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We thank ofo executives for sharing data with us and for tirelessly answering our questions. All data employed in this article are aggregated operating indices without identifiable information on any individual user or any individual behavior. We are only authorized to use these data and the ownership of the data is retained by ofo. Comments from seminar attendants of Peking University are appreciated. All errors are ours. Guangyu Cao personally thanks the fund support for his PhD study from Guanghua-ofo Center for Sharing Economy Research and Will Hunting Capital. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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ABSTRACT

The recent rise of dockless bike-sharing is dominated by two platforms: one started first in 82 Chinese cities, 59 of which were subsequently entered by the second platform. Using these variations, we study how the entrant affects the incumbent's market performance. To our surprise, the entry expands the market for the incumbent, not only boosting its total number of trips but also allowing the incumbent to achieve higher revenue per trip, improve bike utilization rate, and form a wider and more evenly distributed network. These market expansion effects dominate a significant market-stealing effect on the incumbent's old users. Our findings suggest that platform entry can divert the perceived path to winners-take-all in a market with positive network effects, and competition with the outside goods is at least as important as the competition between platforms, especially when users multi-home across compatible networks.

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1. Introduction

Thanks to the ubiquity of digital platforms, platform competition has caught the attention of antitrust agencies. Since platforms often enjoy positive network effects, it is of concern that the network effects could lead to winner-takes-all, where the incumbent dominates the market and competing platforms find it difficult to enter and survive.[1] In the meantime, a growing literature points out that user multi-homing and platform compatibility play an important role alleviating the anti-competitive concerns.[2] How do platforms compete when they face positive network effects and multi-homing users? To what extent does the entry of a competitor expand or steal the user base of the incumbent platform? How do price, sales, and investment of the incumbent change as a result of entry? Are there other competitive considerations besides the potential of winner-takes-all?

We take these questions to the dockless bike-sharing market of China. ofo[3], the first bike-sharing platform in China, was founded in 2015 by a student of Peking University (PKU) when he was an undergraduate there. Due to travel inconvenience on a large college campus, ofo started as a two-sided platform that allowed students to share privately owned bikes on campus via an online app. Soon after, the online-to-offline (O2O) platform decided to supply the GPS-tracked dockless bikes itself and effectively became a one-sided platform.

As documented by a burgeoning literature[4], bike-sharing solves the "last-mile" problem of local

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[1] The main concern is that users may be reluctant to switch from the incumbent platform because they all enjoy the presence of other users in the same network. In some circumstances, users may coordinate on the wrong (inferior) network, the incumbent firm may have incentives to develop a proprietary network to lock in users, and the "excess inertia" may result in winner-takes-all. Even if multiple firms can compete to be the "winner" of the market, such competition can be inefficient from the social planner's point of view (see the review of Farrell and Klemperer 2007).

[2] On multi-homing, Caillaud and Jullien (2003) show that platform competition is more intense if they cannot deter multi-homing. Halaburda and Yehezkel (2013) study platform competition under asymmetric information. They find that platform competition may lead to a lower level of trade and lower welfare than a monopoly, if the difference in the degree of asymmetric information between the two sides is below a certain threshold. Multi-homing can solve the market failure resulting from asymmetric information. On compatibility, Katz and Shapiro (1985) show that large, reputable firms tend to choose incompatibility while small, weak firms tend to choose compatibility. Farrell and Saloner (1986) further show that, if an installed base exists and transition to a new standard must be gradual, early adopters bear a disproportionate share of transient incompatibility costs. This can cause "excess inertia." However, if the new standard is adopted, positive network effects can cause "excess momentum."

[3] "ofo" is the trademark of the platform, symbolizing a person riding a bicycle. To keep the full meaning of the trademark, we do not capitalize the first letter even if a sentence starts with "ofo."

[4] Kabra et al. (2016), Zheng et al. (2018) and O'Mahony and Shmoys (2015) have studied docked bike-sharing platforms in London, New York and Paris. Pan et al. (2018) study the dockless bike-sharing platform of Mobike

transportation. There are direct network effects among bike riders because a user who rides a bike from point A to point B makes the bike available for the next rider at point B. This feature, referred to as "consumption-as-supply," is particularly attractive in dockless bike-sharing. It no longer requires fixed docks at the origin and destination of a trip, which mitigates the potential imbalance of demand and supply in different locations at different times.[5] When thousands of users ride ofo bikes in a small area, the wide availability of ofo bikes persuades more users to adopt the app. In addition, more users on the road motivate ofo to put more bikes on the market, which further increases each user's willingness to use ofo.[6] Thanks to these positive network effects, ofo grew exponentially from a college campus to more than 250 cities in 20 countries by January 2018.[7]

ofo's growth has attracted numerous competitors, of which Mobike is the biggest rival. From the outset, ofo and Mobike were estimated to have more than 90% of the bike-sharing market in China[8], making many cities a de facto monopoly or duopoly depending on when one or both of them entered the city. If both entered the city, most consumers multi-home because the two bikes are almost perfect substitutes at the same time and location, and consumers can freely choose whichever is available at the moment.[9] In this sense, the two platforms are compatible and users are free to multi-home.

By tracking news reports[10] and combining them with ofo's internal data (up to 9/14/2017), we identify 59 cities that were first served by ofo and then joined by Mobike. We label them *ofo First* cities. There are another 23 *ofo Alone* cities and 22 *Mobike First* cities.[11] As a platform, ofo started half a year earlier than Mobike, so it is natural to consider ofo as an incumbent and Mobike as an entrant. With this sequence in mind, we apply difference-in-differences (DID) to the sample of ofo Alone and ofo First

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in China. All of them focus on the operation of a single bike-sharing network, such as network effects, consumer demand for bikes in the existing bike network, the optimal way to locate bike docks, and algorithms that could reduce the imbalance between bike demand and bike supply.

[5] Dockless bike-sharing does not completely solve the imbalance problem. See more detailed discussion in Section 2.

[6] This is similar to the positive feedback between demand and supply on a two-sided platform, though in our case the supply side is integrated with the platform.

[7] See the report from i-yiou at https://www.iyiou.com/p/64688, as of January 17, 2018.

[8] Industry research reports from different sources (such as iResearch, TrustDada and Analysys) cross-validate this number and some even claim that this number is estimated to be larger than 95%.

[9] Both apps adopt Wechat Pay and Alipay, the two most widely accepted electronic payment systems in China.

[10] We track news reports since September 7, 2015.

[11] Our sample does not cover all the 200+ cities serviced by ofo, mostly because some cities do not have complete city attribute data from the 2016 China City Statistical Yearbook. We will elaborate our sample criterion and the definitions of ofo First, ofo Alone and Mobike First cities in Section 2.

cities, while taking Mobike's city-specific entry as the "treatment"[12] and using ofo Alone cities as the control group.[13] Simple regressions suggest that Mobike's entry has expanded the market for ofo, driving up ofo's trip volume by 40.8% and ofo's average revenue per trip by 0.041 RMB.

Could the market expansion be driven by omitted variables or endogenous entry? Arguably, Mobike would choose the most profitable cities to enter first and ofo First and ofo Alone cities may be incomparable. To address this, we test and confirm that ofo First and ofo Alone cities are comparable in pre-treatment trend. We also show that the baseline estimates are robust to heterogeneous time trends, placebo test and subsample regressions. To further address potential endogeneity, we predict Mobike's entry date in a city using the timing of Mobike's venture capital (VC) funding (8 rounds in total) and the city's predetermined attributes such as population, seasonality, and transportation infrastructure. Using the predicted entry date as the instrument variable (IV) for the actual entry date, the IV results confirm that Mobike's entry benefits ofo in both trip volume and revenue per trip.

At the first glance, these findings are *against* the typical prediction from market competition. If two platforms compete fiercely against each other[14], the entrant should steal consumers away from the incumbent and press the incumbent to lower price, unless the entry has increased the overall market demand for both platforms. Even if the overall market expands, there should be significant market stealing between Mobike and ofo, as most consumers multi-home and the two bikes are almost identical except for color, logo and app access. This prediction is confirmed in our data: when we separate new and old users within ofo, we find that Mobike's entry has indeed reduced the percent of old users that remain active on ofo, but this market stealing effect is dominated by the expansion in new users. Another way to unpack market stealing and market expanding effects is by time: if we zoom in the days right after Mobike's entry but before ofo made any new bike investment, we find that ofo lost old users and did not pick up extra new users in this time window.

However, how can we explain the overall market expansion for ofo after Mobike has been in the

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[12] As detailed in Section 3, our estimation uses a long list of controls including weather conditions, air quality, calendar day fixed effects, time since ofo entry and time trends specific to predetermined city attributes.
[13] Since we do not have detailed data from Mobike, it is difficult to examine how ofo entry into Mobike First cities affects the market. Later in the paper we will describe how we use ofo data on Mobike First cities for robustness check.
[14] Though we do not have detailed data from Mobike, many new reports confirm that both ofo and Mobike grew substantially despite their head-to-head competition in many cities.

city for a while? A few possibilities come to mind. First, Mobike's aggressive marketing campaign – including advertising and coupon handouts – could have raised consumer awareness over time and boosted the overall demand for bike-sharing. It is difficult to test this as we do not have detailed data on Mobike's marketing efforts. Putting that aside, the second possibility is that ofo puts more new bikes into the duopoly markets in response to Mobike's entry. Data provides some support for this argument: ofo has indeed put more bikes in the ofo First markets after Mobike's entry, above and beyond the periodical bike investment it made in ofo Alone markets.

Nevertheless, other evidence suggests that ofo's bike investment cannot explain all the market expansion effect of Mobike's entry. For example, ofo's bike utilization rate – measured by the number of trips per ofo bike per day – has also increased significantly upon Mobike entry. This suggests that Mobike's entry has generated positive spillovers for every ofo bike, even after we account for ofo's new bike investment. We also find Mobike's entry allows ofo bikes to reach more grids in the city, if we define each grid as a square kilometer. Conditional on the grids that ofo bikes reach in a particular city-day, we can describe the dispersion of ofo bike usage by a Gini coefficient. This Gini coefficient decreases significantly upon Mobike's entry, suggesting that the entry has made ofo bike trips more evenly distributed in the ofo First cites than in the ofo Alone cities. All these results point to a competition-reinforced network effect: Mobike's entry has likely expanded the overall size of the bike-sharing network, attracted more consumers to join bike-sharing, and helped to expand the ofo network in depth, width, flatness and user reach.

This happens not only because of multi-homing and compatibility, but also because bike-sharing features consumption-as-supply. The more Mobike users there are in the market, the more likely that some of them will ride a Mobike bike to the neighborhoods dominated by ofo users. This will increase the overall bike supply in the neighborhood, encouraging even more residents to adopt ofo, Mobike or both. In addition, the more bike users there are in the market, the greater the density and coverage of the spatial network (ofo + Mobike). This reduces operation costs of both platforms, as bike consumption carries supply to hard-to-find pockets, which reduces the need for platforms to move bikes around to meet unbalanced demand. As the economy of scale kicks in, platforms have even more incentives to invest in new bikes in order to facilitate the positive feedback between bike supply and user base.

Our work is closest to the literature of network markets and digital platforms. By focusing on a market with positive network effects, we show that competition could expand the networks to a bigger market, even though the competing goods are close substitutes. Moreover, the first entrant in a network market does not necessarily exhaust all the positive network effects by itself, especially if late-comers could steal a significant part of the market from the incumbent and therefore have incentives to enter before the incumbent exhausts the market. This implication departs from the typical concern of winner-takes-all, but raises a new concern that competing platforms may not fully internalize the positive spillover between platforms.

Our findings are related to platform compatibility. Though the literature has recognized the beneficial role of compatibility in network competition, most studies focus on the choice of (in)compatibility and assume that the optimal network size is purely driven by exogenous demand factors such as consumer value of network size (Katz and Shapiro 1985).[15] In our context, bike-sharing platforms take compatibility as given but could choose bike investment to encourage user adoption thus endogenizing the network size. In particular, because bike investment is costly and the benefits of that investment may spillover to competing platform(s), competition could generate an incentive to under-invest and free-ride.

Our results also highlight the importance of uncovered market. Restricting platform competition to a covered market emphasizes head-to-head competition between platforms (Armstrong 2005), but assumes away the competition between platforms and the outside good. We show that competition with the outside good could dominate the market stealing effects in the long run, thanks to positive network effects. Therefore, a complete picture of competition must include the outside good.

The rest of the article is organized as follows. Section 2 describes the background. Section 3 provides a simple, conceptual framework. Section 4 summarizes the data. Section 5 describes our main econometric specifications. Section 6 reports the empirical results. Section 7 concludes with policy implications and directions for future work.

