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ABSTRACT

The recent rise of dockless bike-sharing is dominated by two firms in China: one started first in 82 cities, 59 of which were subsequently entered by the second firm. 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 does the entry boost its total number of trips and encourage more bike investment, it but also allows the incumbent to achieve higher revenue per trip, improve bike utilization rate, and form a wider and more evenly distributed network. The market expansion effect on new users dominates a significant market-stealing effect on the incumbent's old users. These findings, together with a theoretical model that highlights consumer search and network effects, suggest that a market with positive network effects is not necessarily winner-takes-all, especially when users multi-home across compatible networks.

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1 Introduction

From telephone to online platforms, many markets feature direct or indirect network effects.[1] It is of concern that positive network effects could lead to winner-takes-all, where the incumbent dominates the market and competing firms find it difficult to enter and survive.[2] In the meantime, multi-homing and compatibility could play an important role alleviating the anti-competitive concerns.[3] How do firms 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? 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[4], the first bike-sharing firm in China, was founded in 2015 by a graduate student of Peking University (PKU). 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 one-sided.

As documented by a burgeoning literature[5], bike-sharing solves the "last-mile" problem of local transportation. There are positive network effects among bike riders because a user who rides a bike from A to 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

[1] Telephone is a classical example of direct network effects: consumers are more willing to join a network if they can reach more people in that network. Many two-sided platforms feature indirect network effects. For example, sellers (buyers) are more willing to join eBay if eBay attracts more buyers (sellers) on the other side; and firms are more willing to list in a yellow page if the yellow page can reach a larger number of consumers.

[2] The main concern is that users may be reluctant to switch away from the incumbent 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)).

[3] On multi-homing, Caillaud and Jullien (2003) and Halaburda and Yehezkel (2013) show that multi-homing tends to intensify competition. But the recent work of Bryan and Gans (2018) suggests that competition equilibrium depends on whether multi-homing occurs on one or two sides of ridesharing platforms. 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 "excess inertia" and "excess momentum" in a dynamic setting.

[4] "ofo" is the trademark of the firm, 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."

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

imbalance of demand and supply in different locations at different times.[6] When thousands of users ride ofo bikes in a small area, the wide availability of ofo bikes increases the expected probability to find a bike at the needed time and location and therefore encourages more users to use bike-sharing. 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.[7] Thanks to these positive network effects, ofo grew exponentially from a college campus to more than 250 cities in 20 countries by January 2018.[8]

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[9], 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.[10] In this sense, the two networks are compatible and users are free to multi-home.

We first demonstrate the effects of Mobike's entry on ofo, and then present a theoretical model to explore the most likely explanations for the empirical facts. More specifically, we track news reports[11] and combine them with ofo's proprietary data. This process identifies 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.[12] Because ofo started half a year earlier than Mobike, 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* cities, while taking Mobike's city-specific entry as the "treatment." [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. This result is robust to heterogeneous time trends, placebo test, and an instrumental variable (IV) approach to address the potential endogeneity of Mobike entry. The instrument we use is the projected Mobike's entry date in a city, where the projection uses the timing of Mobike's venture capital

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

[7]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 firm.

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

[9]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%.

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

[11]We track news reports from 9/7/2015 to 9/14/2017.

[12]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.

[13]As detailed in Section 4, 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. 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.

funding (8 rounds in total) and the city's predetermined attributes such as population, geographic feature and transportation infrastructure. When we separate new and old users within ofo, we find that Mobike's entry has reduced the percent of old users that remain active on ofo, but this market stealing effect is dominated by the expansion in new users. Unlike other markets with positive network effects, bike-sharing allows firms to directly influence the network size by bike investment. Analysis suggests that ofo has put more bikes in the *ofo First* markets after Mobike's entry, above and beyond the investment it made in *ofo Alone* markets; and ofo's bike utilization rate - measured by the number of trips per ofo bike per day - has increased significantly upon Mobike entry.

Above all, competition seems to have motivated the incumbent to invest more and benefit the incumbent in at least three dimensions (trip volume, revenue per trip, and bike utilization). The beneficial effect on bike utilization rate is particularly interesting, because we cannot simply explain it by the incumbent responding to entry by aggressive investment. Moreover, the effects on volume, price and utilization happen despite the fact that bike-sharing features positive network effects, multi-homing and network compatibility. This raises three immediate questions: first, what mechanism leads to the overall market expansion for the incumbent? Second, why the incumbent didn't expand the network as much by itself before the second firm entered? Third, why the incumbent chooses its post-entry investment such that the bike utilization rate is higher after the entry than before the entry?

To answer these questions and to best explain our empirical results, we model bike-sharing in monopoly and duopoly respectively. In both types of market, consumers decide whether to search for a bike, given the price of each firm and the expected probability of finding a bike. In addition to price, firms also decide on bike investment, which influences the matching probability subject to investment costs. Naturally, congestion creates a negative network effect but if the matching technology exhibits increasing return to scale, it also creates positive network effects, as more bikes on the market and more consumers searching increase the matching efficiency. In light of these network effects, we then derive how firm(s) choose price and bike investment in a subgame perfect equilibrium. We only consider symmetric equilibrium in duopoly, given the similarity between ofo and Mobike.

