless shared bikes will randomize the distribution of new bikes soon after they are released. The specification with 10m x 10m grid fixed effects (Table 2, column (e)) helps alleviate this concern.

6.3. Alternative explanations

6.3.1. Contemporaneous changes in local socioeconomic conditions

The inclusion of city-year-month fixed effects does not rule out time-varying confounders within cities. We take three approaches to tackle this issue.

First, we include district-specific year-month fixed effect in model (1). There are 108 districts in the 10 cities. These fixed effects can help to control for time-varying administrative and policy-related factors at the district level, including the average number of shared bikes in each district each month. We obtain nearly identical estimates (Table 7, column (a)) as the main specification.

Second, with 1,421 subway stations and 33 months, it is not statistically feasible to include subway-year-month fixed effects and obtain significant estimates. Instead, we use the apartments' geo-coordinates to partition the sample into 388 6km x 6km grids with 3.7 stations in each grid, and estimate a model with grid-year-month fixed effects. These fixed effects are a finer spatiotemporal control than district-year-month fixed effects, and can capture time-varying factors specific to each grid, including the time-varying numbers of shared bikes in each grid. We obtain a consistent estimate of the effect of bike sharing on the subway housing price premium (Table 7, column (b)). The estimate, 0.008 (s.e. 0.003), is highly significant, but smaller than the baseline estimate. This is because apartments matched to the same station may be divided into different grids, and thus their price gap is partially absorbed by the fixed effects.

Third, we limit our sample period before and after the entry of bike sharing, so that it is less likely to capture contemporaneous changes in unobservables at the community level. In Table 7, columns (c) and (d), we respectively limit the sample period to a 1-year window (183 days before and after entry) and a half-year window (90 days on each side), and find that the effect remains positive and significant. The estimates have smaller magnitude because they only capture the short-run impacts, whereas our original estimates capture relatively long-run impacts.

[Insert Table 7 Here]

6.3.2. Anticipated entry of bike sharing

If the entry of bike sharing is anticipated, housing price gradients would start to flatten prior to entry and our estimates will not fully capture the causal effects. However, as the parallel trends test in Table 5 suggests, there is no evidence of early reaction. Moreover, we conduct two additional tests to rule out this possibility.

In many cities, Ofo was available on university campuses months before its official entry into the whole city. If citywide entry were anticipated due to the presence of campus bikes, housing prices would start to respond sometime between the entry to campuses and the entry to the whole city. In Table 7, column (e), we show that the effect of bike sharing only appears after the citywide entry. The change in housing price gradient between the campus entry and the citywide entry is merely 0.4 ppts and statistically insignificant. Give this result, it is unlikely that Ofo's entry to campuses creates market expectations of citywide entry.

Second, we consider anticipation of new subway stations. It is possible that prospective subway stations will raise surrounding real estate values by reducing future commuting costs. However, the entry of bike sharing may offset the price premium of properties near subway stations. To rule out this possibility, we conduct a falsification test and estimate the effect of bike sharing on the housing price gradient against distance to *planned* subway stations in Beijing—stations that are still in the planning or construction stage and have no commuting value yet. In Table 7, column (f), we find that the gradients are flat and insignificant both before and after the entry of bike sharing, therefore reject the hypothesis of anticipated entry.

In summary, the estimation above implies that anticipation cannot explain the identified effect of bike sharing in our research.

6.3.3. Expansion of public transit system

As Bajic (1983) and Fesselmeyer and Liu (2018) find, expanding a subway network enhances the benefit of living near an existing subway station and results in a steeper housing price gradient. This might countervail the effect of bike sharing and attenuate our estimates. To address this, we estimate model (1) by limiting it to cities that did not have a new subway station opening in the 3 months before and 3 months after the entry of bike sharing and to apartments that are listed between the last opening of stations before entry and the first opening after entry. For these apartments, changes in housing prices cannot be due to the expansion of the subway network. Table 7, column (g) reports estimates using this subsample, and the result remains positive and statistically significant.[10]

Since our sample comprises apartments within 3 km of the nearest subway station at the time of initial listing, the inclusion of new subway stations will also expand the geographic range of our housing sample. Thus, apartments listed before and after the entry of bike sharing may differ in geographic distribution and become less similar. In Table 7, column (h), we focus on apartments within 3 km of a subway station that was in existence by January 1, 2016, which means that the geographic distribution of apartments does not change over time as the subway network expands. The estimated effect of bike sharing remains unchanged.

The housing price gradient will get flatter if cities expand bus services to supplement the subway system, which mainly benefits residents who live farther from subway stations. However, this alternative explanation is easily ruled out, as we find that all of the cities experienced a steady decline in bus service relative to city population and per capita GDP. In Beijing, for example, total bus ridership dropped by 18% from 2015 to 2017, while its population remained unchanged and GDP per capita increased by 13.8%.

6.3.4. Worsened ambience near subway stations

People living too close to subway stations often suffer from worse ambience due to the high volume of traffic and peddlers. The situation may be exacerbated by the entry of bike sharing, since many bikes are parked around the stations and may clog the street. As such, it is possible that bike sharing flattens the housing price gradient because it reduces the value of apartments close to subway stations. However, as shown in Table 7, column (i), the effect of bike sharing on the price gradient of apartments beyond 500 m of the nearest subway station remains the same as that for the whole sample. For these apartments, the change in the housing price gradient cannot be explained by worsened ambience near the stations.

6.3.5. Easier access to shopping malls

Since some subway stations are built next to shopping malls and some shopping malls are developed next to subway stations, another competing explanation for our estimates is that people ride shared bikes to shop rather than to transit to a subway. To rule out this possibility, we estimate model (1) excluding

[10] We interpret the absence of a subway expansion effect from three perspectives. First, relatively few subway stations in the 10 cities were opened between mid-2015 and the end of 2017 (see online Appendix B, Table B1). Second, the new stations are mostly in suburban areas that are rarely visited by people who live near existing stations in urban areas, so their added value to urban transport is limited. Third, construction of new subways is often announced years before actual construction begins, and housing prices could start to respond long before a station opens (Yiu and Wong 2005).

apartments whose nearest subway station is within 200 m of a shopping mall. As Table 7, column (j) shows, the effect of bike sharing on the subway housing price premium remains unchanged. This is expected, as visiting or shopping at a mall is much less frequent than daily commuting to work.

We also analyzed whether people use shared dockless bikes to access parks, in which case the house price premium-distance to park gradient will also become flatter. We do not find any supporting evidence for this, because visits to parks are even less frequent than visits to malls or shopping.

6.3.6. Reduced house viewing cost

Table 4, column (b) shows that the entry of bike sharing increases the frequency of visits to distant apartments relative to proximate ones. We interpret this as potential buyers' heightened interest in distant apartments and are more willing to buy them due to easier access to a subway. However, it could also be that bike sharing reduces the cost of housing viewing visits. As such, potential buyers either have time to view more apartments on the same day, or find it easier to visit apartments distant from subway stations.

To test this explanation, we collect more detailed viewing visit data on apartments in Beijing with the time and visitor ID of each visit. However, we find no support for the explanation. After the entry of bike sharing, the average number of visits per day per viewer declines from 1.65 (s.e. 0.0015) to 1.52 (s.e. 0.0016), while the average distance to a subway of the apartments visited by the same viewer before and after entry experienced no significant change (difference 0.006 km, s.e. 0.006). Therefore, to rationalize our finding in Table 4, the only possible explanation is that bike sharing increases interested buyers' interest in distant apartments.

6.3.7. Larger supply of apartments near subway stations

The effect of bike sharing could result from more listings of apartments proximate to subway stations relative to distant ones. The left panel of online Appendix A, Figure A1 shows that the distribution of housing supply against distance to the nearest subway station becomes more concentrated in the 0.5-0.8 km interval. Since distance to subway will decrease when a new, closer station opens, in the right panel we plot the distribution of apartments by distance to the nearest existing station before mid-2015. Distributions before and after entry are nearly identical. Therefore, there is no change in the distribution of listed apartments by distance to subway, and this supply-side explanation is ruled out.

6.3.8. Regulations on the housing market

During the data period, the Chinese government implemented three waves of housing market regulations on March 25, 2016, September 30, 2016, and March 20, 2017. They primarily aimed to curb the rampant growth of housing sales prices by raising the costs to purchase properties. This could likely increase the demand for and price of cheaper apartments—e.g., those distant from subway stations—and thus narrow the price gap between proximate and distant apartments and compress the distribution of prices around subway stations in the absence of bike sharing (Ouazad and Romain forthcoming).

The inclusion of city-specific year-month fixed effects can address such regulations. As further assurance, we examine the effect of bike sharing on rental prices. As we show in online Appendix B, Figure B4, each regulation corresponds to a price hike in the resale housing prices but does not affect the trend in rental prices. This not only justifies the purpose of the regulations, but also indicates that in China, the property resale and rental markets are largely separated. Therefore, to rule out this competing explanation, we estimate the effect of bike sharing on rental prices. If the change in the resale price gradient is solely due to the regulations, we should find no structural change in rental price upon the entry of bike sharing. Using a sample of rental apartments in the 10 cities, we estimate model (1) with P_{ict} being the monthly rent per apartment. The effect of bike sharing on rents follows the same pattern as that on sales prices: The rent gradient flattens significantly, by 1.0 ppt (s.e. 0.004) (detailed results are available from authors).