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[15] This is often achieved by assuming consumer willingness to pay for a network good is a specific function of the size of the network that is compatible with the good. For example, in a model with two network goods, consumer willingness to pay for good 1 depends on its own network size (N_1) if the two goods are non-compatible, and N_1+N_2 if the two goods are compatible. The model also needs to assume that each firm's compatibility choice involves fixed costs only and the marginal cost of operation is independent of network size.

2. Background

Since the 1960s, bike-sharing systems have gone through a few generations, mostly driven by technological development in electronically-locking racks, telecommunication systems, smartcards and fobs, mobile phone access, and on-board computers (DeMaio, 2003, 2004, 2009). The history of bicycle ownership and usage in China is relatively long and bike-sharing systems have followed diverse development paths in different cities (Zhang et al., 2015). Traditional bike-sharing systems provide bike rental service through stations, which means that each bike is docked at a station, riders must pick up a bike from one station, and return it to this or another station within the same network. The distance between stations and origins/destinations may be far and the capacity of stations is limited, thus the coverage of traditional bike-sharing systems is often restricted.

We focus on the emerging dockless bike-sharing platforms that originated in China. Users no long need to pick up bikes from docked stations, neither do they have to dock bikes at pre-set stations. They can use smart mobile phones to scan the QR code on bike smart locks and reset it after finishing the trip at any authorized area, which is well summarized by an ofo slogan “anytime and anywhere.” From the second half of 2015, the whole bike-sharing industry has gone through explosive growth, which absorbed venture investment up to 4 billion USD and accumulatively placed more than 25 million bikes in hundreds of Chinese cities. It is estimated that the boom of dockless bike-sharing has contributed 221.3 billion RMB to economic development, created more than 390,000 jobs, and led to a welfare improvement equivalent to 175.9 billion RMB in 2017 (China Academy of Information and Communications Technology, 2018). There are also environmental benefits from dockless bike-sharing, in terms of reduced petrol consumption and decreased CO_2 and NO_X emissions (Zhang and Mi, 2018).

Ofo and Mobike are two leading platforms in dockless bike-sharing, both originated in China but now operating worldwide. As the first dockless bike-sharing platform, ofo was launched on September 7, 2015 in Beijing with bikes colored yellow. At the very beginning, ofo restricted its service within college campus and limited bike outflow in many cities, which offers an opportunity for the placebo test described in Section 6. The campus-specific operation strategy was eliminated on November 17, 2016 when ofo declared full embrace of city coverage. Mobike is the main competitor of ofo, which originated in Shanghai on April 22, 2016 with bikes colored orange. As of January 2018, ofo has placed dockless bikes in more than 250 cities in 20 countries. In comparison, Mobike had placed their bikes in 176 cities of 7 countries by the end of 2017.

The quick growth of ofo and Mobike has encouraged entrepreneurs and angel investors to enter the market of dockless bike-sharing. Some estimates suggest that nearly 30 new bike-sharing platforms were established in 2016 alone.[16] However, various industry reports conclude that ofo and Mobike account for 90% to 95% of the bike-sharing markets from the very beginning, so that the other platforms are almost negligible.[17] That is why we focus on the competition between ofo and Mobike, especially how the new entrant (Mobike) affects the incumbent (ofo).

Because we only have access to ofo data, we collect Mobike's entry data from media reports, and cross-validate it with postings on Mobike's Weibo home page.[18] As detailed in Section 4, our sample covers the period from May 29, 2016 to September 14, 2017, and only includes the cities that ofo has entered by September 14, 2017. Within this sample of cities, if Mobike enters the city after ofo's entry, then the city is categorized as "ofo First." If ofo enters the city after Mobike's entry, it is categorized as "Mobike First." If only ofo enters, it is "ofo Alone." In total, our sample consists of 104 cities, of which 59 are ofo First, 23 are ofo Alone, and 22 are Mobike First. In another 6 cities out of our sample, both Mobike and ofo have entered but we could not find the exact entry date of Mobike and therefore could not define the sequence of entry precisely. We also exclude Beijing from the sample because Beijing is the birthplace of ofo and ofo had experimented with many operation policies in Beijing before it started to explore other cities. Appendix Table 1 lists the names of the 104 cities in our sample. Figure 1 plots them on the map of China.

A few bike-sharing studies have examined the network feature of docked bikes. Zheng et al. (2017) set up a structural demand model to estimate consumer preference for docked bikes in the London bike-sharing system, emphasizing that the consumer must plan a trip with both the origin and the destination close to a bike station. Because of this constraint, the scope and location of the station

[16] See the report from National Business Daily: http://www.nbd.com.cn/articles/2017-01-05/1067671.html.

[17] On October 25,2017, two second-tier bike-sharing platforms, Youon and Hellobike, agreed to merge. On April 4, 2018, Meituan took the full control of Mobike at a price of 2.7 billion USD. These two market events may shake the market structure profoundly, whereas both happened after our sample period.

[18] Weibo is one of China's biggest Twitter-like microblogging platforms operated by Sina.

network is important for consumer demand. They demonstrate these network effects and conclude that the existing design of the station network is far from ideal. Using data from a similar bike-sharing system in Paris, Kabra et al. (2016) estimate an even-more detailed demand system. They stress that both station accessibility and bike availability are important for consumer demand, where station accessibility refers to how far a consumer must walk to a nearby bike station and bike availability refers to whether a bike is available when one walks to the station.

Both accessibility and availability problems can be mitigated in dockless bike-sharing, but they are not completely eliminated. When it no longer requires a dock to park the bike, there is a possibility to find a bike near one's home or workplace. However, less constraint on parking location may also make bikes more dispersedly distributed in the city, and therefore reduces bike availability at a particular location. In this sense, consumption-as-supply becomes more important in a dockless system, as consumers rely more on other consumers to "supply" a bike in an accessible hotspot. It also changes the nature of the network effect from a fixed network of bike stations to an evolving network of bikes "floating" throughout the city.

Another problem that dockless bikes can mitigate is bike rebalance. O'Mahony and Shmoys (2015) study this problem in the docked bike-sharing system of New York City. Since demand at certain stations can be highly asymmetric during rush hours, stations at the origin of popular commuting routes will quickly run out of bikes while stations near the destination of the routes will be overwhelmed by bikes without any dock to return to. O'Mahony and Shmoys (2015) design a system that uses bike trailers to rebalance the demand and supply during rush hours and uses trucks to rebalance overnight. This rebalance problem is mitigated in dockless bike-sharing, because dockless bikes no longer need physical docks to complete the trip. However, some imbalance may still exist throughout the day, for example, traffic demand throughout the day may reduce bike supply needed for the afternoon rush hours, rendering a shortage at the popular origin but an excess at other locations. Pan et al. (2018) propose a deep reinforcement learning framework to solve this imbalance problem and demonstrate its effectiveness based on Mobike's transactional data.

Our paper differs from all the above, as we focus on platform competition while taking the nature of network effects as given. Because dockless systems rely on consumers' actual demand to define bike accessibility and bike availability, the two competing systems are substitutes and complements at the same time. On one hand, if ofo and Mobike bikes are available at the same location, they are perfect substitutes. But depletion of ofo bikes can be complemented by the remaining Mobike bikes, hence having the competitor's bikes at the same place could increase bike availability and enhance consumer willingness to use bike-sharing. On the other hand, if ofo and Mobike bikes are placed at different locations, the overall network of bike-sharing is expanded. More consumers will find bikes accessible near the origin, and their usage will increase bike availability at the destination. It can even expand the overall network to new locations. Because the two networks are substitutes and complements to each other, it is hard to predict whether competition would have a net market expanding or market stealing effect on the incumbent.

3. Conceptual Framework

In this section, we present a simple conceptual framework in order to clarify the network nature of bike-sharing and describe how the entrant platform could bring market stealing or market expanding effects to the incumbent. We will also sketch a few incentives that the incumbent and the entrant may have in price and bike investment, as the result of the market expanding or market stealing effects.

3.1 Demand Side

Consider a city of population N in multiple periods. In period 1, the city is served by ofo only, with I_1^{ofo} bikes around. At the beginning of period 2, Mobike enters with I^{Mobike} bikes. Upon Mobike's entry, ofo invest I_2^{ofo} bikes into the market. So the total number of bikes increases from $I_1 = I_1^{ofo}$ in period 1 to $I_2 = I_1^{ofo} + I^{Mobike} + I_2^{ofo}$ in period 2 (assuming bikes are durable goods with no depreciation). After period 2, ofo and Mobike coexist in the market (with potentially new investments in the future).

If consumers are aware of bike-sharing, adoption of bike-sharing app(s) is free. But consumer awareness is a function of total bikes available in the market (I_t) as well as the total number of other consumers that have adopted the app(s) (N_t). For simplicity, we define the "cost" of awareness as

$A_{it}^{adopt} = A(I_t, N_t)$. The expected utility of using bike-sharing is also dependent on I_t and N_t, because they affect bike availability and bike access. For consumer i, we define her utility of using any bike-sharing app as $U_{it} = U(I_t, N_t) - p_t + \varepsilon_{it}$ where p_t is the price of bike-sharing and ε_i is iid noise conforming to a random distribution. If there are more than one platform in the market, we assume they charge the same price because the bikes are perfect substitutes at the same time and location. Normalizing the utility of the outside good (no bike-sharing) as zero, we have consumer i's problem as:

$$\text{Period 1: } \begin{cases} U_{i1} = \max\left(U(I_1, N_1) - p_1 - A(I_1, N_1) + \varepsilon_{i1}, 0\right) \\ I_1 = I_1^{ofo} \\ N_1 = \sum_{i=1}^{N} 1_{U_{i1>0}} \end{cases},$$

$$\text{Period 2: } \begin{cases} U_{i2} = \max\left(U(I_2, N_2) - p_2 + \varepsilon_{i2}, 0\right)\ if\ U_{i1} > 0 \\ U_{i2} = \max(U(I_2, N_2) - p_2 - A(I_2, N_2) + \varepsilon_{i2}, 0)\ if\ U_{i1} = 0 \\ I_2 = I_1^{ofo} + I^{Mobike} + I_2^{ofo} \\ N_2 = N_1 + \sum_{i=1}^{N} 1_{U_{i2>0}\ \&\ U_{i1}=0} \end{cases}.$$

Conditional on bikes available on the market (I_t), there could be direct positive network effects among bike-sharing users, because other users can supply the bike to nearby locations ($\frac{\partial U}{\partial N_t} > 0$) and raise consumer awareness ($\frac{\partial A}{\partial N_t} < 0$). The former is similar to the direct positive network effects among consumers of UBER, Lyft, and Zipcar, whereas the latter has often occurred in technology diffusion driven by word-of-mouth. If the number of riders exceeds the number of bikes to a great extent, the network effects may become negative as riders compete for the limited bike supply ($\frac{\partial U}{\partial N_t} < 0$). We have seen similar non-monotonic network effects in theme parks, where consumers may appreciate the presence of a few other consumers in the same park but their utility declines when the park becomes too crowded.

Although bike-sharing is run by one-sided platforms, it still embodies indirect network effects between demand and supply. More bikes in the market will increase the utility of bike-sharing ($\frac{\partial U}{\partial I_t} > 0$), more bikes displayed on the market will raise consumer awareness ($\frac{\partial A}{\partial I_t} < 0$), and more app users will motivate the platform to invest in more bikes. These indirect network effects are similar to those enjoyed by two-sided platforms, except that the supply response to demand increase is implemented by the platform directly, not by individual sellers, drivers, advertisers, or content providers on the other side of the platform.

From this set up, it is clear that Mobike's entry could have market expanding and market stealing effects at the same time. For the consumers that have adopted ofo in period 1 (N_1), their utility from bike-sharing will increase upon Mobike's entry but part of their bike usage will leak to Mobike. The extent of leakage depends on the number of Mobike and ofo bikes on the market.[19] For example, if ofo's market share in period 2 (s_2^{ofo}) is proportional to the share of ofo bikes among all bikes on the market (i.e. $s_2^{ofo} \propto \frac{I_1^{ofo}+I_2^{ofo}}{I_1^{ofo}+I_2^{ofo}+I^{Mobike}}$), Mobike's market stealing effect (on the existing ofo users) can be written as $N_1 - N_1 \cdot s_2^{ofo}$. In the meantime, the increased bike volume could increase the total user base, because some non-users in period 1 may become aware of bike-sharing and find it attractive to use bike-sharing from a bigger network. A fraction of these new users (s_t^{ofo})[20] will use ofo bikes, thus expanding ofo's user base by $(N_2 - N_1) \cdot s_2^{ofo}$. The overall effect on ofo is therefore $(N_2 - N_1) \cdot s_2^{ofo} - (N_1 - N_1 \cdot s_2^{ofo}) = N_2 \cdot s_2^{ofo} - N_1$, which could be positive or negative depending on whether the market expanding effect on the new users exceeds the market stealing effect on the old users.