The model predicts that, under weak conditions, duopoly always leads to a higher price than monopoly but the comparison on trade volume, bike investment and bike utilization rate depends on a few factors. The first factor is positive network effects modeled as a matching technology with increasing return to scale. When there are significant increasing return in matching, duopoly competition will generate a market expansion effect that is large enough to dominate the business stealing effect. In that case, each duopolist has incentive to make greater bike investment than the monopolist, and as a result serve more trips. When the increasing return is high enough, duopoly could also feature a higher bike utilization rate than monopoly. Another factor is investment cost. If cost per bike is constant, positive network effects would motivate the monopolist to invest in infinite bikes, leaving no room for entry. If cost per bike is increasing – a realistic assumption because it requires more effort to balance and maintain a larger and more diverse network of bikes – each firm must trade off the motive to expand due to positive network effects and the cost of investment. When investment cost (per firm) is convex enough, two firms investing at the same time is more cost-efficient than a single firm making all the investment. With increasing return in matching, competitor's investment also make one's own investment more efficient in persuading more consumers to search and improving the matching rate. The monopolist alone cannot achieve the same efficiency, because it must shoulder the full cost to get to the same scale and it might be too convex to justify the investment.[14]

While increasing return matching and investment cost could explain our empirical facts, the model also offers a couple of alternative explanations for market expansion. The first alternative is that entry may raise consumer awareness (by advertising for example) and therefore increase matching efficiency for any given number of bikes. The model captures this by a multiplier in the Cobb-Douglas matching function. In equilibrium, we show that utilization rate is independent of this multiplier, hence an entry-motivated increase in the multiplier could lead to growth in bike investment but it cannot explain why ofo's bike utilization rate is higher post entry. The second alternative explanation lies in the distribution of consumer's private cost of using alternative transportation (the outside good). If the density of this private cost is downward sloping, an increase in that slope has two opposite effects: first, the next batch of bikes (introduced by the entrant) could persuade more consumers to join bike-sharing than the existing batch invested by the monopolist, thus generating a market expansion effect; second, there are fewer consumers with high private costs when the monopolist invests in the first batch of bikes, which discourages investment. In the model, we show that the second force dominates the first force thus the monopolist tends to invest in fewer bikes if the density is more downward sloping. This prediction is different from the marginal effect of increasing return matching, which motivates us to conduct more data analysis to distinguish these two explanations. We find that variations in private cost distribution cannot explain why the boost on ofo price and trade volume is greater for the cities in which ofo has made more bike investment before Mobike's entry, but this empirical fact can be explained by variations in the increasing return matching technology.

Our model abstracts away from local geography within a market, but it is not difficult to give it a geographic interpretation. Since the monopolist tends to first target consumers that are easiest to convert, the entry – together with the entrant's bike investment – will help persuade the next cohort of consumers who are on the margin of using bike-sharing. To the extent that the attractiveness of the outside good is geographically dispersed, the market expansion effect of the entry also implies a geographic expansion. Using the same DID framework, we find that the entry does help ofo bikes to reach more grids in the city (each grid is defined as a square kilometer), and the network of ofo-reached grids has become more evenly distributed post entry. These findings reinforce the conclusion that competition expands the market and improves the performance of the incumbent.

Our work is closest to the literature of network economy. By focusing on a market with positive network effects, we show that competition expands the overall market, even though the competing goods are close substitutes. As suggested by our model, the monopolist may not exhaust all the positive network effects by itself, because the entrant extends the overall network of bikes and the incumbent can enjoy that positive spillover at a lower cost through competitor's investment than through its own investment. This implication departs from the typical con-

[14]Our model further proves that decreasing return matching could not explain higher utilization rate post entry, nor could constant or concave cost of investment.

cern of winner-takes-all. Moreover, the positive network effects are reinforced by compatibility between competitors. Existing theories tend to focus on the choice of (in)compatibility while assuming users value network size and setting the cost of operation independent of network size (Katz and Shapiro, 1985).[15] In bike-sharing, firms take compatibility as given but choose bike investment endogenously. Because bike investment affects the matching rate, it has a direct impact on network size in equilibrium.

Our work also differs from the empirical literature of network markets. Instead of estimating how the number of users affects user evaluation[16], we document the impact of entry on the incumbent, with a focus on the incumbent's strategic choices (in price and investment) as well as the incumbent's market performance (in trade volume, utilization rate and network reach). In doing so, we identify the effect of competition from the data directly, rather than inferring it from demand estimates and supply-side assumptions.

Finally, our results highlight competition with the outside good. Many theories of two-sided markets, such as Armstrong (2006) and Bryan and Gans (2018), emphasize head-to-head competition between platforms, but assume away competition between platforms and the outside good. In our context, attracting new users to search for a bike is essential to market expansion. The market expansion effect of competition is similar to what has been found in industrial agglomeration and retailer clustering, although typical agglomeration does not feature positive network effects within one or more firms.[17] Because there are positive spillovers between bike-sharing firms, our work contrasts the market stealing effect documented in other network markets (Seamans and Zhu, 2014; Angelucci and Cagé, 2016).

The rest of the article is organized as follows. Section 2 describes the background. Section 3 summarizes the data. Section 4 describes our main econometric specifications. Section 5 reports the baseline empirical results. Section 6 presents a theoretical model that highlights consumer search and network effects. The model also clarifies how positive network effects differ from alternative explanations. Section 7 reports further data analysis in light of the model. Section 8 concludes with policy implications.

[15] Katz and Shapiro (1985) model compatibility through a fixed cost, but they assume the variable cost is constant (zero) regardless of network size.