6.4. Robustness checks

6.4.1. Selection of sample apartments

In the baseline estimates, we limit the sample to apartments within 3 km of the nearest subway station. Table 8, columns (a)-(c) report, respectively, estimates using apartments within 2 km, 4 km, and 5 km of the nearest station. All of the effects of bike sharing remain positive and significant, and diminish as the radius increases. This is consistent with evidence from the surveys that people ride shared bikes only on short-distance commutes. As the distance gets longer, fewer people will use shared bikes to commute to the subway; therefore, bike sharing will have a smaller influence on subway housing price premiums. This also provides indirect evidence that dockless bike sharing is complementary to the subway as a commuting option.

[Insert Table 8 here]

6.4.2. Other measures of distance

In our main analysis, we use geodesic distance between apartments and their nearest subway station. We check the robustness of our findings to the use of walking distance between apartments and their nearest subway station. Table 8, column (d) reports the estimates. We find a similar reduction effect on the housing price gradient by the entry of dockless bike sharing: For every km walking distance from a subway station, housing price will decline by 2.6%; the entry of bike sharing flattens the gradient by 0.9 ppts, or one-third (0.009/0.026). Note that 1 km geodesic distance is about 1.5 km walking distance, so the magnitude of the coefficient would be 1.35 ppts per km in geodesic distance, almost the same as that in Table 2, column (a).

6.4.3. Missing building age and other building characteristics

In addition, we check whether the imputation of missing building age significantly alters our estimates (see footnote 4). Table 8, column (e) reports estimates that do not include building age and the indicator for missing age. Our estimates are still robust.

6.4.4. Clustering standard errors by city

The purpose of our study is to investigate how the entry of bike sharing affects the subway housing price gradient. We estimate the average price gradients before and after entry using apartment-level data, and then infer the impact of bike sharing from the change in gradients. According to Bertrand, Duflo, and Mullainathan (2004) and Donald and Lang (2007), standard errors should be clustered at the city level rather than by subway station. However, with only 10 cities, the traditional clustered standard errors tend to be underestimated. Table 8, column (f) reports bootstrap standard errors clustered by city to adjust for the small number of clusters. The estimate is statistically the same as that when standard errors are clustered by subway station.

7. Conclusion and Managerial Implications

As a green, convenient, and affordable complement to urban transportation, dockless bike sharing helps resolve the last-mile problem by increasing the accessibility of subway service to people who live farther from a subway. Consequently, it increases the attractiveness of distant apartments and narrows the price gap between apartments at different distances to a subway. Using the entry of dockless bike sharing in 10 major Chinese cities as a quasi-experiment, and taking advantage of spatial variations in the resale prices of apartments at different distances to the same subway station, we find that bike sharing flattens the housing price gradient around subway stations by 29%, which is equivalent to an urban resident's 1-year disposable income—an economically significant figure! The effect is heterogeneous across apartments, communities, and cities, and is more salient for larger, higher-floor apartments and apartments with better access to the subway. Further analysis of the transaction process reveals that sellers and buyers both react to the entry of dockless bike sharing, which shifts the housing market to a new equilibrium with a flatter price gradient. A test of parallel pre-trends and the exogeneity of entry, a two-step estimation, and various robustness checks all validate the causal effect of dockless bike sharing on the subway housing price premium.

We contribute to the literature on the sharing economy by demonstrating the causal impact of dockless bike sharing on reducing the subway housing price premium and narrowing the price gap between apartments at different distances to subway stations, exploring the mechanisms for the premium reduction, quantifying the equivalent monetary value in housing price premium reduction, and inferring the reduction in a household's commuting cost brought forward by the availability of dockless bike sharing. We also contribute to the literature on urban economics regarding how improved transportation affects livability. It is noteworthy that dockless bike sharing is a new means of transportation that is powered by modern information and communications technology (ICT). We provide an example of how ICT transforms mobility in a way that may lead to significant impacts on other important markets.

Our findings have significant implications for bike sharing companies, property developers, policymakers, and urban commuters. In most markets, property developers and dockless bike sharing companies are two separate entities. Our findings show that dockless bike sharing substantially reduces commuting costs and increases the relative attractiveness of distant apartments, but dockless bike sharing companies do not fully capture such benefits. One implication might be that property developers could subsidize dockless bike sharing, or dockless bike sharing companies could partner with developers to provide better services. For example, in Singapore, nearly all private condominiums provide their residents with free or subsidized commuting services between home and the nearest subway station, which are often operated by third-party transport companies. This is a win-win strategy for both property developers and transport companies. Chinese property developers can learn from Singapore's experience.

Currently, all dockless shared bikes are provided by private companies. Given that dockless bike sharing offers an effective solution to the last-mile problem and brings huge reductions in commuting costs, governments and city municipalities may considering integrating dockless bike sharing into the entire system of urban transport planning, similar to how they provide stationed public bikes. In this way, they may better harness the benefits and reduce the negative effects of dockless bike sharing. In many cities, such as Beijing, Wuhan, and Hangzhou, governments and bike sharing companies have been experimenting with such joint arrangements.

We focus on one specific benefit of bike sharing: the impact on the subway housing price premium due to its effective solution to the last-mile problem. Dockless bike sharing has other benefits, such as its impacts on health, pollution, traffic congestion, and traffic safety, and costs such as haphazard parking, clogged streets, and bike vandalism. A comprehensive study is needed to fully assess the benefits and costs of dockless bike sharing; the government can then decide how to regulate dockless bike sharing.

An interesting area of research is how the entry of dockless bike sharing affects office space sales and rentals. If bike sharing affects the residential housing market, it may also affect the office space market. Because of the special institutional settings in office spaces in China—for instance, many government agencies and companies build their own office spaces, and office rentals tend to be on long-term lease—the effect might be different. Further, due to data availability, we only investigate the effect on the resale market. It might be worthwhile to take a general equilibrium approach to examine both the resale and new property markets and see how the two interact with each other and how the entry of bike sharing moderates such interactions. We leave these for future exploration.

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Table 1. Summary Statistics

Variables	(a) Unit	(b) Obs.	(c) Mean	(d) Sd.	(e) Min.	(f) Max.
All price	CNY/m^2	617,271	31,536	24,229	4,444	147,929
Initial price	CNY/m^2	399,840	31,945	24,554	4,444	147,929
Last price	CNY/m^2	399,840	31,898	24,462	4,444	147,929
Transaction price	CNY/m^2	42,697	30,580	24,820	4,474	147,730
Price adjustment	Percentage	217,431	7.44	5.57	-15.38	23.75
Number of viewing visits	Count	399,840	6.277	17.08	0	629
Floor number	Count	399,840	8.991	7.827	-8	50
Size	m^2	399,840	90.50	42.71	20	300
Building age	Year	252,465	13.82	7.879	0	68
Number of bedrooms	Count	393,094	2.205	0.851	1	4
Apartment density	Count	617,271	29.89	25.32	1	275
Within a school district	Indicator	399,840	0.505	0.500	0	1
No decoration	Indicator	399,840	0.0396	0.195	0	1
Basic decoration	Indicator	399,840	0.132	0.339	0	1
Intensive decoration	Indicator	399,840	0.197	0.398	0	1
Windows facing east	Indicator	399,840	0.191	0.393	0	1
Windows facing west	Indicator	399,840	0.124	0.329	0	1
Windows facing south	Indicator	399,840	0.771	0.420	0	1
Windows facing north	Indicator	399,840	0.343	0.475	0	1
Bike sharing	Indicator	617,271	0.452	0.498	0	1
Ofo	Indicator	617,271	0.411	0.492	0	1
Mobike	Indicator	617,271	0.437	0.496	0	1
Baidu search index	1000 Count	617,271	0.350	0.508	0	3.471
Geodesic distance to subway	km	617,271	1.083	0.695	0.004	3.000
Walking distance to subway	km	593,430	1.618	0.985	0	5.200
Number of stations within 3 km	Count	617,271	6.935	4.652	1	30
Transit station	Indicator	617,271	0.091	0.287	0	1

Notes: Sample comprises apartments in the 10 cities in online Appendix B, Table B1, initially listed from mid-2015 to 2017, within 3 km of the nearest subway station.