In the conceptual framework, we do not model how often a user uses bike-sharing, so the market stealing/expanding effects are expressed in the number of users. In the empirical section, we will quantify these effects by number of users and number of trips separately.

3.2 Supply Side

What is the supply-side implication of the market stealing and market expanding effects? A complete answer to this question requires careful modeling on the supply side. Since both platforms are VC-funded in a nascent market, it is difficult to pin down their objective function. Without an adequate objective function, we are not sure whether the platform behavior observed in the data reflects optimal

[19] In reality, how the two platforms split the market also depends on where they place their bikes, which is a complicated, strategic decision. Here we abstract from that for simplicity.

[20] Here we assume old and new users utilize the two platforms in the same way, and ofo cannot apply different prices on old and new users. By this assumption, the market share of ofo is the same for old and new users.

behavior in the long run equilibrium, or is simply a result of liquidity constraint, learning by doing, or bounded rationality. With this caveat in mind, we sketch the strategic incentives that could arise on the supply side but caution that they are too speculative to guide empirical estimation.

In our framework, the key decisions facing the platforms are price and investment.[21] If we assume each platform's objective (Π) is the sum of current profit and the continuation value, we can write platform j's problem as:

$$\max_{I_t^j, p_t^j} \Pi_{jt} = (p_t^j - MC(I_{jt}, s_t^j, I_t, N_t)) \cdot N_t \cdot s_t^j - I_t^j + \delta \cdot V_{t+1}^j(N_{t,} I_t, s_t^j)$$

where $MC\left(I_{jt}, s_t^j, I_t, N_t\right)$ is the marginal cost of operation, $V_{t+1}^j(N_{t,} I_t, s_t^j)$ is the continuation value, and δ is the discount factor. Since the two platforms are modeled as perfect substitutes (and we do not model their potential differentiation in bike location), they must charge the same price.

Intuitively, the equilibrium price should depend on consumer willingness to pay and operation cost. As discussed before, consumers expect higher utility from a bigger network. Hence consumer willingness to pay will likely increase with Mobike's entry. In addition to direct and indirect network effects, there could also be economy of scale in the operation of bike-sharing platforms, because consumption-as-supply may reduce the need to address the imbalance of demand and supply in the whole market ($\frac{\partial MC}{\partial N_t} < 0$; $\frac{\partial MC}{\partial I_t} < 0$). This effect could drive the platforms to compete harder in price, which counters the incentive to raise price in response to higher consumer willingness to pay. How the market price changes upon Mobike's entry is thus an empirical question.

As for investment, it is clearly a strategic decision that could impact current profits and the continuation value. With no clear functional form assumption on the continuation value, we will focus the discussion on Period 2 profits only.

From Mobike's point of view, bike investment has the benefits of expanding the overall market from zero to N_2, and a share of this expanded market $\left(1 - s_2^{ofo}\right)$ is captured by Mobike. The corresponding operational profits in period 2, namely $N_2 \cdot \left(1 - s_2^{ofo}\right) \cdot (p_2 - MC^{Mobike})$, is part of the benefits that Mobike weighs against the cost of I^{Mobike} when it considers entry. More specifically,

[21] In reality, platforms also choose which city to enter and when. Our conceptual framework focuses on one city and assumes a fixed sequence of entry, so we shy away from these long run decisions.

if Mobike takes I_2^{ofo} as given (which may not be true given the sequence of action), Mobike realizes that its own investment (I^{Mobike}) could have market expanding and market stealing effects at the same time. The market expanding effect is embodied in a larger user base for bike-sharing ($\frac{\partial N_2}{\partial I^{Mobike}} > 0$), while the market stealing effect is embodied in a bigger market share among bike riders ($\frac{\partial(1-s_2^{ofo})}{\partial I^{Mobike}} > 0$). Both will motivate Mobike to enter.

From ofo's point of view, it is subject to the market expanding and market stealing effects of new bike investments in period 2 ($I^{Mobike} + I_2^{ofo}$), but it only needs to incur the cost of I_2^{ofo}. Again, ofo's investment (I_2^{ofo}) could expand the whole market ($\frac{\partial N_2}{\partial I_2^{ofo}} > 0$) and guard against the loss of market share to Mobike ($\frac{\partial s_2^{ofo}}{\partial I_2^{ofo}} > 0$). The former generates positive spillover to Mobike, while the latter is a negative spillover.

If the net effect of $I^{Mobike} + I_2^{ofo}$ is market expansion for ofo (i.e. $N_2 \cdot s_2^{ofo} - N_1 > 0$), ofo will trade off this market expanding effect against the cost of I_2^{ofo}. In that situation, both platforms could enjoy net positive spillovers from the competitor's investment but do not account for the positive spillovers that their own investment may generate for the competitor. This will generate an incentive to free-ride and under-invest, as compared to the ofo-Alone market. Conversely, if the overall effects of $I^{Mobike} + I_2^{ofo}$ is market stealing for ofo (which corresponds to $N_2 \cdot s_2^{ofo} - N_1 < 0$), then competition could lead to over-investment as compared to the ofo-Alone market, because Mobike's investment is motivated by stealing the market from ofo, which is a negative externality on ofo that Mobike does not take into account when it enters. Similarly, ofo's investment could be motivated by guarding against the market stealing from Mobike, which can lead to over-investment by ofo (as compared to ofo Alone).

The linkage between entry and market stealing/market expanding effects has been studied extensively in the excessive-entry literature (Chamberlain 1933; Mankiw and Winston 1986). The main insight from that literature is that, if entry involves a large fixed cost and the effect of the entry is mostly market stealing rather than market expansion, there will be excessive entry under competition. This is because entrants do not incorporate the negative externality (market stealing) it imposes on the incumbent. Alternatively, monopoly (or a cartel among competitors) will internalize all the externality among competitors but does not consider how its decision affects consumer surplus. As a result, the monopoly will under-invest as compared to the social planner (who maximizes total welfare including consumer surplus). Berry and Waldfogel (1999) confirm this insight in radio stations, an example of two-sided platforms before the digital era. They find that entry of new radio stations has a significant market stealing effect on existing stations, which generates incentives for excessive entry.

As shown below, we find that Mobike's entry has a market stealing effect on ofo before ofo responded to the entry with extra bike investment. This explains why Mobike was motivated to enter. We also find that Mobike's entry has a market expanding effect on ofo after ofo has invested in more bikes post-entry. The sequential investment could be explained by ofo investing to guard against the market stealing by Mobike but the two platforms' joint investment produces an overall market expansion due to the positive network externality in bike-sharing.

It is also worth noting that our framework follows the literature of network compatibility: we assume that the network effects depend on the total number of bikes available in the market and the total number of consumers that use bike-sharing, not the bikes or users on a particular platform. This setting is similar to many markets with compatible network goods (such as telephone). However, in traditional settings, the equilibrium network size (N_t) is determined by consumer willingness to pay for network size ($\frac{\partial U}{\partial N_t}$), which is often assumed to be exogenous and out of the control of the platforms. Here, consumer utility from bike-sharing depends on both the size of the user network (N_t) and the size of the bike network (I_t). Since the platforms can use their investment (I_t) to influence the equilibrium network size (N_t), network size is endogenized in bike-sharing.

Though we focus on bike-sharing, similar considerations could arise in traditional network goods. For example, telephone service providers could invest in more or less transmission equipment, which affects the speed and quality of telephone calls; cellular companies could construct new towers; and internet backbones could upgrade the bandwidth of internet cables. Given these similarities, what we learn from competition in bike-sharing could be useful to understand other network markets with compatibility.

4. Data and Sample Construction

We combine data from several resources: ofo aggregates transactional data by time and geography, a few online platforms provide data about weather and air quality, and city attributes are available in the *2016 China City Statistical Yearbook*. Below we first explain each data source, and then describe our sample construction.

4.1 Transactional Data from ofo

ofo has kept full records of consumer usage, including the start and end times of each trip, longitude and latitude of the origin and the destination, listing price for the ride, and the amount actually paid after coupon redemption. From the first usage time of each physical bike, we can also calculate ofo's bike placement in each city over time. To protect user privacy, consumer data are aggregated to grid or city level.

We start with **daily trip volume** $\boldsymbol{q_{gct}}$, the total number of ofo bike trips that are consumed in city c, day t and grid g. Grids are defined according to the longitude and latitude of the origin up to two decimal places. For example, trips originating from (23.1632°N, 113.3578°E) and (23.1677°N, 113.3529°E) will be counted as trips within the same grid (23.16°N, 113.35°E). Aggregating it to the city level, we have $\mathbf{log}(\boldsymbol{Q_{ct}}) = \mathbf{log}\,(\sum_{\boldsymbol{g}} \boldsymbol{q_{gct}})$ for city c at day t.

Daily trip volume also provides an opportunity to describe the spatial distribution of bike trips. We construct two measures: one is $\mathbf{log}\,(\boldsymbol{\#Grids})$, namely the total number of unique grids covered by (the origin) of any ofo bike trips in a city-day. This measure aims to describe the width of the spatial network of ofo bikes as realized by consumption. The second measure aims to describe how evenly the consumption is distributed in this network, which corresponds to the flatness of the network. In particular, we follow the definition of the Gini Coefficient, whereas "inequality" refers to trip distribution among grids instead of income distribution among population. Adopting the same method as Alesina et al. (2016), we define the base as all grids that are ever covered by ofo within a city throughout our sample period. If at day t city c no trip occurs in grid g, then $q_{gct} = 0$. Assuming that there are n grids in the city and g = 1 to n are indexed in the non-decreasing order, we define **the *Gini Coverage Index*** as:

$$Gini_{ct} = \frac{1}{n}\left[n + 1 - 2\frac{\sum_{g=1}^{n}(n+1-g)q_{gct}}{\sum_{g=1}^{n} q_{gct}}\right].$$

Another way to define $Gini_{ct}$ is conditional on the grids that ofo has already covered in the city before Mobike's entry, which is a subset of the base used in the first version of $Gini_{ct}$. We will report results on both measures of $Gini_{ct}$.

Both ofo and Mobike charge consumers by trip and time spent in the trip. ofo's listing price is 1 RMB per hour, while Mobike's listing price is 1 RMB per 30 minutes. The two prices are essentially identical, because bike-sharing platforms position themselves as "means of transportation for the last mile" and ofo data indicates that more than 99% of the trips end in less than 30 minutes. On top of the listing price, both platforms engaged in aggressive marketing campaigns such as trip coupons, free riding day, and monthly card for 1 RMB. These campaigns led to fluctuations in price actually paid. We thus define two variables to capture the transaction price: the first is ***Average Revenue per Trip*** **(**$\boldsymbol{p_{ct}}$), which is the simple average of total amount actually paid per ride within a city-day. It is a proxy for the average transaction price per trip. Considering that many consumers can ride for free because of coupon or other marketing activities, we also compute ***Percent of Free Trips (***%$\boldsymbol{Free_{ct}}$***)*** as an alternative measure of price within a city-day.

To examine market expansion and market stealing, it is important to distinguish old and new users on the ofo platform. If user i registers on the ofo app at day t, she is a new user on day t and becomes an old user in any day after t. From all users' registration history, we define ***log(#NewUsers)*** based on the total number of new users that register on ofo in that particular city-day. We also define ***%ActiveOld*** as the percent of old users that have used any ofo bike in that city-day, and ***#Trips_perOld*** as the ratio between the total trips initiated by old users and the total count of old users.

As mentioned in Section 2, in some cities ofo started on a college campus and gradually expanded to the rest of the city. We define the dummy $\boldsymbol{1_{campus}}$ equal to 1 if ofo restricts its operation within the college campus and 0 otherwise.