[16] The empirical literature has estimated network effects in many settings. For one-sided markets, the literature has estimated the direct network effects of spreadsheet, ATM, compact disk player, and VCR, and studied strategic pricing and technology adoption in light of the network effects (Saloner and Shepard, 1995; Gandal, 1994; Gandal, Kende and Rob, 2000; Park, 2004). For two-sided markets, the literature has documented the indirect network effects in yellow pages, magazines, newspapers, video games, and online platforms, and examined the implication of these network effects on pricing, advertising, product positioning, and market structure (Rysman, 2004; Kaiser and Wright, 2006; Kaiser and Song, 2009; Dubé, Hitsch and Chintagunta, 2010; Kim, Prince and Qiu, 2014; Angelucci and Cagé, 2016).

[17] Researchers have shown that competing retailers may choose to cluster at the same mall because it lowers consumer search cost (Vitorino, 2012), automobile dealers may locate near each other despite the intensified competition (Murry and Zhou, 2018), and industries may agglomerate in the same region to enjoy positive spillovers in consumers, supplies, labors, and ideas (Ellison, Glaeser and Kerr, 2010).

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, smart-cards and fobs, mobile phone access, and on-board computers (DeMaio, 2003; DeMaio and Gifford, 2004; DeMaio, 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 firms in dockless bike-sharing, both originated in China but now operating worldwide. As the first dockless bike-sharing firm, 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 5. 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.[18] 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 firms are almost negligible.[19] That is why we focus on the competition between

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

[19]On October 25,2017, two second-tier bike-sharing firms, 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.

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.[20] As detailed in Section 3, 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 A1 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. (2018) 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 network are 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, Belavina and Girotra (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

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

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 the 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 takes a full model to describe how consumer search and network effects affect each firm's pricing and investment decisions, and whether competition would have a net market expanding or market stealing effect on the incumbent.

3 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 the 2016 China City Statistical Yearbook reports city attributes. Below we first explain each data source, and then describe our sample construction.

3.1 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 q_{gct}, defined as the total number of ofo bike trips 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 $\log(Q_{ct}) = \log(\sum_g q_{gct})$ 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 $\log(\#Grids_{ct})$, 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. 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, Michalopoulos and Papaioannou (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. 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 (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 coupons or other marketing activities, we also compute percent of free trips ($\%Free_{ct}$) as an alternative measure of price within a city-day.

We define $Utilization_{ct}$ as the trip volume of a city-day divided by the total number of ofo bikes on the market at that city-day. Because bike investment is sparse, we aggregate the number of new bikes that ofo places in city c of month m as $Investment_{cm}$, thus the regressions on bike investment are organized by city-month instead of city-day.

To examine market expansion and market stealing, it is important to distinguish old and new users of ofo. 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 $\log(\#NewUsers_{ct})$ based on the total number of new users that register on ofo in that particular city-day. We also define $\%ActiveOld_{ct}$ as the percent of old users that have used any ofo bike in that city-day, and $\#Trips\_perOld_{ct}$ 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 1_{campus} equal to 1 if ofo restricts its operation within the college campus and 0 otherwise.

3.2 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 et al., 1989; Nankervis, 1999) and explored the impact of air pollution exposure on commuting modes (Hertel et al., 2008; 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.[21] 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 as the measure of air quality in a city-day.[22]

3.3 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[23] 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[24]: 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. All these attributes are summarized in Panel B of Table 1 and hereinafter referred to as city attributes.

3.4 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 the 2016 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 the dummy of post entry, 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

[21]Please see Vicente-Serrano, Saz-Sánchez and Cuadrat (2003) for detailed introduction of co-kriging interpolation.

[22]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.

[23]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.

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

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 1 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 bike-sharing firms 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. We do not report summary statistics on bike investment and bike utilization rate, because ofo designates them confidential.

4 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. In principle, we could include *Mobike First* cities in the control group as well, and transform the comparison into monopoly-vs-duopoly as in the theoretical model. However, we do not observe Mobike's data before ofo's entry into the *Mobike First* cities, nor can we use instrumental variable to address the endogeneity of ofo entry because we do not have data for the time that ofo had not entered. For this reason, our main specification focuses on *ofo First* and *ofo Alone* cities only, and we do not include *Mobike First* cities until robustness check.

Specifically, the baseline specification is:

$$Y_{ct} = \alpha_c + \gamma_t + \beta PostEntry_{ct} + X_{ct}'\pi + (S_c \times f(t))'\theta + \mu G_c \cdot t + \epsilon_{ct} \tag{1}$$

where Y_{ct} represents outcome variables such as $\log(Q_{ct})$, p_{ct}, $\%Free_{ct}$, and $Utilization_{ct}$ 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. As stated before, we only 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 ($f(t)$).[25] 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, LaLonde and Sullivan, 1993; Autor, 2003). Specifically, we use the following equation to test pre-treatment trends:

$$Y_{ct} = \alpha_c + \gamma_t + \sum_{k=2}^{21} \lambda_{-k} A_{ck} + \beta PostEntry_{ct} + X_{ct}^{'}\pi + (S_c \times f(t))^{'}\theta + \mu G_c \cdot t + \epsilon_{ct} \qquad (2)$$

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 $\{\lambda_{-k}\}_{k=2}^{k=21}$ 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.

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

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.