Table 2. Bike Sharing and the Subway Housing Premium

Variables	(a) Baseline estimates	(b) Ofo's entry	(c) Mobike's entry	(d) Baidu search index	(e) 10m x 10m grid fixed effects	(f) Effect dynamics	(g) 2-step estimator
Distance to subway (β_1)	-0.042	-0.042	-0.042	-0.040	0.006	-0.042	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	
Bike sharing (β_2)	-0.011	-0.010	-0.001	0.001	-0.003		0.014
	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)		(0.005)
Distance x bike sharing (β_3)	0.012	0.013	0.011	0.010	0.012		
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		
Distance x 1st month of entry						0.000	
						(0.004)	
Distance x 2nd month of entry						0.009	
						(0.003)	
Distance x 3rd and later month of entry						0.013	
						(0.003)	
Observations	617,271	617,271	617,271	617,271	617,271	617,271	329
Apartments	399,840	399,840	399,840	399,840	385,356	399,840	n.a.
Subway stations	1,422	1,422	1,422	1,422	1,421	1,422	n.a.
R^2	0.91	0.91	0.91	0.91	0.98	0.91	0.60

Notes: Columns (a)-(e): estimated by OLS with subway-station fixed effects and city-year-month fixed effects; samples comprise apartments initially listed from mid-2015 to 2017, within 3 km of the nearest subway station; the dependent variable is logarithm of price per m^2. All estimates control for apartment characteristics, apartment density, and indicators for initial/last price; robust standard errors clustered by subway station are in parentheses. Columns (a), (e), (f), and (g): *bike sharing* is an indicator for the first entry by Ofo or Mobike; Columns (b)-(d): *bike sharing* indicates Ofo's entry, Mobike's entry, and Baidu search index, respectively. Column (g): the dependent variable is estimated price gradients by city-year-month combination, estimated by generalized least squares with city fixed effects weighted by number of price records in each combination; robust standard errors clustered by city.

Table 3. Effect Heterogeneity and Moderators

Variables	(a) Size	(b) Floor number	(c) In a school district	(d) Transit station	(e) # Nearby stations
Distance to subway	-0.042	-0.042	-0.042	-0.042	-0.043
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Bike sharing	-0.011	-0.012	-0.012	-0.012	-0.019
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Distance x bike	0.011	0.013	0.012	0.012	0.022
sharing	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Distance x bike	0.007	0.004	0.001	0.018	0.009
sharing x moderator	(0.001)	(0.001)	(0.003)	(0.005)	(0.002)
Observations	617,271	617,271	617,271	617,271	617,271
Apartments	399,840	399,840	399,840	399,840	399,840
Subway stations	1,422	1,422	1,422	1,422	1,422
R^2	0.91	0.91	0.91	0.91	0.91

Notes: Estimated by OLS with subway-station fixed effects and city-year-month fixed effects. Samples comprise apartments initially listed from mid-2015 to 2017, within 3 km of the nearest subway station. Dependent variable: logarithm of price per m^2. All estimates control for apartment characteristics, apartment density, and indicators for initial/last price. Column (a) and (b): the effect of bike sharing entry on housing price premium moderated by standardized apartment size and floor number, respectively; Column (c): effect moderated by whether an apartment is in a school district; Column (d): effect moderated by whether an apartment is near a transit station; Column (e): effect moderated by number of subway stations within 3 km of the apartment. Robust standard errors clustered by subway station in parentheses.

Table 4. Mechanisms

Variables	(a) Initial Prices	(b) Visit viewings	(c) Last prices	(d) Transaction prices	(e) Price adjustment
Distance	-0.043	-0.018	-0.043	-0.048	-0.031
	(0.003)	(0.005)	(0.003)	(0.004)	(0.027)
Bike sharing	-0.011	0.025	-0.010	0.017	0.286
	(0.007)	(0.024)	(0.007)	(0.018)	(0.172)
Distance x bike sharing	0.015	0.016	0.015	0.013	0.003
	(0.003)	(0.006)	(0.003)	(0.005)	(0.039)
Observations	399,840	399,840	399,838	42,697	217,431
Apartments	399,840	399,840	399,838	42,697	119,589
Subway stations	1,420	1,420	1,422	1,185	1,387
R^2	0.91	0.36	0.91	0.93	0.16

Notes: Estimated by OLS with subway-station fixed effects and city-year-month fixed effects. Samples comprise apartments initially listed from mid-2015 to 2017, within 3 km of the nearest subway station (except column (d), which limits to sold apartments). Dependent variables: Column (a): logarithm of initial price per m^2; Column (b): logarithm of number of viewing visits plus one; Column (c): logarithm of latest price per m^2; Column (d): logarithm of transaction price per m^2; Column (e): percentage adjustment from the previous price to the current price. All estimates control for apartment characteristics and apartment density. Robust standard errors clustered by subway station in parentheses.

Table 5. Parallel Trends before Entry

VARIABLES	(a)	(b)	(c)	(d)	(e)	(f)
Distance to subway	-0.042	-0.042	-0.042	-0.042	-0.042	-0.042
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Distance x month of entry	0.012	0.012	0.012	0.012	0.012	0.012
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Distance x 1st month before entry	0.002	0.002	0.002	0.002	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Distance x 2nd month before entry		-0.000	-0.000	-0.000	-0.000	-0.000
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Distance x 3rd month before entry			-0.001	-0.001	-0.001	-0.001
			(0.004)	(0.004)	(0.004)	(0.004)
Distance x 4th month before entry				0.004	0.004	0.004
				(0.004)	(0.004)	(0.004)
Distance x 5th month before entry					-0.000	-0.000
					(0.004)	(0.004)
Distance x 6th month before entry						-0.002
						(0.003)
Observations	617,271	617,271	617,271	617,271	617,271	617,271
Apartments	399,840	399,840	399,840	399,840	399,840	399,840
Subway stations	1,422	1,422	1,422	1,422	1,422	1,422
R^2	0.91	0.91	0.91	0.91	0.91	0.91

Notes: Estimated by OLS with subway-station fixed effects and city-year-month fixed effects. Samples comprise apartments initially listed from mid-2015 to 2017, within 3 km of the nearest subway station. Dependent variable: logarithm of price per m^2. All estimates control for apartment characteristics, apartment density, and indicators of initial/last price. Robust standard errors clustered by subway station in parentheses.

Table 6. Placebo Test on the Exogenous Entry of Bike Sharing

Variables	(a) City	(b) Subway station	(c) Apartment	(d) Observation
Distance	-0.040	-0.041	-0.040	-0.040
	(0.004)	(0.003)	(0.003)	(0.003)
Bike sharing	-0.006	-0.007	-0.005	-0.006
	(0.006)	(0.004)	(0.002)	(0.002)
Distance x bike sharing	0.005	0.008	0.006	0.005
	(0.004)	(0.003)	(0.002)	(0.003)
Observations	617,271	617,271	617,271	617,271
Apartments	399,840	399,840	399,840	399,840
Stations	1,422	1,422	1,422	1,422
R-squared	0.91	0.91	0.91	0.98

Notes: Estimated by OLS with subway-station fixed effects and city-year-month fixed effects. Samples comprise apartments initially listed from mid-2015 to 2017, within 3 km of the nearest subway station. Dependent variable is logarithm of price per m^2. All estimates control for apartment characteristics, apartment density, and indicators for initial/last price. The entry date of bike sharing to each city (column (a)), subway station (column (b)), apartment (column (c)), and price record (column (d)) is randomized by a uniform distribution from July 1, 2015 to March 12, 2018. Robust standard errors clustered by subway station in parentheses.

Table 7. Alternative Explanations

Variables	(a) District-level time trends	(b) 6km x 6km grid-level time trends	(c) 1-year time window	(d) Half-year time window	(e) Ofo campus
Distance to subway	-0.040	-0.041	-0.043	-0.045	-0.043
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Bike sharing	-0.011	-0.007	-0.008	-0.006	-0.010
	(0.005)	(0.006)	(0.00)	(0.006)	(0.006)
Distance x bike sharing	0.013	0.008	0.008	0.006	0.010
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Distance x Ofo campus					0.004
					(0.004)
Observations	617,271	617,271	240,904	112,834	617,271
Apartments	399,840	399,840	162,887	79,269	399,840
Subway stations	1,421	1,421	1,380	1,341	1,422
R^2	0.92	0.92	0.90	0.91	0.91
Variables	(f) Planned stations	(g) Excl. new stations	(h) Excl. new stations	(i) Excl. nearest 500 m	(j) Ex. shopping mall
Distance to subway	-0.003	-0.036	-0.041	-0.045	-0.041
	(0.014)	(0.007)	(0.003)	(0.004)	(0.003)
Bike sharing		-0.029	-0.009	-0.011	-0.012
		(0.020)	(0.007)	(0.006)	(0.006)
Distance x bike sharing	0.006	0.022	0.015	0.012	0.011
	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
Observations	69,930	114,875	409,100	480,268	589,826
Apartments	41,699	72,887	292,856	311,102	382,641
Subway stations	75	511	1,368	1,419	1,422
R2	0.76	0.85	0.91	0.91	0.91