4.2 Weather Data and Air Quality

Weather conditions and air quality have profound impacts on the choice of travel means. Long before the emergence of bike-sharing, researchers had examined the effects of weather on bike use

(Hanson and Hanson, 1977; Hopkinson, 1989; Nankervis, 1999) and explored the impact of air pollution exposure on commuting modes (Hertel et al., 1989; Chertok et al., 2004). We use a website crawler to obtain relevant data from two open-source databases. *China Meteorological Data Service Center (*CMDSC) provides an inquiry interface for hourly data from meteorological stations, which is averaged within each calendar day and completed through co-kriging interpolation if data from some stations are missing.[22] *China Air Quality Online Monitoring and Analysis Platform* collects historical air quality data from the Ministry of Ecology and Environment and makes it available to the public. We choose Air Quality Index (AQI) as the measure of air quality in a city-day.[23]

4.3 Predetermined City-Level Attributes

From media report and published executive interviews, we identify four groups of city attributes that may affect whether a platform enters a city: (i) economic development and overall population size are the principal determinants of potential market scale; (ii) public transportation such as bus and taxi[24] may complement bike-sharing; (iii) penetration of mobile Internet and smartphones are fundamental because bike-sharing relies on real-time communication among the electronic lock of the bike, the user's mobile phone app, and the platform's system servers; (iv) topography (e.g. steep slope) and land forms (e.g. unpaved roads) could restrict the usage of bikes, because bikes provided by the platforms are all non-automatic.

To control for the first three aspects, we collected seven city-level variables from *the 2016 China City Statistical Yearbook*[25]: log of population, GDP per capita, the number of taxis, the number of buses, road surface, the number of mobile phones, and the number of households that have access to the Internet, which are all rescaled by total population except for log population itself. To measure terrain ruggedness, we utilize Digital Elevation Model (DEM) to calculate the average gradient for each city.

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[22] Please see Vicente-Serrano et al. (2003) for detailed introduction of co-kriging interpolation.

[23] One potential threat to this measure lies in that air quality data disclosed by China government is under suspicion of being manipulated. However, Liang et al. (2016) finds that data from the U.S. diplomatic posts and the nearby Ministry of Environmental Protection sites produced highly consistent air quality assessment in five major cities.

[24] Unfortunately, the 2016 China City Statistical Yearbook does not include data on subway. But all our specifications include city fixed effects, which will absorb any time-invariant effect of subway and other omitted public transportation means.

[25] *China City Statistical Yearbook 2016* reports statistics by the end of 2015, thus predetermined for our sample.

All these attributes are summarized in Panel B of Table 1 and hereinafter referred to as city attributes.

4.4 Sample Construction

The original data extracted from ofo spans from September 7, 2015 to September 14, 2017. We then clean the data in a few steps: first, we exclude all autonomous prefectures and administrative districts, because they are not included in *China City Statistical Yearbook*. Second, we exclude the 6 cities that Mobike entered but with missing entry dates. Without a specific entry date, we cannot confirm the entry sequence of ofo and Mobike and thus cannot define *PostEntry*, which is the core independent variable of interest and will be introduced in the next Section. Third, we exclude Beijing from the sample. Because Beijing is the birthplace of ofo, ofo had experimented with its pricing and operation strategies in Beijing extensively before it entered the second city, Shanghai. Thus, Beijing is hardly comparable to any other cities. After data cleaning, we arrive at a sample of 19,631 city-day observations, which cover 104 cities from May 29, 2016 to September 14, 2017.

Table 2 summarizes the sample in two panels: one for variables at the city-day level and the other for variables at the city level. We report both panels by full sample first and then by ofo First, ofo Alone and Mobike First cities. To protect ofo's business secrets, we mask the mean of trip volume and revenue per ride in Panel A. But from Panel B, it is obvious that ofo First cities are bigger than ofo Alone cities in almost all dimensions, including population, public transportation, and mobile/internet access. ofo First cities also have higher GDP per capita, better air quality index and lower average gradient than ofo Alone cities. Mobike First cities are more similar to ofo First cities than to ofo Alone cities. These summary statistics are consistent with the facts that platforms tend to enter bigger and more developed cities first. Such selection prompts us to pay close attention to the comparability between ofo First and ofo Alone cities. We will deal with it in the next section.

5. Econometric Framework

Our main specification is difference-in-differences (DID), where we define Mobike's entry as the "treatment" in ofo First cities, and use ofo Alone cities to control for the organic growth of ofo. Specifically, the baseline specification is:

$$Y_{ct} = \alpha_c + \gamma_t + \beta \cdot PostEntry_{ct} + \pi \cdot X_{ct} + \theta \cdot \left(S_c \cdot f(t)\right) + \mu \cdot G_c \cdot t + \varepsilon_{ct}. \quad (1)$$

where Y_{ct} represents outcome variables such as *Log(Q), P, and %Free* at city c and date t; α_c and γ_t denote city and time fixed effects respectively; X_{ct} denotes weather and air quality variables; S_c denotes city attributes as of 2016; and ε_{ct} is the error term. It is noteworthy that γ_t contains two sets of time fixed effects: the first set represents calendar date fixed effects. They aim to capture nationwide shocks on specific dates, including national holiday, nationwide news about bike-sharing, and nationwide advertising campaigns initiated by any bike-sharing platform. The second set of γ_t captures the intrinsic growth of ofo and is therefore defined by the number of days since ofo began operation in city *c*. We refer to them as relative day fixed effects.

$PostEntry_{ct}$ is the key regressor of interest, which takes the value of one if Mobike exists in city *c* on date *t*. For ofo First cities, $PostEntry_{ct}$ is zero before Mobike's entry and becomes one at and after Mobike's entry. For ofo Alone cities, $PostEntry_{ct}$ is always zero. For Mobike First cities, $PostEntry_{ct}$ is always one. Therefore, data on Mobike First cities do not help us identify changes pre- and post-entry, though they could sharpen our understanding of ofo performance when it competes against Mobike. For this reason, our main specification restricts the sample to ofo First and ofo Alone cities. We will include Mobike First cities for robustness check.

To address the possibility that bike-sharing may diffuse differently in different types of cities, we follow Duflo (2001) to interact city attributes (S_c) with multiple functions of time ($f(t)$).[26] In particular, $f(t)$ includes: (i) a third-order polynomial function of the relative days since ofo's entry; (ii) calendar date fixed effects, and (iii) relative day fixed effects. In addition, we also control for linear time trends specific to ofo First cities by adding the interaction between linear time trend t and a dummy variable indicating ofo First cities (G_c).

DID relies on the assumption of parallel pre-treatment trends, which could be checked by a standard event-study regression (e.g., Jacobson, 1993; Autor, 2003). Specifically, we use the following equation to test pre-treatment trends:

$$Y_{ct} = \alpha_c + \gamma_t + \sum_{k=2}^{21} \lambda_{-k} \cdot A_{ck}$$
$$+\beta \cdot PostEntry_{ct} + \pi \cdot X_{ct} + \theta \cdot \left(S_c \cdot f(t)\right) + \mu \cdot G_c \cdot t + \varepsilon_{ct}. \quad (2)$$

[26] City attributes alone will be absorbed by city fixed effects.

where A_{ck} is a set of dummies indicating that date t is k days before Mobike's entry into city c. We pool all days more than three weeks before Mobike's entry as k = 21, and choose the day before Mobike's entry (i.e., k = 1) as the omitted default category. Thus, the coefficients $\{\lambda_{-k}\}_{k=2}^{21}$ test the comparability between ofo First and ofo Alone cities for every day up to 3 weeks before Mobike's entry. If the two groups of cities are statistically comparable, λs should be jointly indistinguishable from zero.

Although including time trends and allowing them to be heterogeneous by city attributes could mitigate the concern of omitted variable bias, reverse causality is still a key identification challenge. If Mobike's entry decision is a strategic response to ofo's performance in a specific city, the coefficient of $PostEntry_{ct}$ could reflect the endogenous entry decision and does not represent the causal effect of competition on ofo. To address this concern, we need an instrumental variable that is correlated with Mobike's entry into a city but independent of ofo's market performance in that city. We construct the instrument based on the predicted Mobike entry date, which is the date on which we predict Mobike to enter city c according to Mobike's VC funding rounds and c's pre-determined city attributes.

In particular, we assume Mobike could enter any city since its company establishment date (November 1, 2015). Thus, the time span between November 1, 2015 and Mobike's actual entry date into city c is the "survival time" in a typical duration model. This is well defined for every ofo First city. For ofo Alone cities, since Mobike has not entered the city by the end of our sample, we treat the survival time as censored at 683, exactly the number of days between November 1, 2015 and September 14, 2017. We then fit the survival time in a proportional hazard duration model, where the explanatory variables are predetermined city attributes, the timing and amount of the 8-round Mobike financing from venture capital, and a new variable describing the cumulative number of days since Mobike's latest round of VC finance. From the estimates of the duration model, we then predict the median survival time for each city and add it to the starting date (November 1, 2015). This defines the predicted entry date of Mobike. From the predicted entry date, we can compute a new post-entry dummy ($\widehat{PostEntry}_{ct}$) as the IV for $PostEntry_{ct}$.

We argue that the predicted Mobike entry date is likely exogenous to city-specific unknowns, because city attributes are all pre-determined and Mobike's VC funding is not driven by a particular city. More specifically, Mobike's VC funding may depend on ofo's nationwide performance, which is controlled by calendar date fixed effects in the main specification, but we assume it is independent of ofo's performance in a particular city at a particular time. We will perform statistical tests on the IV when we present the baseline results.

6. Empirical Results

In this section, we report three sets of empirical results: the first set is baseline results on trip volume and revenue per ride, including results with instrument and robustness checks. The second set aims to unpack market stealing and market expanding effects by new and old users and by time since Mobike's entry. The third set describes changes in the ofo network after Mobike's entry.

6.1 Baseline Results

Following Equation (1), Table 2 reports the baseline DID results, where the key dependent variables are total trip volume (log (Q_{ct}), revenue per ride (p_{ct}), and percent of free trips $(\%Free)$. For each dependent variable, we report the coefficient of $PostEntry_{ct}$ (β) from a series of OLS regressions. The simplest one includes only city and time fixed effects (Column 1), the median ones add interactions between $f(t)$ and city attributes (Columns 2 to 4), and the most sophisticated ones add linear time trends specific to the ofo First group (Columns 5 to 7). All these columns convey the same message: Mobike's entry has increased ofo's trip volume and boosted ofo's revenue per ride. If we take Column 7 as the preferred specification, it suggests that ofo's trip volume goes up 40.8% after Mobike's entry, ofo's revenue per ride goes up by 0.041 RMB, and the percent of free trips goes down by 3.7 percentage points. These findings suggest a strong market expanding effect from Mobike's entry. As shown in Appendix Table 2, similar results can be achieved when we drop ofo Alone cities from the sample (which effectively reduces the DID into just before-after comparison), or add Mobike First cities into the sample (which increases observations for post entry).

To test the assumption of comparable pre-treatment trends, Figure 2 plots the point estimates of $\left\{\lambda_{-k}\right\}_{k=2}^{21}$ from Equation (2), along with the estimated 95% confidence intervals. The three panels of Figure 2 correspond to the three key dependent variables (log (Q_{ct}), p_{ct}, and $\%Free$). All these estimates are statistically indistinguishable from zero, neither do they imply any obvious trends jointly.

This suggests that, after our control of observables, ofo Alone and ofo First cities follow similar trends before Mobike's entry, although the two sets of cities differ in absolute population and other attributes.

To further address the concern of endogenous entry, we use the predicted entry date to construct an IV for $PostEntry_{ct}$. Table 3 first reports the first stage (Column 1) and then the IV results for $\log(Q_{ct})$, p_{ct}, and $\%Free$ (Column 2 to 4). The Kleibergen-Paap F Test is over 8000, suggesting that our IV is strongly correlated with $PostEntry_{ct}$. After using the IV, the key coefficients of $PostEntry_{ct}$ (β) have the same sign and similar magnitudes as in the OLS regressions.

We perform two robustness checks on the IV results. First, since the proportional hazard model relies on the functional form of baseline hazard, we confirm that results are stable when we use Weibull (reported), log-normal, or log-logistic distribution for baseline hazard. Second, Mobike was established on November 1, 2015 but did not enter the first city (Shanghai) until April 22, 2016. We have tried to use December 1, 2015, January 1, 2016, February 1, 2016, March 1, 2016 and April 1, 2016 as alternative starting dates. Results under these alternatives are similar to what is reported in Table 3.[27] Above all, the IV results suggest that the market expanding effects found in the baseline regressions are not driven by reverse causality or omitted variable bias.

As mentioned in Section 2, ofo had experienced a "campus period" when it restricted its operation within a college campus. In contrast, Mobike always regards the whole city as the target market and does not differentiate operation on and off campus. These institutional details offer an opportunity for a placebo test: the competition effects should be weaker in the "campus period" of ofo because ofo does not compete head to head with Mobike in this period. To carry out the test, we decompose $PostEntry_{ct}$ into $1_{campus} \cdot PostEntry_{ct}$ and $(1 - 1_{campus}) \cdot PostEntry_{ct}$, and estimate their coefficients separately. The OLS and IV results are shown in Table 4. Compared with the baseline results (Table 2 and Table 3), we find that the market expanding effects are solely driven by the time when ofo expanded into the city. This finding confirms that the market expansion effects occur because ofo and Mobike compete head-in-head in the city.