We apply the same specifications to bike investment, but at the city-month level instead of city-day. Accordingly, we redefine $PostEntry$ as % of days in month m that Mobike is present in city c. Weather and air quality variables are aggregated into monthly average, and the control of time fixed effects is monthly instead of daily.

5 Baseline Empirical Results

This section reports two sets of baseline results: the first set is on trip volume, revenue per ride, bike investment and bike utilization rate, including results with instrument and robustness checks. The second unpacks market stealing and market expanding effects by new and old users.

5.1 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 ($\%Free_{ct}$). For each dependent variable, we report the coefficient of $PostEntry_{ct}$ from a series of OLS regressions. The simplest one includes only city and time fixed effects (Column 1), the middle 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 A2, 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 $\{\lambda_{-k}\}_{k=2}^{k=21}$ from Equation (2), along with the estimated 95% confidence intervals. The first three panels of Figure 2 correspond to the three key dependent variables ($\log(Q_{ct})$, p_{ct}, and $\%Free_{ct}$). 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. We also 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. Results are reported in Figure 3, along with the estimated 95% confidence interval. The first 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.

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 $\%Free_{ct}$ (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.

Table 4 reports the OLS and IV results for the effect of entry on bike utilization rate and bike investment. The utilization regressions are at the city-day level, while the investment regressions are at the city-month level. For the OLS columns, we use the specification that includes the most extensive set of controls, as in Column 7 of Table 2. For the 2SLS columns with IV, we use the same instrument as before, except that the instrument is aggregated into a monthly average, i.e. % of days in month m that we predict Mobike to be present at city c. Both OLS and 2SLS results suggest that Mobike's entry have motivated ofo to place more bikes in the city and enjoy a significant boost in bike utilization.

We perform two robustness checks on the IV results in Appendix Table A3. 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 and Table4, except that the results on bike investment lose statistical significance at the 90% level if we assume the baseline hazard distribution is log-logistic or lognormal. One possible explanation is that investment is sparse and therefore sensitive to functional form. However, even in these marginal results, the coefficient of $Postentry_{ct}$ has the same sign and similar magnitude as in the baseline result.

Above all, we find that Mobike's entry has increased ofo's trip volume and revenue per trip, has encouraged the incumbent to place more new bikes on the market, and has helped ofo to enjoy a higher bike utilization rate. Robustness checks further suggest that these effects are unlikely driven by omitted variable bias or endogenous entry.

5.2 New and Old Users

If entry has led to an increase in price and trade volume at the same time, it suggests market expansion. However, since Mobike and ofo bikes are almost perfect substitutes at the same time and location, the entry could have a market stealing effect as well. We examine this possibility by separating new and old users within ofo. 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[26]. 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 old users, Columns 5-6 show that the average number of trips they take on ofo does not change significantly post Mobike entry. As shown in Columns 7-10, Mobike's entry has increased revenue per trip for both new and old users, at a similar magnitude. 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.

To summarize, Mobike's entry has created a net market expansion for ofo, despite some market stealing effects on old users. A potential explanation is that Mobike's marketing campaign, including the sight of orange bikes on the road, may have motivated more consumers to use bike-sharing. Both Mobike and ofo have issued coupons to lure new users, which could contribute to market expansion as well. However, the entry has a significant, *positive* effect on price, suggesting that the market expansion is not solely driven by the price competition between the two firms. What is the mechanism behind such price-boosting market expansion? Why does ofo find it worthwhile to put even more bikes on the market after Mobike has entered the market with many orange bikes? If bike investment is just another form of marketing, how could bike utilization rate *increase* post entry? And if the higher bike utilization rate implies that bike investment is effective in attracting more users, why didn't ofo make the extra bike investment until Mobike entered? We attempt to answer these questions in a theoretical model.

6 Theoretical Model

In this section, we develop a theoretical model to explain the empirical findings presented in the previous section. Our goal is to use the simplest model to explain how entry could generate higher price, higher trade volume, higher investment and higher utilization rate in a unified framework. It is not difficult to come up with a story to explain higher price and higher trade volume, or even higher investment. For example, Mobike's marketing campaign can be one of the potential explanations. But the real challenge is to explain why bike utilization rate is higher post entry. As detailed below, this requires a particular combination of consumer search, network effects and investment cost.

6.1 Model Setup

We consider a market consisting of measure 1 of consumers. Each consumer has to finish a trip with value normalized to 1. A consumer can use either bike-sharing or his own way to finish this trip (the outside good). If he uses his own way such as buying his own bike, driving his private car or calling a taxi, the private cost is distributed on the interval $[0, 1]$ according to the distribution function $F(c) = 1 - (1 - c)^\theta$ where $\theta > 0$ is common knowledge. Obviously,

[26]We are not allowed to report the sample mean because it is a business secret.

when $\theta = 1$, this distribution function is the same as the uniform distribution. When $\theta > 1$, the density function is decreasing in c; while when $\theta < 1$, the density function is increasing in c.