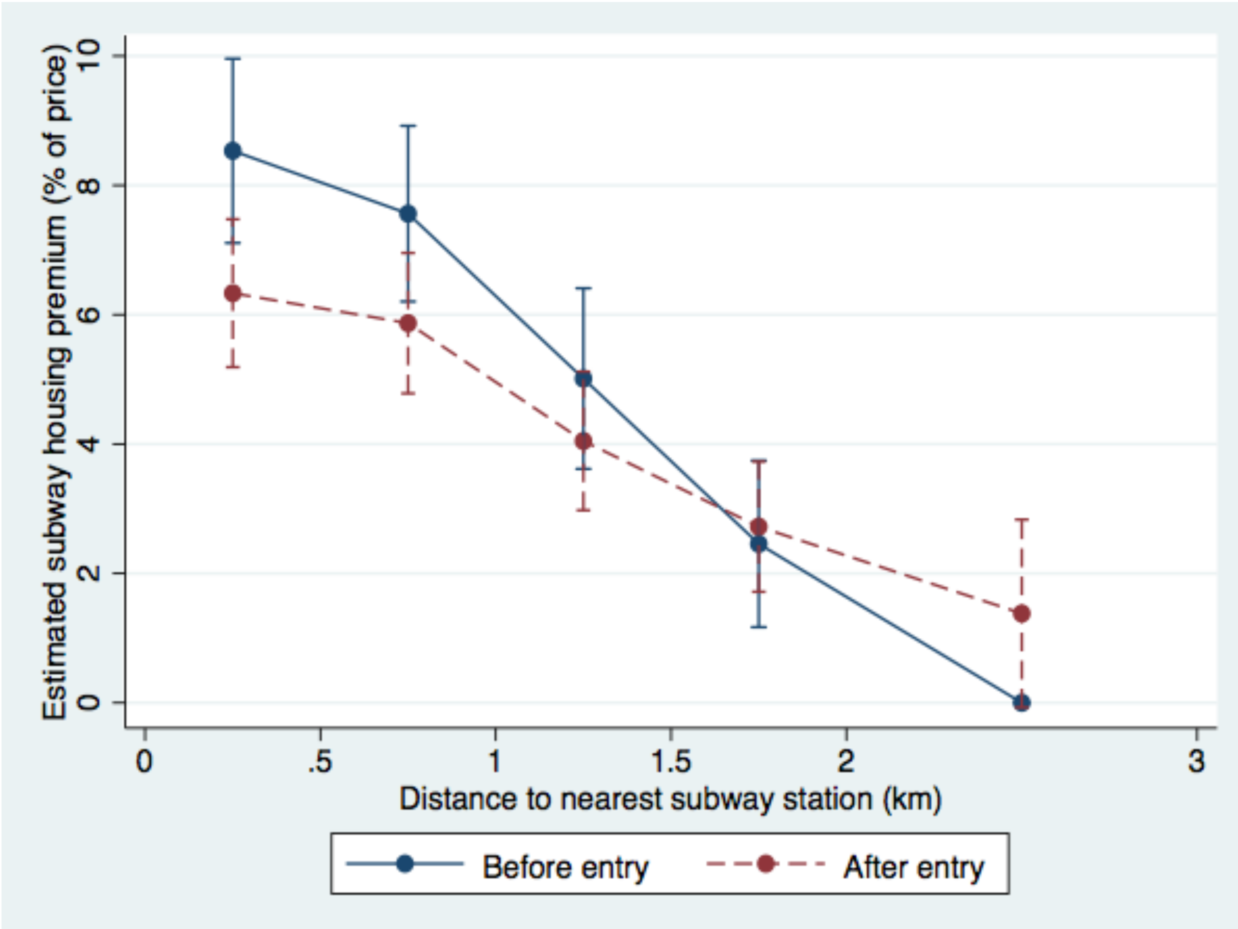
Notes: Estimated by OLS with subway-station fixed effects and city-year-month fixed effects. Samples comprise apartments initially listed from mid-2015 to 2017, within 3 km of the nearest subway station. Dependent variable is logarithm of price per m^2. All estimates control for apartment characteristics, apartment density, and indicators for initial/last price. Column (a) controls for district-year-month fixed effects; Column (b) divides the sample into 388 6km x 6km grids and controls for grid-year-month fixed effects; Columns (c) and (d) limit to apartments listed 183 and 90 days, respectively, before and after the entry of bike sharing. Column (e) controls for Ofo's entry to campus and its interaction with *distance to subway*; Column (f) limits to apartments in Beijing, within 3 km of the nearest *planned* subway station; Column (g): limits to city periods with no subway station open 3 months before and after the entry of bike sharing (Beijing, Dec 26, 2015 to Dec 21, 2016; Hangzhou, Nov 24, 2015 to Jul 3, 2017; Nanjing, Jul 1, 2015 to Jan 8, 2017; Wuhan, Dec 28, 2015 to Dec 28, 2016). Column (h): limits to apartments whose nearest station opened before 2016; Column (i): limits to apartments beyond 500 m of the nearest station; Column (j): excludes apartments whose nearest subway station is within 200 m of a shopping mall. Robust standard errors clustered by subway station in parentheses.

Table 8. Robustness Checks

Variables	(a) Within 2 km	(b) Within 4 km	(c) Within 5 km	(d) Walking distance	(e) Excl. age controls	(f) Cluster std. errors by city
Distance to subway	-0.041	-0.040	-0.039	-0.026	-0.037	-0.041
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
Bike sharing	-0.009	-0.007	-0.007	-0.014	-0.012	-0.002
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Distance x bike sharing	0.014	0.008	0.007	0.009	0.012	0.011
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
Observations	541,482	655,719	676,231	593,429	617,271	617,271
Apartments	349,911	424,407	437,418	385,356	399,840	399,840
Subway stations	1,417	1,424	1,425	1,422	1,421	1,422
R^2	0.91	0.91	0.91	0.91	0.91	0.91

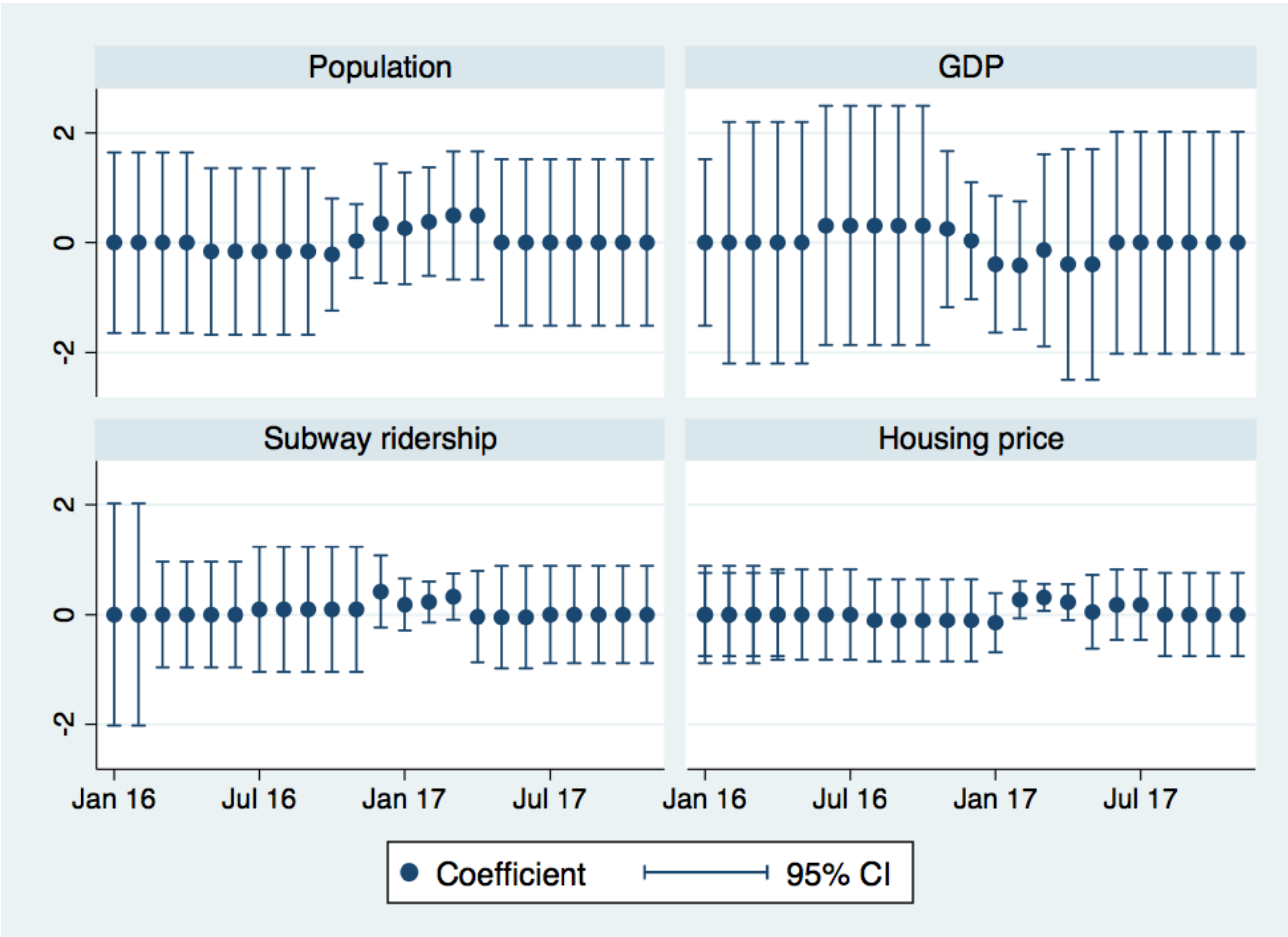
Notes: Estimated by OLS with subway-station fixed effects and year-month fixed effects. Samples comprise apartments initially listed from mid-2015 to 2017, within 3 km of the nearest subway station; dependent variable: logarithm of price per m^2; all estimates control for apartment characteristics, apartment density, and indicators for initial/last price. Columns (a)-(c): limit to apartments within 2 km, 4 km, and 5 km of the nearest subway station; Column (d): distance to subway measured by the walking distance from apartment to the nearest subway station; Column (e): does not control for building age and indicator of missing building age; Column (f): reports bootstrap standard errors clustered by city to adjust for the small number of clusters. Columns (a)-(e): Standard errors clustered by subway station.