Finally, we perform a falsification test by focusing on pre-entry data only (ofo First pre-entry plus ofo Alone data) and assuming a false entry on 1, 2, …, 7 days before the publicly announced entry date.

[27] Results for the robustness check of 2SLS estimates are reported in Appendix Table 3.

Results are reported in Figure 3, along with the estimated 95% confidence interval. The three panels correspond to the three dependent variables. For comparison, we also plot the baseline OLS results (Table 2 column 7) on the very right. In short, the coefficients of false entry are all statistically insignificant from zero, which is very different from the baseline results. This suggests that our Mobike entry dates are accurate and the effects are attributable to the actual entry of Mobike.

6.2 Marketing expanding or market stealing?

As described in Section 3, Mobike's entry may be motivated by both expanding the market to new users and stealing the market from ofo. Since ofo can track when a user started to use the ofo app, we repeat our DID specification for new and old users separately. Note that both new and old are from ofo's point of view, as we do not know whether a user has also downloaded the Mobike app or not.

Results are presented in Table 5. The OLS results suggest that Mobike's entry has increased the number of new users (for ofo) by 65.2%, and this effect is even greater if we use the instrument (73.5%). However, percent of active old users declines 4.1~4.4 percentage points post entry, which is a significant fraction of the sample mean[28]. Because every new user becomes an old user after the registration day, the pool of old users is cumulative over time. Thus 4.1~4.4% of this pool is a significant market stealing effect if all of them switch to Mobike. Conditional on older users on ofo, Table 5 shows that the average number of trips they take on ofo does not change significantly post Mobike entry. In short, we observe market expansion into new users and market stealing of old users, the sum of which gives rise to the overall market expansion effects documented in the baseline results.

Another way to unpack the market expanding and market stealing effects is by timing of bike investment. Within the 59 ofo First cities, ofo put new bikes on the market right after Mobike's entry in 21 cities, ofo did not invest any new bikes after the entry in 5 cities, and ofo invested with a delay in the remaining 32 cities[29]. In the last group, the average time window between Mobike's entry date and ofo's first new bike investment date (post-entry) is 19 days. Thus, we define a dummy variable 1_{window} equal to one for the days post-Mobike entry but before ofo makes any new bike investment post-entry.

[28] We are not allowed to report the sample mean because it is a business secret.
[29] Bike placement records are missing for 1 ofo First city and 2 ofo Alone cities.

We then replace $PostEntry_{ct}$ with two separate variables ($PostEntry_{ct} \cdot 1_{window}$ and $PostEntry_{ct} \cdot (1 - 1_{window})$) in the DID specification. This allows us to detect whether Mobike's entry has different effects in the "window" period versus afterwards.

Results are reported in Table 6. Interestingly, in the window period, Mobike's entry has a negligible effect on ofo's total trip volume, does not push up revenue per ride for ofo, but steals away some bike usage from ofo's old users. However, these effects are reversed into market expansion after ofo started to invest new bikes in the ofo First cities. Obviously, when to invest new bikes and how much to invest could be ofo's strategic decisions, so we do not know whether the reversion from market stealing to market expansion is driven by ofo's investment decision or something else. This is the topic we will explore in the next subsection.

6.3 Changes in the ofo network

The network of dockless bike-sharing is highly dynamic: platform investment directly affects when and where a bike is first available to the public; however, the realized network of bikes depends on consumption. If platforms put all new bikes in the central subway station, they can be quickly dissipated into nearby neighborhoods and form a consumption-driven network. Because bikes are dockless, the network will evolve over time, not only by how many bikes are used by ofo consumers from where to where, but also by how many Mobike bikes are available nearby and how many consumers choose ofo over Mobike. In this sense, the market presence of Mobike can shape the width and depth of the ofo network, through market expanding and market stealing. We try to quantify this impact in this subsection.

We start by checking out ofo's investment decisions. Ofo executives told us that ofo often has planned bike investment in a particular city by stages. If Mobike entry occurs between two stages, they do not have a company-wide policy to systematically respond to the entry by additional investment. That being said, a city-specific decision is made by local managers, who may adjust the investment plan over time. Thus, it is unclear whether the ofo investment we have observed in the data (post-entry) is ofo's strategic response to entry or is simply the investment that ofo would have made anyway. Raw data check confirms this ambiguity. We plot the timing and magnitude of investment city by city; some of them seem to have sped up investment post-Mobike's entry, while others have slowed down post entry. We have also tried to include new or accumulative bike investment on the right-hand of the regression equation, but it would be absorbed by the heterogeneous trends that already exist in the specification. Thus we conclude that, without knowing the initial investment plan city by city, it is impossible to project how much of the observed investment is due to ofo's strategic response to Mobike's entry.

One crude way to compare investment before and after Mobike's entry is to compare ofo's total bike investment to population. Figure 4 plots the horizontal axis as calendar time. The green solid line plots the ratio of the total population of the cities with Mobike competition to the total population of the cities that ofo has covered at that time. This ratio grows drastically after August 2016, because more and more cities witness the ofo-Mobike competition. The red dashed line plots the ratio of the total bike investment that ofo has made in cities with Mobike competition to the total bike investment that ofo has made across all cities. If ofo always invests proportionally to city population, the two lines should coincide. Figure 4 shows that the investment line is above and grows faster than the green line, suggesting that overall ofo has made more bike investment in the cities with Mobike competition.

Without a better way to single out ofo's strategic investment decision, we try to control for it in bike utilization rate, which is defined as the total number of ofo trips per city-day divided by the total number of ofo bikes in that city day. It reflects the average number of trips an ofo bike completes in the city-day.

Changes in utilization rate can be demand driven and supply driven. On the demand side, a user who rides a bike from A to B will facilitate another user to use the same bike at B. If these are the only two trips completed by this bike, the bike's utilization rate is 2. If no one uses that bike again at B in that day, the utilization rate is 1. On the supply side, if the platform's truck relocates the bike from B to C, the usage from point C and on will also count in the bike's utilization in that day. If Mobike's entry mostly steals consumers away from ofo, it should reduce ofo's average utilization rate. If Mobike's entry encourages more new users to try ofo and reduces ofo's relocation effort, it could increase ofo's average utilization rate.

In Table 7 Column 1, we use log (bike utilization rate) as the dependent variable (because it is highly skewed) and report the DID coefficient on $PostEntry_{ct}$. With and without instruments, the coefficient is consistently positive and significant with at least 95% confidence. The magnitude (0.392~0.457) implies a huge improvement in bike utilization rate, suggesting that Mobike's entry has positive spillovers on ofo, even after we account for the new bike investments that ofo has made after Mobike's entry.

The rest of Table 7 uses three variables to describe the width of the ofo network (# of grids reached), the flatness of the ofo network (Gini Coefficient Index), and the flatness of the ofo network within the grids that ofo has reached before Mobike's entry. The last one depends on Mobike's entry, so we can only compare it before and after the entry, without any control group. For the other two variables, we use the same DID specification as Equation 1.

Again, results are consistent with and without instruments. They suggest that Mobike's entry allows ofo bikes to reach more grids in the city and makes the ofo bikes distributed more evenly throughout the city. One potential explanation is that competition integrates the two bike-sharing networks and the market expansion on new users expands the network coverage. However, we cannot rule out the possibility that ofo strategically put bikes at more obscure places upon Mobike's entry, which will directly expand and flatten the ofo network.

7. Conclusion

Based on the sequential entries of two bike-sharing platforms, we document how the entrant affects the market performance of the incumbent platform. Since bike-sharing features positive network effects but bike usage is geographically restricted, we have a rare opportunity to observe variations in platform competition. We find that the entrant expands the overall market, resulting in higher quantity, higher price, better bike utilization, and a wider, flatter network for the incumbent. However, the entrant also steals a significant fraction of the old users away from the incumbent, which justifies the entry decision.

Since the market is still under development and both platforms are VC funded, we do not take any position on how and why the two platforms make the observed investment decisions. But we note that market expanding effects from the competitor could generate an incentive to free-ride and under invest, while market stealing effects could generate an incentive for over-investment and excessive entry. How these two forces play out in the platforms' investment decision is a topic worth study in the future.

More generally, our work challenges the classical "winner-takes-all" concern in a nascent market with network effects. According to that concern, positive network effects would enable the incumbent to become a natural monopoly and then abuse its monopoly power to the harm of consumers. However, even if the incumbent intends to follow this path, it takes time to get to "winner-takes-all" and competitor(s) can enter the market during this time. In a nascent market where the incumbent has energized the potential demand, entrants have incentives to free ride on the opening of the new market and steal consumers from the incumbent. Consequently, competition could push the market to evolve away from the simple "winner-takes-all" trajectory, as the incumbent and entrants would play a dynamic game and their incentives in investment, marketing and product enhancement could all be modified, depending on the market expanding and market stealing effects of these actions.

Lastly, our findings also highlight the importance of the outside good when we consider platform competition with network effects. Since platform entry generates both market expanding and market stealing effects, our work suggests that the competition with the outside good is at least as important as the between-platform competition in bike-sharing.

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Table 1 Data Summary (mean of key outcomes are masked by "NA" for confidentiality)

Sample	Full Sample			ofo First			ofo Alone			Mobike First		
Variables	N	Mean	Std. Dev	N	Mean	Std. Dev	N	Mean	Std. Dev	N	Mean	Std. Dev
Panel A City-Day Level Variables												
Dummy for Post-entry Status	19631	0.616	0.486	13560	0.639	0.480	2633	0	0	3438	1	0
Log (Trip Volume)	19631	NA	2.124	13560	NA	2.074	2633	NA	1.386	3438	NA	1.968
Average Revenue per Trip (RMB)	19631	NA	0.207	13560	NA	0.195	2633	NA	0.229	3438	NA	0.230
Percent of Free Trips (0-100)	19631	NA	22.774	13560	NA	23.716	2633	NA	19.869	3438	NA	20.276
Log (# of New Users)	19631	NA	1.997	13560	NA	1.974	2633	NA	1.789	3438	NA	1.648
Percent of Active Old Users	19631	NA	13.668	13560	NA	12.955	2633	NA	16.471	3438	NA	13.905
Average # of Trips per Active Old User	19631	NA	0.388	13560	NA	0.410	2633	NA	0.351	3438	NA	0.305
Log (Number of Grids Covered by ofo)	19631	5.469	1.210	13560	5.539	1.265	2633	4.709	0.862	3438	5.777	0.959
Gini Coverage Index	19631	0.864	0.090	13560	0.882	0.086	2633	0.788	0.092	3438	0.852	0.067
Dummy for ofo Operation within Campus	19631	0.163	0.369	13560	0.220	0.415	2633	0.000	0.000	3438	0.061	0.240
Speed of Wind	19631	2.677	0.883	13560	2.661	0.901	2633	2.679	0.861	3438	2.740	0.823
Temperature	19631	21.276	7.690	13560	20.167	8.164	2633	23.515	5.708	3438	23.935	5.838
Precipitation	19631	0.171	0.486	13560	0.152	0.455	2633	0.208	0.519	3438	0.219	0.567
Relative Humility	19631	73.831	16.310	13560	72.662	16.786	2633	74.259	16.763	3438	78.115	12.990
AQI (Air Quality Index)	19631	84.196	47.688	13560	87.795	51.345	2633	77.956	37.909	3438	74.782	36.304
Panel B City Level Variables												
Logarithmic Population (10,000)	104	6.101	0.632	59	6.196	0.558	23	5.814	0.818	22	6.143	0.535
GDP per Capita (10,000 RMB)	104	6.699	3.356	59	6.940	3.254	23	5.981	3.118	22	6.804	3.885
Number of Taxis	104	5076.103	6903.375	59	6351.334	6265.299	23	2040.783	1951.386	22	4829.455	10325.500
Number of Buses	104	3029.936	4474.697	59	3774.835	4871.471	23	942.235	730.883	22	3214.847	5073.091
Road Surface (10,000 Square Meters)	104	3281.349	3189.038	59	3951.990	3476.455	23	1627.596	1267.843	22	3211.735	3248.628
Number of Mobile Phone Users (10,000)	104	688.125	585.702	59	806.576	603.333	23	366.957	217.516	22	706.227	689.128
Number of Internet Households (10,000)	104	142.173	159.780	59	170.593	184.558	23	70.609	44.449	22	140.773	145.571
Average Gradient (‰)	104	458.766	570.863	59	447.244	547.904	23	596.891	745.032	22	345.262	391.150