If a consumer uses bike-sharing, he pays a price for the service. However, the consumer may not find a bike nearby. We assume that the probability of finding a bike is determined by an aggregate matching function. In particular, if there are measure u of consumers searching for a bike and there are measure v of bikes in the market, then the total measure of matches is given by $m(u, v) = Av^{\alpha}u^{\beta}$ with $1 \geq \alpha, \beta > 0$. This Cobb-Douglass matching function is widely used in the literature. It is usually assumed that the matching function exhibits constant return to scale: $\alpha + \beta = 1$. But we do not impose this assumption here, and also allow decreasing or increasing return to scale $\alpha + \beta > 1$.[27] An increasing return matching technology could reflect the positive network effect in the bike-sharing industry: the consumers are actually transporting bikes for the firm when they are using the service of bike-sharing. Therefore, as more consumers are sharing bikes, it is more likely for other consumers to find a bike. In comparison, the multiplier A is another parameter that governs matching efficiency. Since A is a constant independent of the number of bikes (v) and the numbers of searching consumers (u), it captures network-neutral technology factors such as consumer awareness of bike-sharing and the quality of bike-sharing apps.

Under the above matching function, the probability for a consumer to find a bike is given by $q = \frac{m(u,v)}{u} = Av^{\alpha}u^{\beta-1}$. We assume that a consumer only search once. If he could not find a bike, then he receives an outside value of 0. This assumption reflects the fact the bike-sharing aims to solve the "last mile" problem for the consumer. If a consumer cannot find a bike for the trip, he usually will try other ways of transportation instead of keeping searching bikes.[28]

We will consider two cases. In the first case, there is one monopolist operating in the market; while in the second case, there are two duopoly firms competing in the market. In both cases, the sequence of move is that first, the firms set up the prices and total measures of bikes put into the market; and then the consumers then choose between bike-sharing and their own ways to finish the task. If a consumer chooses bike-sharing, he finds a bike with some probability. If he finds a bike, he will use it as long as the price charged is lower than 1. Otherwise, he will take the outside option.

In the first monopoly case, it is the monopoly firm who sets the price p and the total measure of bikes v put into the market. We assume that the investment cost function is $\psi(v) = \frac{1}{\gamma}\phi v^{\gamma}$ with $\gamma > 0$ capturing the concavity/convexity of the cost function. In the second duopoly case, we assume that firm 1 is the same as the monopoly firm while firm 2 is a new entrant with the same cost function $\psi(v)$.[29] In this case, the two duopoly firms simultaneously choose the measures of

[27]Such an assumption is also adapted in many other studies, e.g., Gan and Zhang (2006), Petrongolo and Pissarides (2006), Gavazza (2011), Bleakley and Lin (2012).

[28]In reality, a consumer that could not find a bike may still use alternative transportation to complete the trip, but there is a delay as compared to using the alternative transportation at the very beginning. For example, one may get to work on time if she calls a taxi at time t or searches for a bike at time t and rides the bike at time $t + 1$. However, she will be late for work if she calls a taxi at time $t + 1$. Our assumption on the value of ride sharing and alternative transportation (before search) is just a normalization. In the above example, it is equivalent to assuming the value of getting late to work is 0, the value of biking to work on time is 1, and the value of calling taxi to work on time is $1 - c$.

[29]In general, there is no need to assume that the firms have the same cost function. But the symmetric

bikes put into the market (v_1, v_2) and the prices (p_1, p_2). Given v_1 and v_2, the probability for a consumer to find a firm 1's bike is given by $q_1 = A(v_1+v_2)^{\alpha}u^{\beta-1}\frac{v_1}{v_1+v_2}$, where $A(v_1+v_2)^{\alpha}u^{\beta-1}$ is the probability of finding a bike and $\frac{v_1}{v_1+v_2}$ is the probability that this bike belongs to firm 1. The underlining assumption is that search is purely random and the consumers cannot target which bike to search. Similarly, the probability for a consumer to find a firm 2's bike is given by $q_2 = A(v_1+v_2)^{\alpha}u^{\beta-1}\frac{v_2}{v_1+v_2}$.

We aim to solve the subgame perfect equilibria of this model. In the first monopoly case, the key is to solve the monopoly price p^m and bike investment v^m in equilibrium, while in the second duopoly case, the key is to solve the price and investment of firm 1 p_1^d and v_1^d in equilibrium. The final step is to investigate the impact of firm 2's entry by comparing (p^m, v^m) with (p_1^d, v_1^d).

6.2 Equilibrium Analysis

6.2.1 Monopoly Case

We solve the subgame perfect equilibrium in the monopoly case by backward induction. Given p and v, a consumer will choose bike-sharing if

$$q^*(1-p) \geq 1-c,$$

or

$$c \geq 1 - q^*(1-p),$$

where q^* is the equilibrium probability that a consumer finds a bike. Hence, under the distributional assumption of c, the total measure of searching consumers is given by $u = (q^*(1-p))^{\theta}$. This together with the condition $q = \frac{m(u,v)}{u} = Av^{\alpha}u^{\beta-1}$ pins down q^*:

$$q^* = Av^{\alpha}((q^*(1-p))^{\theta})^{\beta-1},$$

which implies

$$q^* = A^{\frac{1}{1+\theta(1-\beta)}} v^{\frac{\alpha}{1+\theta(1-\beta)}} (1-p)^{\frac{\theta(\beta-1)}{1+\theta(1-\beta)}}.$$

When the monopolist sets the price and total measure of bikes, the objective is to maximize:

$$Av^{\alpha}(q^*(1-p))^{\theta\beta}p - \psi(v),$$

where $Av^{\alpha}(q^*(1-p))^{\theta\beta}$ is the total measure of matches and for each match, the monopolist receives a revenue of p. Plugging the expression of q^* into the above maximization problem yields

$$A^{\frac{1+\theta}{1+\theta(1-\beta)}} v^{\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}} (1-p)^{\frac{\theta\beta}{1+\theta(1-\beta)}} p - \psi(v).$$