Figure 1. Housing Price Gradient: Estimates by Distance Segment



Notes: The plot depicts the estimated average subway housing price premium by distance segment (0-0.5 km, 0.5-1 km, 1-1.5 km, 1.5-2 km, 2-3 km) from model (1), before and after the entry of bike sharing. We estimate model (1) on logarithm of housing price per m^2 against indicators of distance segments, indicator of bike sharing interacted with indicator of each segment, subway-station fixed effects, city-year-month fixed effects, and apartment covariates (apartment floor number, size, building age, number of bedrooms, apartment density, whether near a public school, decoration status, window directions, and indicators of initial/last price), using apartments initially listed during mid-2015 to 2017, within 3 km of the nearest subway station. Vertical bars denote 95% confidence intervals.

Figure 2. Test on Exogenous Entry of Bike Sharing



Notes: The figure plots the point estimates of $\boldsymbol{\theta}$ from model (3) with 95% confidence intervals. The test specification follows Zervas, Proserpio, and Byers (2017), but we drop the city fixed effects to identify all city-year-month interactions. City characteristic variables are standardized to have zero mean and unit standard deviation.

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

Online Appendix A. Calculation of Distance to the Nearest Subway Station

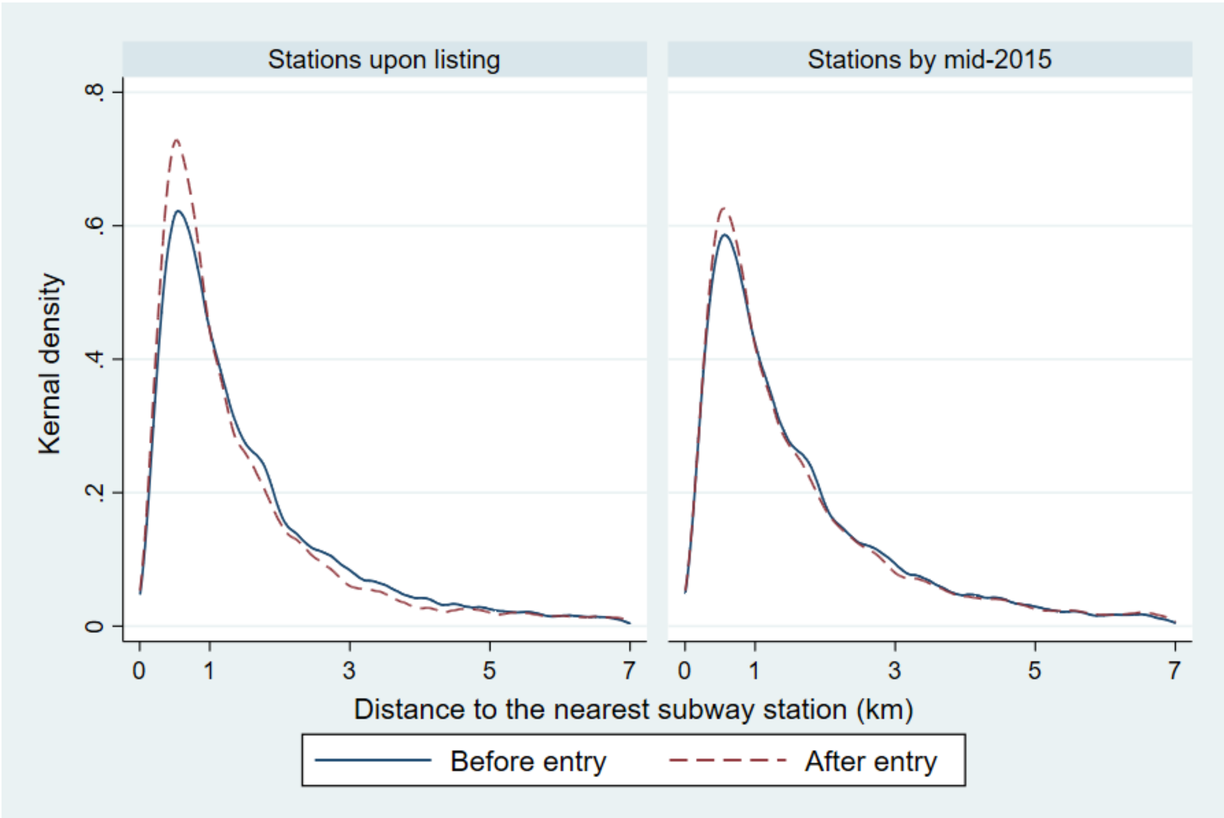
An apartment can have more than one record due to upward or downward price adjustments or change in sales status with a time stamp for the change. For each record, we define distance as that between the apartment and the nearest subway station which is open when the price record is created. Seventy percent of the apartments only have one price record. Their distances to subway stations are calculated only once and do not vary with time. But for apartments with multiple records, it is possible their distances to subway will vary with time: The distances typically decrease when a new and closer subway station is built. However, the distances do not change if the new station is further away from the apartment or its opening falls outside the listing period of the apartment. In the follows paragraph we give several examples to illustrate this idea.

As shown in Table A1, suppose Apartment *A* has three price records [1]-[3], created on May 15, June 15 and July 15, 2017, respectively. Before May 31, 2017, the nearest subway station (S0) to this apartment was 2.5 km away. On June 1, 2017, a new subway line was built, and a new station (S1) 1.5 km away from the apartment came into use. Opening at the same time was another new station (S2) 3.5 km away. Then on September 1, 2017, a third new station (S3) 1 km away came into use. In this case, Apartment *A*'s three observations [1]-[3] will have different distances to subway: Observation [1]'s distance to subway is 2.5 km. Observation [2]'s distance to subway is 1.5 km (the opening of S2 did not play a role because it was further from A than S0). Finally, Observation [3]'s distance to subway remains 1.5 km, because the nearest station by July 15 was still S1, and the opening of S3 has no effect because it opened after price record [3] was created.

Table A1. Illustration of how distance is measured

	Open date and distance from Apartment A			
Price record date	S0 (opened before May 15, 2017; 2.5 km away)	S1 (opened on June 1, 2017; 1.5 km away)	S2 (opened on June 1, 2017; 3.5 km away)	S3 (opened on Sep 1, 2017; 1 km away)
May 15, 2017	2.5 km			
June 15, 2017		1.5 km		
July 15, 2017				1.5 km

Figure A1. Distribution of Apartments by Distance to Nearest Subway Station



Note: Samples comprise apartments initially listed during mid-2015 to 2017, within 7 km to subway. Each apartment is matched to the nearest subway station at the time of listing (the left panel), or at July 1, 2015 (the right panel). The blue solid line and the red dashed line depict the kernel density distribution of apartments before and after the entry of bike sharing against distance to subway, respectively.

Online Appendix B. Additional Tables and Figures

Table B1. City Characteristics

City	(a) Bike sharing entry date			(b) # Subway stations		(c) # Apartments	(d) Average price (CNY/m²)	(e) Average size (m²)	(f) Income per capita (CNY)
	Ofo campus	Ofo	Mobike	Jul 2015	Dec 2017				
Beijing	6 Jun 2015	10 Oct 2016	1 Sep 2016	265	288	62,689	58,668	91.81	52,350
Chengdu	22 Aug 2016	16 Dec 2016	16 Nov 2016	48	100	53,294	12,233	95.35	35,902
Chongqing	10 Jan 2017	10 Jan 2017	1 May 2017	108	119	35,650	9,242	97.30	29,610
Dalian	26 Jun 2017	26 Jun 2017	16 Apr 2017	41	65	32,457	11,054	82.41	38,050
Hangzhou	12 Sep 2016	20 Feb 2017	16 Apr 2017	44	56	19,562	27,251	93.02	52,185
Nanjing	22 Aug 2016	8 Jan 2017	12 Jan 2017	113	128	34,073	26,247	89.02	49,997
Shanghai	9 May 2016	10 Oct 2016	22 Apr 2016	279	294	59,031	50,880	87.17	55,358
Shenzhen	11 Sep 2016	9 Dec 2016	16 Oct 2016	118	167	37,816	54,255	86.81	48,695
Tianjin	27 Aug 2016	13 Jan 2017	12 Feb 2017	84	105	29,969	26,833	77.28	34,074
Wuhan	18 Apr 2016	6 Jan 2017	29 Dec 2016	75	123	35,299	15,716	102.2	39,737

Notes: Column (a): Entry date of Ofo (campus only), Ofo (citywide) and Mobike (citywide); The first and third columns are from Cao, Jin and Zhou (2018) and the second column is collected from the Internet by authors; In subsequent tables, the entry of bike sharing is defined as the earlier citywide entry of Ofo or Mobike (as underlined). Column (b): Number of subway stations by mid-2015 and the end of 2017, calculated by authors; Columns (c)-(e): Number of apartments, average price per m^2 and average apartment size, calculated from the sample; Column (f): Income per capita in 2016, collected from *China City Statistical Yearbook 2017*, Beijing: China Statistics Press, 2018.