Table 2 Competition Effects on Usage Volume and Price

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A Dependent Variable				*Log (Trip Volume)*			
PostEntry	0.370*	0.439**	0.535***	0.491**	0.346**	0.402**	0.408**
	(0.211)	(0.181)	(0.199)	(0.207)	(0.166)	(0.181)	(0.185)
Within Adjusted R^2	0.104	0.233	0.106	0.111	0.241	0.120	0.117
Panel B Dependent Variable				*Average Revenue per Trip*			
PostEntry	0.029***	0.027***	0.030***	0.035***	0.031***	0.031***	0.041***
	(0.009)	(0.008)	(0.010)	(0.011)	(0.008)	(0.010)	(0.011)
Within Adjusted R^2	0.075	0.122	0.049	0.057	0.123	0.049	0.059
Panel C Dependent Variable				*Percent of Free Trips (0-100)*			
PostEntry	-2.288**	-2.311**	-3.132**	-3.589**	-2.170**	-2.717**	-3.695***
	(1.131)	(1.117)	(1.487)	(1.563)	(0.971)	(1.287)	(1.399)
Within Adjusted R^2	0.085	0.140	0.073	0.070	0.140	0.074	0.070
Dummy for Operation within Campus	YES	YES	YES	YES	YES	YES	YES
Weather Condition	YES	YES	YES	YES	YES	YES	YES
Air Quality	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES	YES
Treatment Group Trend					YES	YES	YES
Linear Time Trend		YES			YES		
City Attributes×Date FE			YES			YES	
City Attributes×Day FE				YES			YES
Number of Clusters	82	82	82	82	82	82	82
Observations	16193	16193	16193	16193	16193	16193	16193

Notes: Column 1 only controls for city fixed effects and time fixed effects. Column 2 adds the interaction between predetermined city attributes and a third-order polynomial function of the relative days since ofo's entry. Column 3 and 4 interact the city attributes with calendar date fixed effects and relative day fixed effects respectively. Column 5-7 further include linear time trends specific to the ofo First group cites. The specification of Column 7 is taken as benchmark settings in the following analyses. Standard errors are in parentheses and are clustered at the city level. ***Denotes significance at the 1%, ** 5 %, and * 10% level.

Table 3 2SLS Estimates

	(1)	(2)	(3)	(4)
Dependent Variables	*PostEntry*	*Log (Trip Volume)*	*Average Revenue per Trip*	*Percent of Free Trips*
Models	*First-Stage*	*2SLS*	*2SLS*	*2SLS*
Predicted PostEntry	0.949^{***}			
	(0.011)			
PostEntry		0.478^{**}	0.045^{***}	-3.999^{***}
		(0.199)	(0.012)	(1.493)
Dummy for Operation within Campus	YES	YES	YES	YES
Weather Condition	YES	YES	YES	YES
Air Quality	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Day FE	YES	YES	YES	YES
Treatment Group Trend	YES	YES	YES	YES
City Attributes×Day FE	YES	YES	YES	YES
Kleibergen-Paap F Test	8000.251	/	/	/
Number of Clusters	82	82	82	82
Observations	16193	16193	16193	16193

Notes: The instrument variable *Predicted PostEntry* is derived from a duration model which treats the time span between Mobike entry dates and November 1, 2015 as "survival time" and uses city attributes and VC finance of Mobike as regressors. We assume that the baseline hazard follows Weibull distribution. Column 1 reports the first-stage with the Kleibergen-Paap F test larger than 8000. Column 2-4 show 2SLS estimates under the benchmark settings, which are similar to baseline results in both significance and magnitude. Further robustness checks of starting date choice and the assumption of baseline hazards are reported in Appendix Table 3. Standard errors are in parentheses and are clustered at the city level. ***Denotes significance at the 1%, ** 5 %, and * 10% level.

Table 4 Placebo Test Using ofo Campus Period

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables	*Log(Trip Volume)*		*Average Revenue per Trip*		*Percent of Free Trips*	
Models	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*
PostEntry×Dummy for Operation within Campus	-0.371	-0.211	0.000	0.016	0.367	-0.758
	(0.298)	(0.293)	(0.027)	(0.028)	(4.100)	(4.068)
PostEntry×Dummy for Operation in the Whole City	0.618***	0.673***	0.060***	0.063***	-5.451***	-5.688***
	(0.190)	(0.200)	(0.012)	(0.013)	(1.505)	(1.588)
Dummy for Operation within Campus	NO	NO	NO	NO	NO	NO
Weather Condition	YES	YES	YES	YES	YES	YES
Air Quality	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES
Treatment Group Trend	YES	YES	YES	YES	YES	YES
City Attributes×Day FE	YES	YES	YES	YES	YES	YES
Number of Clusters	82	82	82	82	82	82
Within Adjusted R^2	0.107	/	0.042	/	0.056	/
Observations	16193	16193	16193	16193	16193	16193

Notes: The key independent variable $PostEntry_{ct}$ is decomposed into $1_{campus} \cdot PostEntry_{ct}$ and $(1- 1_{campus}) \cdot PostEntry_{ct}$, where 1_{campus} is the dummy for operation within campus in benchmark settings. Every two columns under the same outcome variable report OLS and 2SLS estimates separately. Column 1-6 point to the common conclusion that the market expanding effects emerge when ofo expanded to the whole city while absent during "campus period." Standard errors are in parentheses and are clustered at the city level. ***Denotes significance at the 1%, ** 5 %, and * 10% level.

Table 5 Market Expanding vs. Market Stealing Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables	*Log (# of New Users)*		*Percent of Active Old Users*		*Average # of Trips per Active Old User*	
Models	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*
PostEntry	0.652***	0.735***	-4.126***	-4.353***	-0.005	-0.003
	(0.228)	(0.243)	(1.446)	(1.551)	(0.036)	(0.039)
Dummy for Operation within Campus	YES	YES	YES	YES	YES	YES
Weather Condition	YES	YES	YES	YES	YES	YES
Air Quality	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES
Treatment Group Trend	YES	YES	YES	YES	YES	YES
City Attributes×Day FE	YES	YES	YES	YES	YES	YES
Number of Clusters	82	82	82	82	82	82
Within Adjusted R^2	0.265	/	0.075	/	0.006	/
Observations	16193	16193	16193	16193	16193	16193

Notes: Every two columns under the same outcome variable report OLS and 2SLS estimates separately which adopt the benchmark settings in Table 2 Column 7. Standard errors are in parentheses and are clustered at the city level. ***Denotes significance at the 1%, ** 5 %, and * 10% level.

Table 6 Market Expanding vs. Market Stealing Effects: Unpacked by the Timing of Investment

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables	*Log(Trip Volume)*	*Average Revenue per Trip*	*Percent of Free Trips*	*Log (# of New Users)*	*Percent of Active Old Users*	*Average # of Trips per Active Old User*
Panel A Model				*OLS*		
PostEntry×Dummy for Window without New Investment	0.039	0.037**	-1.886	0.432*	-2.696	-0.121***
	(0.179)	(0.015)	(1.530)	(0.233)	(1.633)	(0.042)
PostEntry×Dummy for Window with New Investment	0.628**	0.046***	-4.078***	0.788***	-5.253***	0.065
	(0.241)	(0.014)	(1.423)	(0.292)	(1.725)	(0.045)
Within Adjusted R^2	0.111	0.062	0.072	0.243	0.076	0.018
Panel B Model				*2SLS*		
PostEntry×Dummy for Window without New Investment	0.084	0.042***	-2.117	0.507**	-2.778	-0.126***
	(0.191)	(0.016)	(1.566)	(0.244)	(1.691)	(0.045)
PostEntry×Dummy for Window with New Investment	0.654***	0.048***	-4.222***	0.821***	-5.268***	0.065
	(0.244)	(0.014)	(1.456)	(0.296)	(1.766)	(0.045)
Dummy for Operation within Campus	YES	YES	YES	YES	YES	YES
Weather Condition	YES	YES	YES	YES	YES	YES
Air Quality	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES
Treatment Group Trend	YES	YES	YES	YES	YES	YES
City Attributes×Day FE	YES	YES	YES	YES	YES	YES
Number of Clusters	79	79	79	79	79	79
Observations	15770	15770	15770	15770	15770	15770

Notes: The key independent variable $PostEntry_{ct}$ is decomposed into $1_{window}\cdot PostEntry_{ct}$ and$(1-1_{window})\cdot PostEntry_{ct}$, where 1_{window} is a dummy for the window period when Mobike enters some city while ofo has not invested new bikes. Bike investment data is missing for 3 cities so the number of clusters decrease to 79 in this table. Panel A and Panel B report OLS and 2SLS estimates respectively. Standard errors are in parentheses and are clustered at the city level.
***Denotes significance at the 1%, ** 5 %, and * 10% level.

Table 7 Bike Utilization and Geographical Reach

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variables	*Log (Bike Utilization Rate)*		*Log (# of Grids covered by ofo)*		*Gini Coverage Index*		*Gini Coverage Index of Pre-Entry Grids*	
Models	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*
PostEntry	0.392**	0.457**	0.195**	0.225**	-0.035***	-0.038***	-0.027**	-0.031***
	(0.185)	(0.198)	(0.081)	(0.086)	(0.008)	(0.008)	(0.010)	(0.011)
Dummy for Operation within Campus	YES	YES	YES	YES	YES	YES	YES	YES
Weather Condition	YES	YES	YES	YES	YES	YES	YES	YES
Air Quality	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES	YES	YES
Treatment Group Trend	YES	YES	YES	YES	YES	YES	NO	
City Attributes×Day FE	YES	YES	YES	YES	YES	YES	YES	YES
Sample	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark	ofo Alone Excluded	ofo Alone Excluded
Number of Clusters	79	79	82	82	82	82	59	59
Within Adjusted R^2	0.092	/	0.202	/	0.112	/	0.041	/
Observations	15770	15770	16193	16193	16193	16193	13560	13560

Notes: Bike investment data is missing for 3 cities so the number of clusters decreases to 79 in Column 1 and 2. “Pre-Entry Grids” could not be defined for ofo Alone group cities, which are excluded in Column 7 and 8. Every two columns under the same outcome variable report OLS and 2SLS estimates separately which adopt the benchmark settings in Table 2 Column 7. Standard errors are in parentheses and are clustered at the city level. ***Denotes significance at the 1%, ** 5 %, and * 10% level.

Table A1 List of Cities

City Name	Administrative Area Code	ofo Entry Date	Mobike Entry Date	Group
Tianjin	120000	27-Aug-16	12-Feb-17	ofo First
Shijiazhuang	130100	31-Aug-16	6-Mar-17	ofo First
Tangshan	130200	1-Apr-17	17-Apr-17	ofo First
Qinhuangdao	130300	28-Apr-17	12-Jun-17	ofo First
Handan	130400	14-Apr-17	6-May-17	ofo First
Baoding	130600	9-Mar-17	19-Jun-17	ofo First
Langfang	131000	20-Apr-17	17-May-17	ofo First
Taiyuan	140100	17-Aug-16	14-May-17	ofo First
Datong	140200	3-Mar-17	27-Jun-17	ofo First
Jinzhong	140700	6-May-17	17-May-17	ofo First
Xinzhou	140900	10-Jul-17	/	ofo Alone
Hohhot	150100	1-May-17	/	ofo Alone
Wuhai	150300	30-Jun-17	/	ofo Alone
Erdos	150600	9-Jun-17	8-May-17	Mobike First
Shenyang	210100	8-May-17	17-May-17	ofo First
Dalian	210200	26-Jun-17	16-Apr-17	Mobike First
Shanghai	310000	9-May-16	22-Apr-16	Mobike First
Nanjing	320100	14-Jun-16	12-Jan-17	ofo First
Wuxi	320200	2-Mar-17	3-Mar-17	ofo First
Suzhou	320500	15-Jan-17	18-Jun-17	ofo First
Nantong	320600	29-Apr-17	/	ofo Alone
Yangzhou	321000	20-Apr-17	9-Mar-17	Mobike First
Zhenjiang	321100	28-Apr-17	/	ofo Alone
Hangzhou	330100	12-Sep-16	16-Apr-17	ofo First
Ningbo	330200	14-Jan-17	6-Dec-16	Mobike First
Wenzhou	330300	14-May-17	8-Apr-17	Mobike First
Jiaxing	330400	6-Apr-17	27-Apr-17	ofo First
Jinhua	330700	31-Mar-17	20-May-17	ofo First
Taizhou	331000	18-May-17	1-Jul-17	ofo First
Hefei	340100	24-Aug-16	13-Feb-17	ofo First
Wuhu	340200	16-Mar-17	26-Mar-17	ofo First
Maanshan	340500	28-Dec-16	11-May-17	ofo First
Anqing	340800	6-Dec-16	/	ofo Alone
Fuzhou	350100	19-Aug-16	7-Feb-17	ofo First
Xiamen	350200	17-Dec-16	20-Dec-16	ofo First
Quanzhou	350500	14-Mar-17	8-Mar-17	Mobike First
Zhangzhou	350600	13-Mar-17	9-Mar-17	Mobike First
Ningde	350900	25-Apr-17	/	ofo Alone