Clearly, on the one hand, by putting more bikes into the market, the total revenue will increase by generating more matches, but the cost also increases. On the other hand, by setting a higher price, the revenue for each match will increase, but the total measure of matches also decreases as fewer consumers choose bike-sharing. Based on this tradeoff, the monopoly chooses

case is easy to solve theoretically. Moreover, in reality, the two leading bike-sharing firms, ofo and Mobike, are quite symmetric.

the amount of total investment and price, v^m and p^m are solved from the first order conditions. First of all, the monopoly price is given by

$$\frac{\theta\beta}{1+\theta(1-\beta)}p^m = 1 - p^m,$$

which implies that

$$p^m = \frac{1+\theta(1-\beta)}{1+\theta} < 1.$$

Second, when $\frac{\alpha(1+\theta)}{1+\theta(1-\beta)} < \gamma$, the optimization problem is concave in v, and hence the monopoly investment v^m satisfies

$$\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}A^{\frac{1+\theta}{1+\theta(1-\beta)}}v^{\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}-1}(1-p^m)^{\frac{\theta\beta}{1+\theta(1-\beta)}}p^m = \phi v^{\gamma-1},$$

which implies

$$v^m = \left[\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}\frac{A^{\frac{1+\theta}{1+\theta(1-\beta)}}(1-p^m)^{\frac{\theta\beta}{1+\theta(1-\beta)}}p^m}{\phi}\right]^{\frac{1}{\gamma-\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}}}.$$

The above result can be summarized by the following lemma:

Lemma 6.1 *Assume that* $\frac{\alpha(1+\theta)}{1+\theta(1-\beta)} < \gamma$. *Then, there exists a unique subgame perfect equilibrium in the monopoly case. In this equilibrium, the price is*

$$p^m = \frac{1+\theta(1-\beta)}{1+\theta} \tag{3}$$

and the investment is

$$v^m = \left[\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}\frac{A^{\frac{1+\theta}{1+\theta(1-\beta)}}(1-p^m)^{\frac{\theta\beta}{1+\theta(1-\beta)}}p^m}{\phi}\right]^{\frac{1}{\gamma-\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}}}. \tag{4}$$

Notice that the condition $\frac{\alpha(1+\theta)}{1+\theta(1-\beta)} < \gamma$ does not rule out the possibility of $\gamma < 1$. For example, if $\alpha + \beta = 1$, there exists $\gamma < 1$ satisfying the above condition. Moreover, for $\gamma \geq 1$, the above condition is satisfied when

$$\alpha + \beta < 1 + \frac{\gamma - \alpha + \theta(\gamma-1)(1-\beta)}{\theta}.$$

So there exists $\alpha + \beta > 1$ satisfying $\frac{\alpha(1+\theta)}{1+\theta(1-\beta)} < \gamma$.

6.2.2 Duopoly Case

Now we move to the duopoly case. In this case, we also first solve the consumer's problem of whether to choose bike-sharing or not. Denote q_1^* to be the equilibrium probability that a consumer finds bike 1, and q_2^* to be the equilibrium probability that a consumer finds bike 2. Recall that given v_1 and v_2, these two probabilities are given by $q_1 = A(v_1+v_2)^\alpha u^{\beta-1}\frac{v_1}{v_1+v_2}$ and $q_2 = A(v_1+v_2)^\alpha u^{\beta-1}\frac{v_2}{v_1+v_2}$.

A consumer will choose bike-sharing if

$$q_1^*(1-p_1) + q_2^*(1-p_2) \geq 1 - c,$$

or

$$c \geq 1 - q_1^*(1-p_1) - q_2^*(1-p_2).$$

Similar to the monopoly case, we can solve the equilibrium probabilities as:

$$q_1^* = A(v_1+v_2)^\alpha (q_1^*(1-p_1) + q_2^*(1-p_2))^{\theta(\beta-1)} \frac{v_1}{v_1+v_2}$$

and

$$q_2^* = A(v_1+v_2)^\alpha (q_1^*(1-p_1) + q_2^*(1-p_2))^{\theta(\beta-1)} \frac{v_2}{v_1+v_2}.$$

Firm 1's profit then can be written as:

$$A(v_1+v_2)^\alpha \frac{v_1}{v_1+v_2} (q_1^*(1-p_1) + q_2^*(1-p_2))^{\theta\beta} p_1 - \psi(v_1).$$

Compared with the profit in the monopoly case

$$Av^\alpha (q^*(1-p))^{\theta\beta} p - \psi(v),$$

we can observe two opposing effects. The first business stealing effect comes from the observation that $(v_1+v_2)^\alpha \frac{v_1}{v_1+v_2} < v_1^\alpha$ for any $v_2 > 0$. Basically, the operation of firm 2 decreases firm 1's total measure of matches for a given v_1, because some of the consumers are stolen by firm 2. The second market expansion effect comes from the term $q_1^*(1-p_1) + q_2^*(1-p_2)$. The existence of firm 2 attracts more consumers into the market, and hence increases the total measure of matches for firm 1.