Table B2. City-specific Coefficient Estimates

Variables	(a) Beijing	(b) Chengdu	(c) Chongqing	(d) Dalian	(e) Hangzhou
Distance to subway	-0.055	-0.039	-0.008	-0.057	-0.037
	(0.007)	(0.008)	(0.007)	(0.011)	(0.020)
Distance x bike sharing	0.029	0.003	0.015	0.008	0.010
	(0.005)	(0.012)	(0.006)	(0.006)	(0.015)
Variables	(f) Nanjing	(g) Shanghai	(h) Shenzhen	(i) Tianjin	(j) Wuhan
Distance to subway	-0.025	-0.065	-0.023	-0.069	-0.047
	(0.014)	(0.007)	(0.009)	(0.009)	(0.008)
Distance x bike sharing	-0.007	0.037	0.021	-0.002	0.020
	(0.011)	(0.005)	(0.005)	(0.005)	(0.006)
Observations	617,271				
Apartments	339,840				
Subway stations	1,422				
R^2	0.91				

Notes: Estimated by OLS with subway-station fixed effects and year-month fixed effects. Samples comprise apartments initially listed from mid-2015 to 2017, within 3 km of the nearest subway station. The dependent variable is the logarithm of price per m^2. All estimates control for apartment characteristics, apartment density, and indicators for initial/last price. Robust standard errors clustered by subway station in parentheses.

Table B3. City-level Estimates

Variables	(a) Beijing	(b) Chengdu	(c) Chongqing	(d) Dalian	(e) Hangzhou
Distance to subway	-0.053	-0.041	-0.009	-0.054	-0.039
	(0.007)	(0.008)	(0.006)	(0.010)	(0.020)
Distance x bike sharing	0.030	0.002	0.015	0.004	0.012
	(0.005)	(0.011)	(0.006)	(0.006)	(0.015)
Observations	105,543	84,579	53,224	55,790	33,313
Apartments	62,689	53,294	35,650	32,457	19,562
Subway stations	285	100	117	62	56
R^2	0.75	0.54	0.51	0.57	0.64
Variables	(f) Nanjing	(g) Shanghai	(h) Shenzhen	(i) Tianjin	(j) Wuhan
Distance to subway	-0.024	-0.065	-0.028	-0.068	-0.046
	(0.014)	(0.006)	(0.008)	(0.009)	(0.008)
Distance x bike sharing	-0.009	0.036	0.021	0.001	0.017
	(0.011)	(0.005)	(0.005)	(0.005)	(0.006)
Observations	56,564	60,681	62,419	55,045	50,113
Apartments	34,073	59,031	37,816	29,969	35,299
Subway stations	121	294	163	102	122
R^2	0.60	0.65	0.60	0.67	0.60

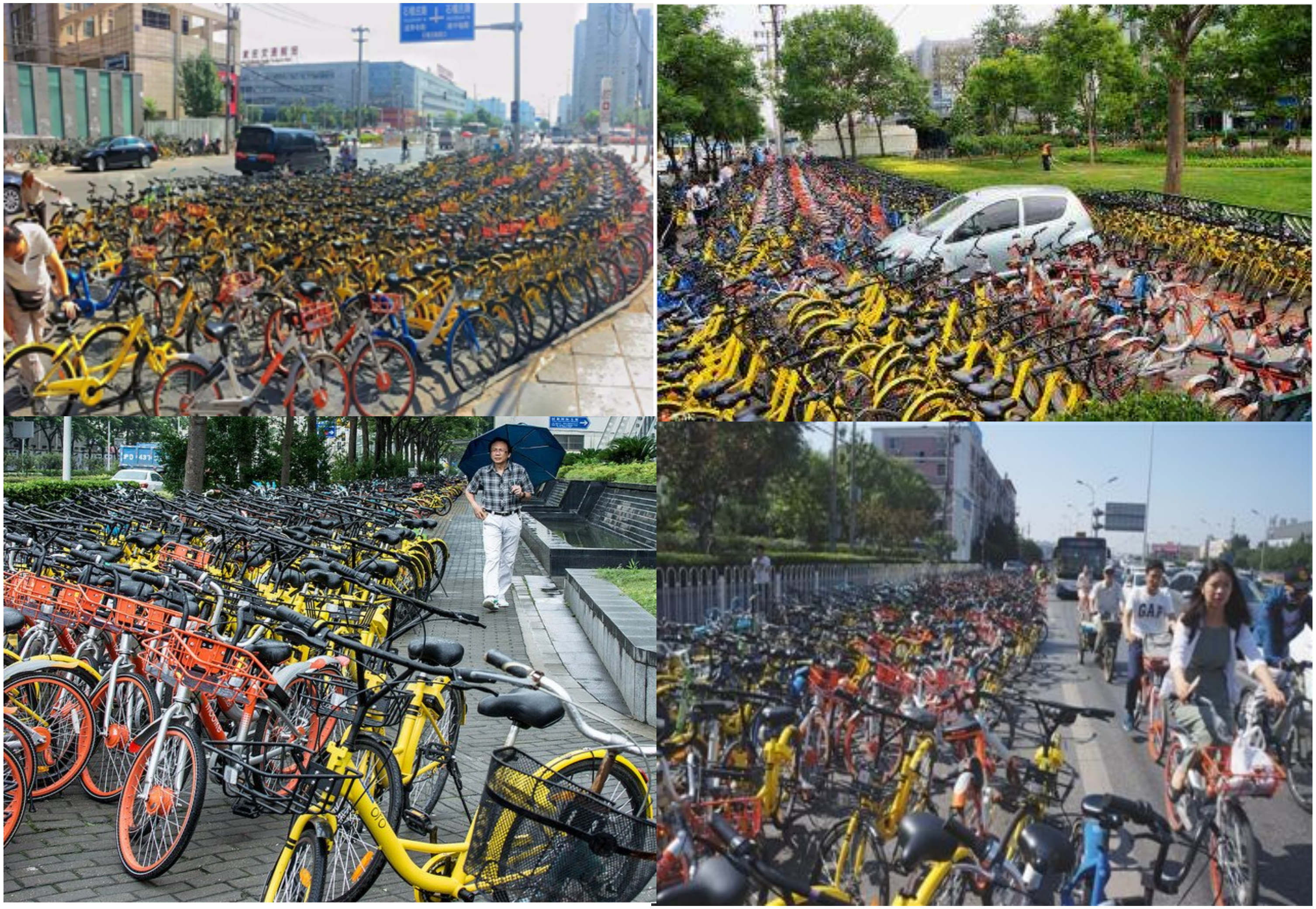
Notes: Estimated by OLS with subway-station fixed effects and year-month fixed effects. Samples comprise apartments initially listed from mid-2015 to 2017, within 3 km of the nearest subway station. The dependent variable is the logarithm of price per m^2. All estimates control for apartment characteristics, apartment density, and indicators for initial/last price. Robust standard errors clustered by subway station in parentheses.

Table B4. Exogenous Entry of Bike Sharing: The Hazard Rate Test

Variables	(a) Coefficients	(b) Hazard ratios
End-of-year population	-0.380	0.684
	(1.247)	(0.853)
Annual GDP	1.741	5.701
	(1.779)	(10.14)
Annual subway ridership	4.045	57.12
	(2.416)	(138.0)
Annual average housing price	0.613	1.846
	(0.712)	(1.314)
Observations	125	
Cities	10	
Log pseudolikelihood	-13.30	