Nanchang	360100	20-Aug-16	24-Feb-17	ofo First
Jiujiang	360400	20-Apr-17	20-May-17	ofo First
Ganzhou	360700	20-Apr-17	16-Jun-17	ofo First
Shangrao	361100	14-May-17	/	ofo Alone
Jinan	370100	29-Aug-16	25-Jan-17	ofo First
Qingdao	370200	21-Feb-17	7-May-17	ofo First
Zibo	370300	3-Apr-17	/	ofo Alone
Zaozhuang	370400	29-Jun-17	17-May-17	Mobike First
Yantai	370600	5-May-17	/	ofo Alone
Weifang	370700	28-Apr-17	/	ofo Alone
Jining	370800	17-Jun-17	17-May-17	Mobike First
Tai'an	370900	10-Apr-17	23-May-17	ofo First
Weihai	371000	25-Apr-17	7-May-17	ofo First
Rizhao	371100	29-Apr-17	19-Mar-17	Mobike First
Dezhou	371400	23-May-17	27-Apr-17	Mobike First
Zhengzhou	410100	11-Aug-16	6-Mar-17	ofo First
Kaifeng	410200	17-May-17	17-May-17	ofo First
Luoyang	410300	20-Apr-17	10-Apr-17	Mobike First
Puyang	410900	22-Jul-17	11-Aug-17	ofo First
Xuchang	411000	4-Jun-17	/	ofo Alone
Sanmenxia	411200	19-Jun-17	/	ofo Alone
Wuhan	420100	18-Apr-16	29-Dec-16	ofo First
Shiyan	420300	19-Aug-17	/	ofo Alone
Yichang	420500	9-Apr-17	7-Apr-17	Mobike First
Xiangyang	420600	2-Apr-17	1-May-17	ofo First
Ezhou	420700	16-May-17	16-Jul-17	ofo First
Xiaogan	420900	10-May-17	/	ofo Alone
Huanggang	421100	15-May-17	25-Aug-17	ofo First
Xianning	421200	6-Jun-17	12-Jun-17	ofo First
Changsha	430100	26-Aug-16	14-Feb-17	ofo First
Zhuzhou	430200	24-Apr-17	/	ofo Alone
Xiangtan	430300	24-Apr-17	/	ofo Alone
Guangzhou	440100	8-Jun-16	27-Sep-16	ofo First
Shaoguan	440200	1-Jun-17	/	ofo Alone
Shenzhen	440300	11-Sep-16	16-Oct-16	ofo First
Zhuhai	440400	20-Oct-16	21-Jan-17	ofo First
Shantou	440500	12-Apr-17	19-Feb-17	Mobike First
Jiangmen	440700	10-Apr-17	27-Mar-17	Mobike First
Heyuan	441600	9-Jun-17	/	ofo Alone
Dongguan	441900	24-Feb-17	13-Jan-17	Mobike First
Zhongshan	442000	7-Apr-17	16-Jun-17	ofo First
Jieyang	445200	17-Apr-17	/	ofo Alone

Nanning	450100	7-Sep-16	21-Feb-17	ofo First
Guilin	450300	1-Mar-17	30-May-17	ofo First
Haikou	460100	28-Feb-17	17-Feb-17	Mobike First
Chengdu	510100	22-Aug-16	16-Nov-16	ofo First
Deyang	510600	22-Apr-17	9-Mar-17	Mobike First
Mianyang	510700	17-Mar-17	6-Mar-17	Mobike First
Leshan	511100	10-May-17	17-May-17	ofo First
Nanchong	511300	8-May-17	17-May-17	ofo First
Meishan	511400	8-Jul-17	23-Jun-17	Mobike First
Ziyang	512000	1-Jun-17	23-May-17	Mobike First
Guiyang	520100	6-Mar-17	9-Apr-17	ofo First
Liupanshui	520200	6-May-17	/	ofo Alone
Zunyi	520300	27-Apr-17	21-May-17	ofo First
Kunming	530100	27-Aug-16	8-Jan-17	ofo First
Xi'an	610100	27-May-16	19-Feb-17	ofo First
Xianyang	610400	29-Apr-17	17-May-17	ofo First
Weinan	610500	20-May-17	21-May-17	ofo First
Yan'an	610600	22-May-17	16-Aug-17	ofo First
Yulin	610800	23-May-17	3-Aug-17	ofo First
Lanzhou	620100	25-Aug-16	10-Jul-17	ofo First
Xining	630100	8-May-17	/	ofo Alone
Yinchuan	640100	25-Apr-17	25-Apr-17	ofo First
Urumqi	650100	5-Jul-17	7-Jul-17	ofo First
Karamay	650200	22-Aug-17	/	ofo Alone

Notes: This list only includes cities in our final sample. Beijing and the 6 cities without detailed entry sequence are excluded. Administrative Area Code is a unique number to identify administrative area, which is issued by the China central government. / means that entry dates are missing for ofo Alone cities.

Table A2 Robustness Check of Different Subsamples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variables	*Log (Trip Volume)*				*Average Revenue per Trip*				*Percent of Free Trips*			
Subsamples	*ofo Alone Excluded*		*Mobike First Included*		*ofo Alone Excluded*		*Mobike First Included*		*ofo Alone Excluded*		*Mobike First Included*	
Models	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*
PostEntry	0.401**	0.473**	0.373*	0.428**	0.044***	0.048***	0.039***	0.042***	-3.245**	-3.510**	-3.600***	-3.804***
	(0.192)	(0.206)	(0.190)	(0.202)	(0.013)	(0.014)	(0.011)	(0.012)	(1.307)	(1.387)	(1.297)	(1.376)
Dummy for Operation within Campus	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Weather Condition	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Air Quality	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Treatment Group Trend	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
City Attributes×Day FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of Clusters	59	59	104	104	59	59	104	104	59	59	104	104
Within Adjusted R^2	0.103	/	0.133	/	0.074	/	0.053	/	0.079	/	0.061	/
Observations	13560	13560	19631	19631	13560	13560	19631	19631	13560	13560	19631	19631

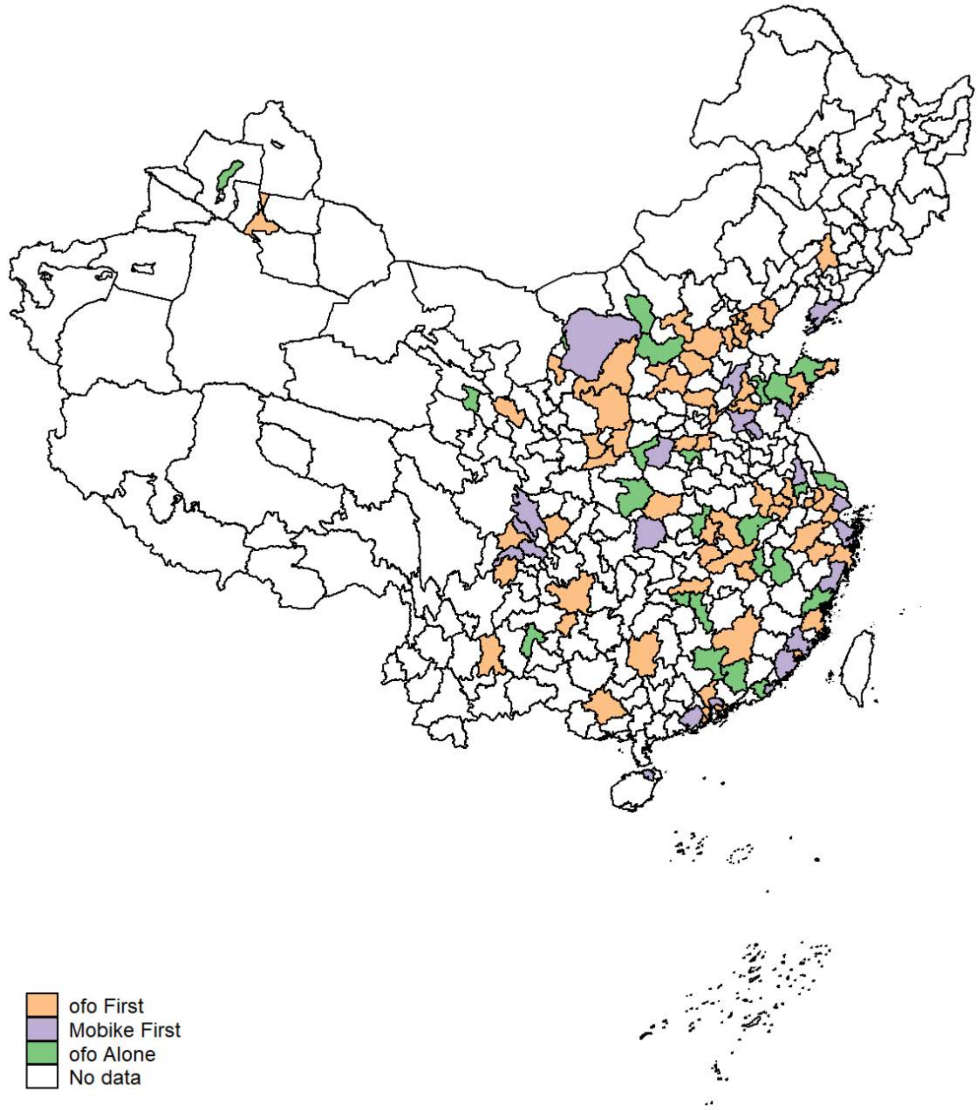
Notes: This table further examines the robustness of results in Table 2 and 3. Column 1,2,5,6,9 and 10 drop ofo Alone cities and re-estimate the coefficients under the benchmark specification, resulting from the concern that our list of controls could not fully guarantee the comparability between ofo First and ofo Alone cities. The other columns include the Mobike First group which is equivalent to the "always-treated" group in the context of DID framework and make full use of the data sample. Standard errors are in parentheses and are clustered at the city level. ***Denotes significance at the 1%, ** 5 %, and * 10% level.

Table A3 Robustness Check of 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)
Panel A Dependent Variables			*Log (Trip Volume)*		
Starting Dates / *Distribution*	12/1/15	1/1/16	2/1/16	3/1/16	4/1/16
Weibull	0.484**	0.480**	0.487**	0.498**	0.505**
	(0.201)	(0.202)	(0.204)	(0.205)	(0.206)
Loglogistic	0.450**	0.456**	0.464**	0.469**	0.479**
	(0.198)	(0.199)	(0.200)	(0.201)	(0.205)
Lognormal	0.456**	0.459**	0.461**	0.469**	0.477**
	(0.199)	(0.201)	(0.202)	(0.204)	(0.207)
Panel B Dependent Variables			*Average Revenue per Trip*		
Starting Dates / *Distribution*	12/1/15	1/1/16	2/1/16	3/1/16	4/1/16
Weibull	0.045***	0.045***	0.046***	0.046***	0.046***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
Loglogistic	0.043***	0.044***	0.044***	0.045***	0.046***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
Lognormal	0.044***	0.043***	0.043***	0.043***	0.043***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
Panel C Dependent Variables			*Percent of Free Trips*		
Starting Dates / *Distribution*	12/1/15	1/1/16	2/1/16	3/1/16	4/1/16
Weibull	-4.023***	-4.031***	-4.101***	-4.153***	-4.158***
	(1.502)	(1.508)	(1.522)	(1.534)	(1.537)
Loglogistic	-3.796**	-3.804**	-3.889**	-3.962**	-4.017**
	(1.496)	(1.506)	(1.508)	(1.519)	(1.542)
Lognormal	-3.872**	-3.832**	-3.804**	-3.851**	-3.837**
	(1.489)	(1.505)	(1.517)	(1.533)	(1.554)