We can first solve q_1^* and q_2^* as functions of v_1, v_2, p_1, p_2. Plugging these functions into the firms' profits yields:

$$\pi_1 = A^{\frac{1+\theta}{1+\theta(1-\beta)}} v_1^{\frac{1+\theta}{1+\theta(1-\beta)}} (v_1+v_2)^{-\frac{(1+\theta)(1-\alpha)}{1+\theta(1-\beta)}} \left[(1-p_1) + \frac{v_2}{v_1}(1-p_2)\right]^{\frac{\theta\beta}{1+\theta(1-\beta)}} p_1 - \psi(v_1),$$

and

$$\pi_2 = A^{\frac{1+\theta}{1+\theta(1-\beta)}} v_2^{\frac{1+\theta}{1+\theta(1-\beta)}} (v_1+v_2)^{-\frac{(1+\theta)(1-\alpha)}{1+\theta(1-\beta)}} \left[(1-p_2) + \frac{v_1}{v_2}(1-p_1)\right]^{\frac{\theta\beta}{1+\theta(1-\beta)}} p_2 - \psi(v_2).$$

The firms simultaneously choose (v_1^d, p_1^d) and (v_2^d, p_2^d) to maximize profits. We will focus on the symmetric equilibrium: $v_1^d = v_2^d$ and $p_1^d = p_2^d$.

First, the first order condition with respect to p_1 is:

$$\frac{\theta\beta}{1+\theta(1-\beta)} p_1 = (1-p_1) + \frac{v_2}{v_1}(1-p_2).$$

In the symmetric equilibrium, it is straightforward to derive

$$p_1^d = p_2^d = p^d = \frac{2}{2 + \frac{\theta\beta}{1+\theta(1-\beta)}}.$$

Second, we can take first order conditions with respect to v_1 in the firm 1's profit function. The equilibrium investments v_1^d and v_2^d can be solved by plugging p_1^d and p_2^d into the first order conditions. In the symmetric equilibrium, we obtain $v_1^d = v_2^d = v^d$, with v^d satisfying:

$$A^{\frac{1+\theta}{1+\theta(1-\beta)}} \left[\frac{1+\theta}{1+\theta(1-\beta)} - \frac{(1+\theta)(1-\alpha)}{2[1+\theta(1-\beta)]} - \frac{\theta\beta}{2[1+\theta(1-\beta)]}\right] \omega = \phi v^{\gamma - \frac{\alpha(1+\theta)}{1+\theta(1-\beta)}},$$

where

$$\omega = 2^{\frac{\theta\beta - (1+\theta)(1-\alpha)}{1+\theta(1-\beta)}} (1-p^d)^{\frac{\theta\beta}{1+\theta(1-\beta)}} p^d.$$

The above result can be summarized by the following lemma:

Lemma 6.2 *Assume that* $\frac{\alpha(1+\theta)}{1+\theta(1-\beta)} < \gamma$. *Then, there exists a unique symmetric subgame perfect equilibrium in the duopoly case. In this equilibrium, both firms set prices to be*

$$p^d = \frac{2}{2 + \frac{\theta\beta}{1+\theta(1-\beta)}} \tag{5}$$

and investments to be

$$v^d = \left[A^{\frac{1+\theta}{1+\theta(1-\beta)}}\left[\frac{1+\theta}{1+\theta(1-\beta)} - \frac{(1+\theta)(1-\alpha)}{2[1+\theta(1-\beta)]} - \frac{\theta\beta}{2[1+\theta(1-\beta)]}\right]\frac{\omega}{\phi}\right]^{\frac{1}{\gamma - \frac{\alpha(1+\theta)}{1+\theta(1-\beta)}}}. \tag{6}$$

6.3 Equilibrium Comparison

In this section, we compare the unique subgame perfect equilibrium in the monopoly case with the unique symmetric subgame perfect equilibrium in the duopoly case. We aim to compare prices, investments, trade volumes, and utilization rates in different cases. Trade volume is defined as the total measure of successful matches for firm 1. In the monopoly case, it is $TV^m = m(u^m, v^m)$, while in the duopoly case, it is $TV^d = m(u^d, v_1^d + v_2^d)\frac{v_1^d}{v_1^d+v_2^d}$. Utilization rate is defined as the average number of match per bike. It is $r^m = \frac{TV^m}{v^m}$ in the monopoly case, and $r^d = \frac{TV^d}{v_1^d}$ in the duopoly case.

Our first observation is the following:

Proposition 1 *In equilibrium, it is always the case that* $p^d > p^m$.

Proof From equations (3) and (5), we obtain

$$p^d = \frac{2}{2 + \frac{\theta\beta}{1+\theta(1-\beta)}} > p^m = \frac{1}{1 + \frac{\theta\beta}{1+\theta(1-\beta)}}.$$

□

The above proposition claims that the duopoly price is always higher than the monopoly price. This result is very intuitive. When there is only one firm in the market, raising price will reduce the number of searchers and this negative impact is fully incorporated in the monopolist's pricing decision. If the prevailing price is already optimal for the monopolist, the marginal benefit of the price hike (higher profit per match) is equal to the marginal cost of the hike (fewer consumers searching). In contrast, if the firm faces competition in duopoly, its price hike will affect the number of searchers as before but this hurts both firms. Since each firm does not incorporate the negative externality its price hike imposes on the competitor, competition reduces the marginal cost of price hike, while the marginal benefit remains the same. In other words, competition blunts the negative impact of price hike for each firm's *individual* demand. This is equivalent to reducing the demand elasticity facing each firm, creating an extra incentive to raise price. For this reason, the model shows that price increases when the market moves from monopoly to duopoly, regardless of the shape of the private cost distribution or the efficiency of the matching technology.