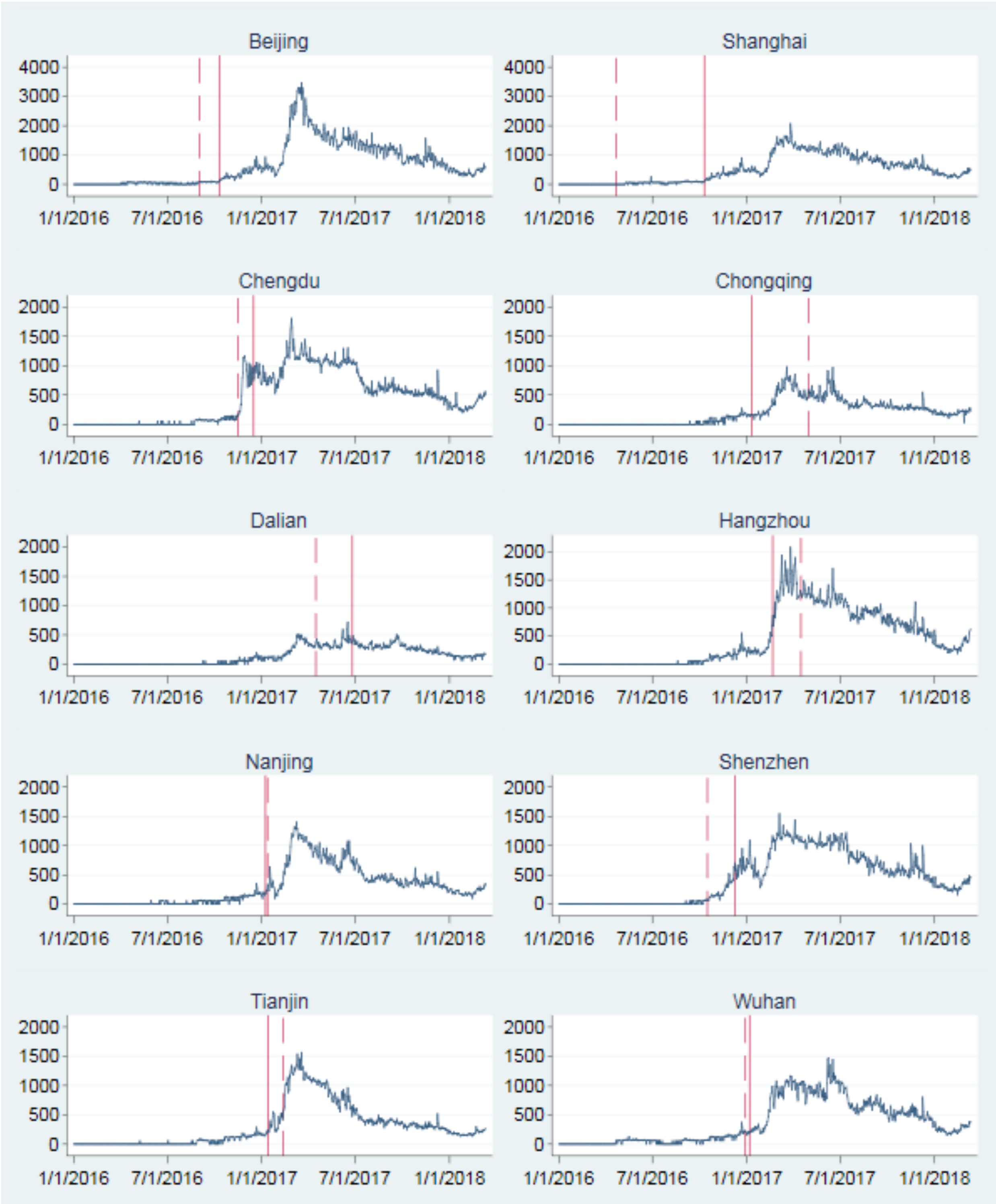
Notes: Estimated by a hazard rate model using Stata routine, stcox. Sample comprises city-year-months from January 2016 to the month of entry of bike sharing. Explanatory variables are standardized to zero mean and unit standard deviation. Column (a) reports the coefficients and column (b) reports the respective hazard ratios. Robust standard errors clustered by city in parentheses.

Figure B1. Photos of Dockless Shared Bikes in Chinese Cities



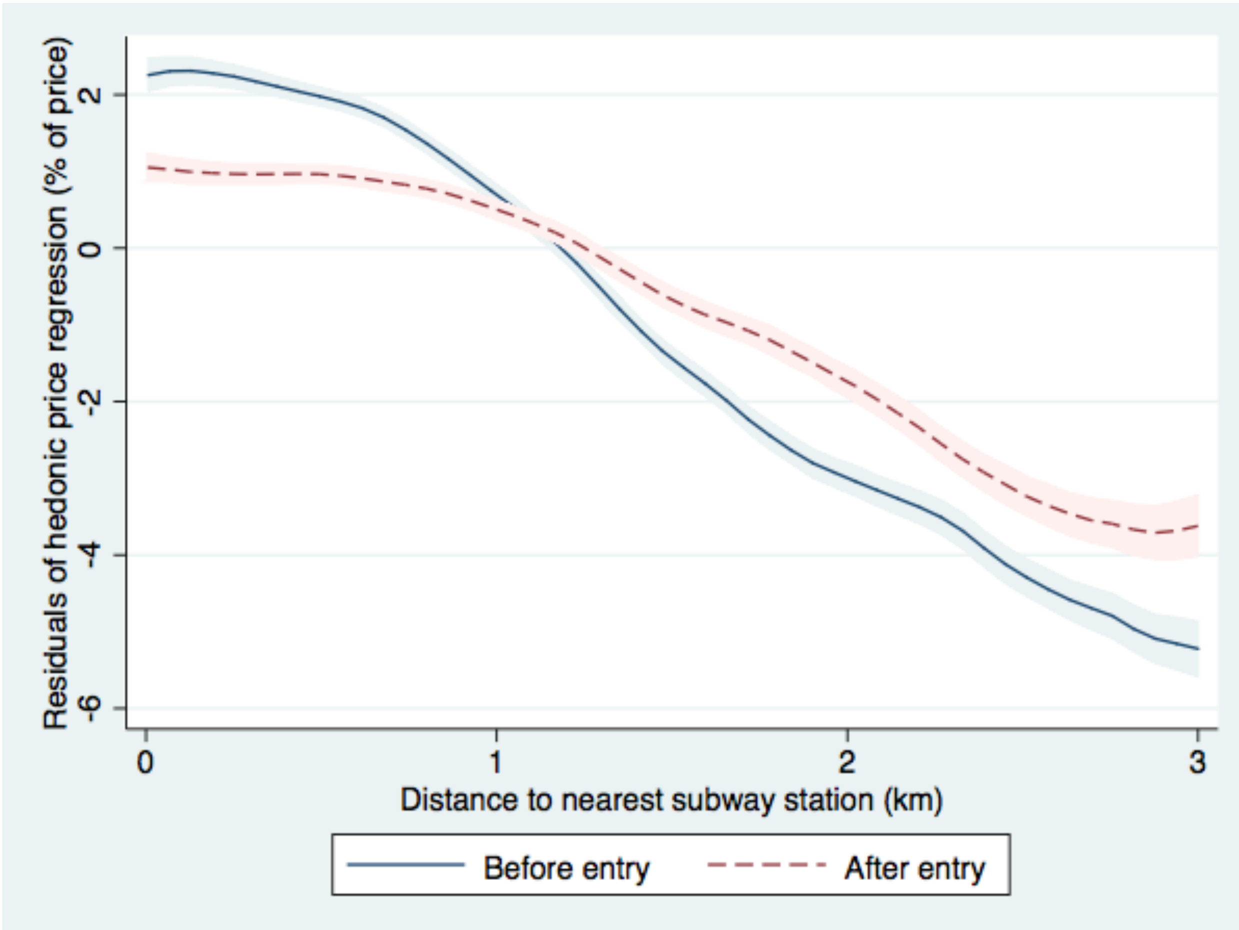
Source: Upper-left: http://www.010lf.com/news/2017/09/11/193632.html; upper-right: http://www.jlonline.com/ news/2017-0509/357030.shtml; bottom-left: https://www.planetizen.com/news/2018/03/97982-friday-eye-candy-dockless-bikes-far-eye-can-see; bottom-right: http://www.rmzxb.com.cn/c/2017-08-04/1698939_2.shtml; retrieved May 12, 2018.

Figure B2. Baidu Index for "Bike Sharing"