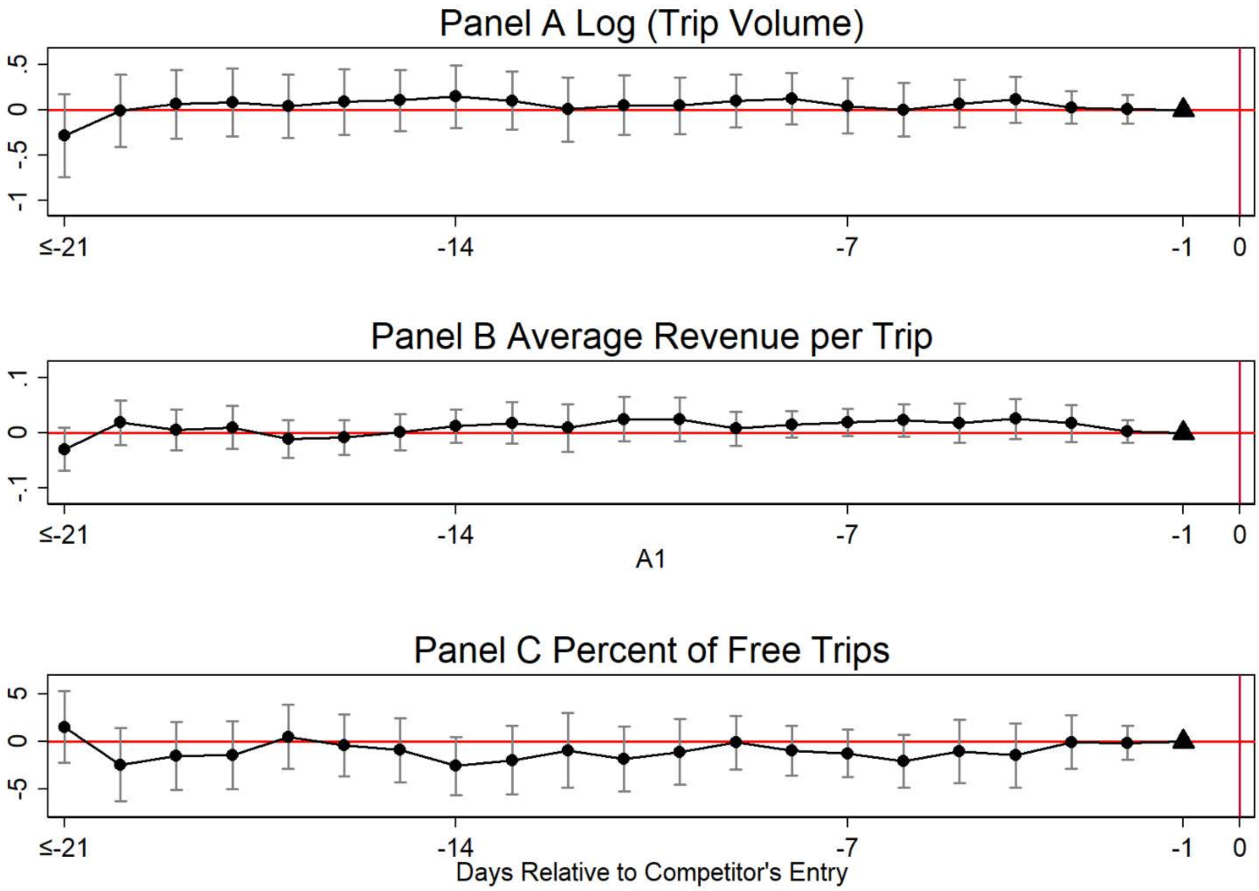
Notes: The three panels experiment with instrument variables constructed from duration models that use December 1, 2015, January 1, 2016, February 1, 2016, March 1, 2016 and April 1, 2016 as starting dates of Mobike, under different assumptions for the functional form of baseline hazard (that is, Weibull, log-log and log-normal distributions). For each outcome variable, there are 5*3 = 15 estimates of β. This table provides further support to Table 3 in the sense that results in Table 3 are not driven by the choice of starting dates or distribution function. Standard errors are in parentheses and are clustered at the city level. ***Denotes significance at the 1%, ** 5 %, and * 10% level.

Figure 1 Geographical Distribution of Different City Groups



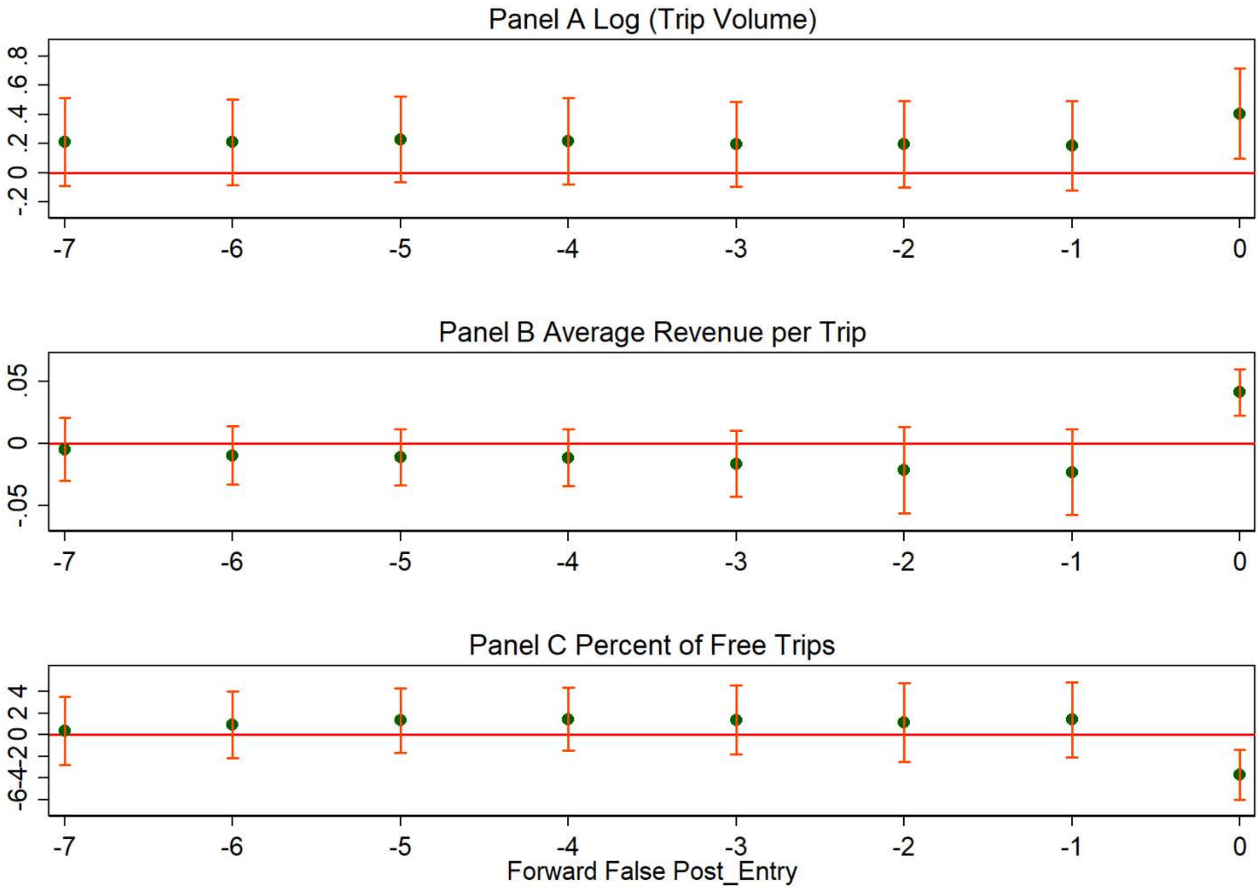
Notes: This figure depicts the geographical distribution of 3-type cities. Cities in our final sample are labeled with different color. Beijing and the 6 cities without detailed entry sequence are excluded. The base map of China comes from Resource and Environment Data Cloud Platform (http://www.resdc.cn).

Figure 2 Test of Common Pre-Trend Assumption



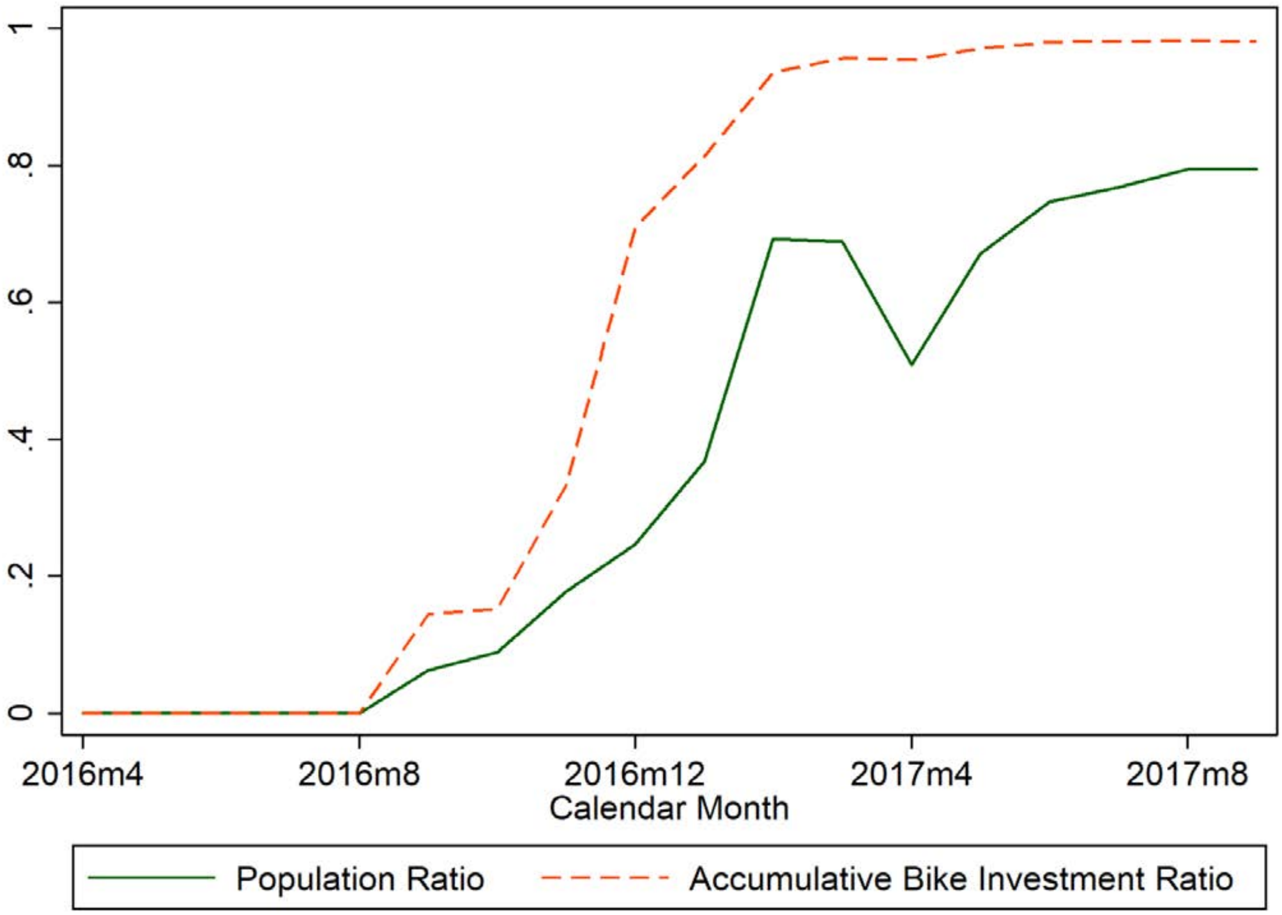
Notes: Point estimates of $\{\lambda_{-k}\}_{k=2}^{21}$ in equation 2 as well as corresponding 95% confidence interval. The day before Mobike's entry is omitted as base and days more than 3 weeks before the entry are all counted as 21. All the coefficients are indistinguishable from 0 even at the 10% significance level, which implies that ofo Alone and ofo First cities follow similar pre-entry trends. All the other controls are the same as Table 2 Column 7. Standard errors are in parentheses and are clustered at the city level.

Figure 3 Falsification Test of Forwards of *PostEntry*



Notes: We restrict the sample to ofo Alone cities and pre-entry observations of ofo First cities, and generate false entry on 1,2,…,7 days before the publicly announced Mobike entry. Point estimates of the false entry as well as 95% confidence interval are depicted together with the baseline estimates from Table 2 Column 7 plotted on the very right. Standard errors are in parentheses and are clustered at the city level.

Figure 4 Comparison between Population and Bike Investment Distribution



Notes: The horizontal axis is calendar month. The green solid line is the ratio of population of cities with Mobike competition to the total population of all cities that ofo has entered at that time. The red dashed line is the ratio of accumulative number of bike placement of cities with Mobike competition to the total bike investment in all cities that ofo has entered at that time. It is noteworthy that both numerator and denominator change as Mobike enters more cities and we could not guarantee that both of these two ratios keep increasing all the time.