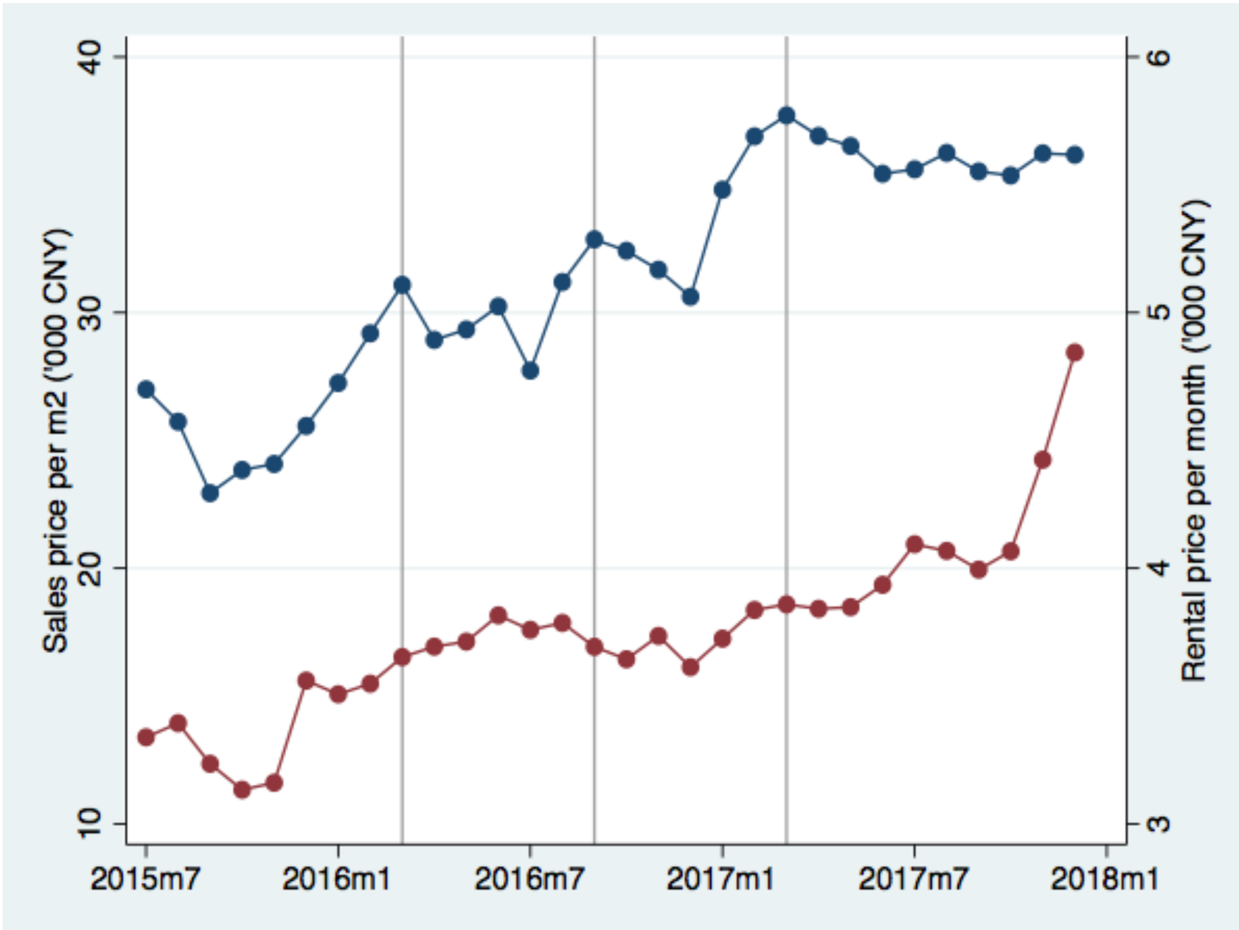
Notes: Blue curves depict daily Baidu search index for "bike sharing" from January 1, 2016 to March 12, 2018 by city (indices prior to 2016 all equal zero). Red solid lines represent entry time of Ofo and red dashed lines represent entry time of Mobike.

Figure B3. Housing Price Gradient: Non-parametric Estimates



Notes: The plot depicts hedonic price residuals from estimating model (1) against distance to the nearest subway station, before and after the entry of bike sharing. We estimate model (1) on logarithm of housing price per m^2 against subway-station fixed effects, city-year-month fixed effects, and apartment characteristics (apartment floor number, size, building age, number of bedrooms, apartment density, whether in a school district, decoration status, window directions, and indicators for initial/last price), using apartments initially listed from mid-2015 to 2017, within 3 km of the nearest subway station. Blue solid line and red dashed line represent non-parametric estimates of the hedonic price residuals as a smooth function of distance, for apartments listed before and after the entry of bike sharing, respectively. The shadows represent the 95% confidence intervals.

Figure B4. Monthly Average Prices of Resale and Rental Apartments in Beijing



Note: Samples comprise rental and resale apartments initially listed from mid-2015 to 2017, within 3 km of the nearest subway station. The blue dots depict the average price per m^2 of resale apartments in each month; the red dots depict the average rents per month of rental apartments. The grey vertical lines represent the housing market regulations on March 25, 2016, September 30, 2016, and March 20, 2017, respectively**.**

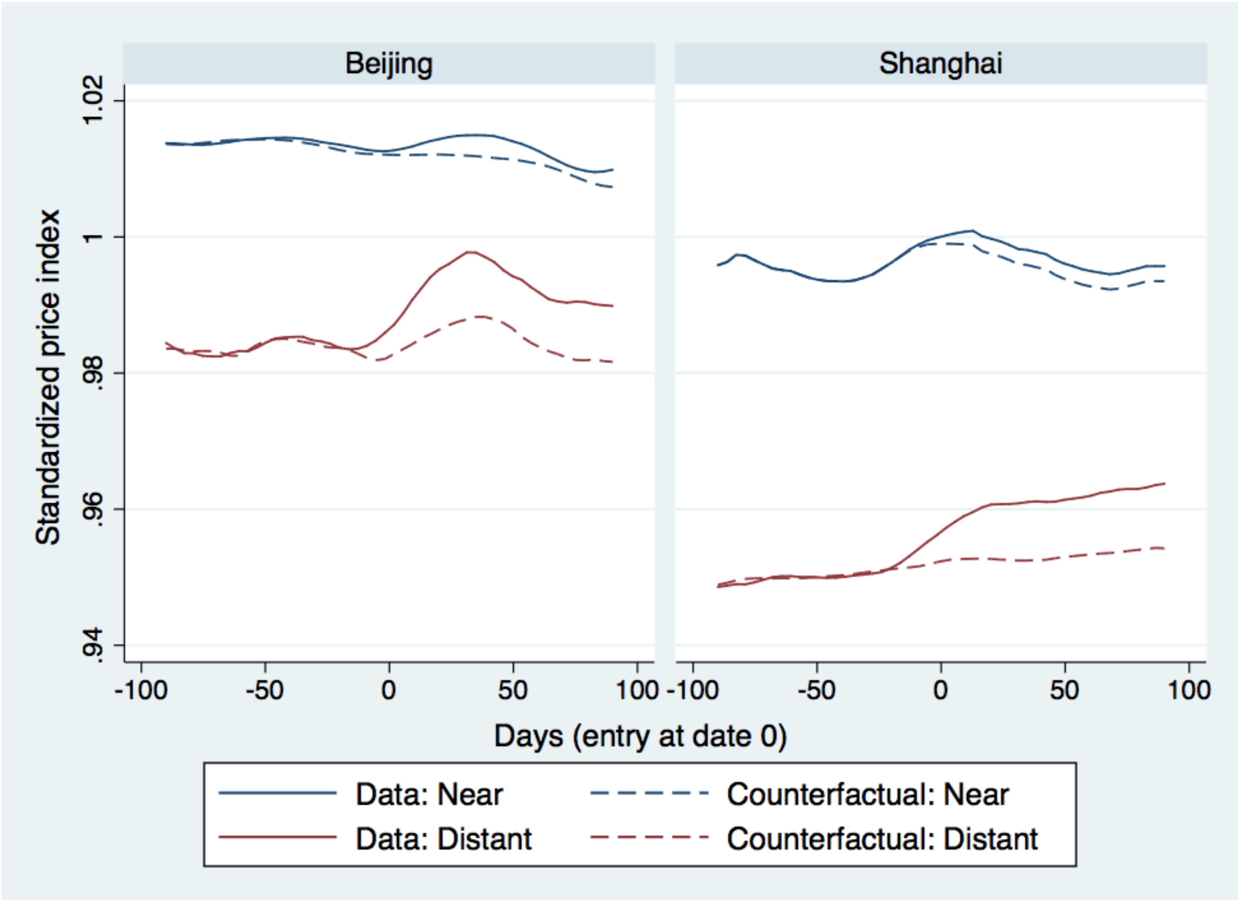
Online Appendix C. Back-of-the-envelope Calculation of Commuting Cost Reduction

The calculation method is as follows: (1) for each apartment listed after the entry, we use the estimates in Table 2, Column (a) to obtain the predicted total price (predicted price per m^2 x apartment size) and the counterfactual total price assuming no entry of bike sharing; and (2) we treat the difference between the predicted and counterfactual total prices as the total reduction in commuting costs, and amortize it into 30, 40, 50, 60 and 70 years of annual values. Columns (a) and (b) use the compound interest rate for 5-year fixed deposits (2.86% per annum) and 5-year treasury bills (3.86% per annum) as discounter factors, respectively. Exchange rate between CNY and USD is 6.7:1.

Table C1. Reduction in Commuting Costs per Annum

Discount duration	(a) 2.86% per annum	(b) 3.86% per annum
30 years	1,893 CNY, or 282 USD	2127 CNY, or 317 USD
40 years	1,597 CNY, or 238 USD	1,851 CNY, or 276 USD
50 years	1,429 CNY, or 213 USD	1,700 CNY, or 254 USD
60 years	1,324 CNY, or 198 USD	1,610 CNY, or 240 USD
70 years	1,255 CNY, or 187 USD	1,554 CNY, or 232 USD

Figure C1. Counterfactual Prices without Bike Sharing



Note: Samples comprise apartments in Beijing and Shanghai, listed 90 days before and after the entry of bike sharing. The figure plots housing price residuals from Equation (1), smoothed by local polynomial regressions and absent from subway-station fixed effects and city-year-month fixed effects.