Note that we are not the first one finding price increase with competition. In a model of price search, Stahl (1989) shows that the equilibrium price approaches monopoly price when the number of firms increase, because the probability of finding the lowest price decreases exponentially with the number of firms. In a market where each seller faces loyal and switching consumers, Rosenthal (1980) shows that competition may reduce each seller's share of the switching group and therefore incentivize it to charge higher price among the remaining loyal consumers. Allowing product differentiation, Chen and Riordan (2008) show that price may increase from monopoly to duopoly, if consumer preferences for the two products are sufficiently diverse and negatively correlated. Our model differs from all of them, because we assume consumers only search once (per episode) and therefore price shopping does not occur within the bike search.

Our next results focus on the comparison of the utilization rates r^d and r^m. By definition, we obtain

$$r^m = \frac{A^{\frac{1+\theta}{1+\theta(1-\beta)}}(v^m)^{\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}}(1-p^m)^{\frac{\theta\beta}{1+\theta(1-\beta)}}}{v^m}.$$

And the first order condition with respect to v^m implies that $\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}r^m p^m = \phi(v^m)^{\gamma-1}$, which implies

$$r^m = \frac{\phi(v^m)^{\gamma-1}}{\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}p^m}. \tag{7}$$

Similarly, we derive

$$r^d = \frac{\phi(v^d)^{\gamma-1}}{\left[\frac{1+\theta}{1+\theta(1-\beta)} - \frac{(1+\theta)(1-\alpha)}{2[1+\theta(1-\beta)]} - \frac{\theta\beta}{2[1+\theta(1-\beta)]}\right]p^d}. \tag{8}$$

The above equations implies that the comparison of r^d and r^m does not depend on A. Hence, we can even allow A to increase in the duopoly market and get the same result. The increase of A could occur if the entry of the second firm makes more consumers aware of bike-sharing or leads to a higher consumption value to the consumers (e.g., Mobike's marketing campaign).[30] Although the increase in A will lead to a higher investment, it cannot lead to a higher utilization rate. To obtain higher utilization rate in equilibrium, we need the following condition:

Proposition 2 *It is possible to have both higher investment $v^d > v^m$ and higher utilization rate $r^d > r^m$ in equilibrium only when $\gamma > 1$. And when $\gamma > 1$, $r^d > r^m$ is satisfied only if $v^d > v^m$.*

Proof From equations 7 and 8, we obtain $r^d > r^m$ if

$$\frac{p^d}{p^m} < (\frac{v^d}{v^m})^{\gamma-1}\frac{\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}}{\frac{1+\theta}{1+\theta(1-\beta)} - \frac{(1+\theta)(1-\alpha)}{2[1+\theta(1-\beta)]} - \frac{\theta\beta}{2[1+\theta(1-\beta)]}}.$$

Rearranging terms implies that

$$(\frac{v^d}{v^m})^{\gamma-1} > \frac{\alpha(1+\theta)+(1+\theta)-\theta\beta}{\alpha[2(1+\theta)-\theta\beta]} > 1.$$

Therefore, if $v^d > v^m$, the above inequality can be satisfied only when $\gamma > 1$. Moreover, when $\gamma > 1$, in order to get $r^d > r^m$, we must have $v^d > v^m$. □

The above proposition implies that higher investment and higher utilization rate can both exist only when the investment cost function is convex. So we will make the assumption that $\gamma > 1$ in the subsequent analysis. Since a higher investment is a prerequisite for a higher utilization rate, our next proposition investigates when the equilibrium investments satisfy $v^d > v^m$.

[30] For example, consider the case that the total measure of consumers increase from 1 to $\eta > 1$ due to the fact that more consumder are aware of bike-sharing. This is equivalent to an increase in the matching efficiency increases from A to $A\eta^\beta > A$.

Proposition 3 *The equilibrium investments satisfy $v^d > v^m$ if*

$$2^{\frac{\theta\beta-(1+\theta)(1-\alpha)}{1+\theta(1-\beta)}} > \frac{2\alpha(1+\theta)}{\alpha(1+\theta)+1+\theta(1-\beta)} \frac{(1-p^m)^{\frac{\theta\beta}{1+\theta(1-\beta)}} p^m}{(1-p^d)^{\frac{\theta\beta}{1+\theta(1-\beta)}} p^d}. \tag{9}$$

Moreover, when $\theta\beta-(1+\theta)(1-\alpha) \leq 0$, we must have $r^d < r^m$.

Proof Condition(9) directly comes from equation (4) and (6). $v^d > v^m$ if

$$\left[\frac{1+\theta}{1+\theta(1-\beta)} - \frac{(1+\theta)(1-\alpha)}{2[1+\theta(1-\beta)]} - \frac{\theta\beta}{2[1+\theta(1-\beta)]}\right]\omega > \frac{\alpha(1+\theta)}{1+\theta(1-\beta)}(1-p^m)^{\frac{\theta\beta}{1+\theta(1-\beta)}} p^m,$$

which implies condition (9). From equations 7 and 8, we know that the comparison of r^d and r^m depends on the comparison of $(\frac{v^d}{v^m})^{\gamma-1}$ and

$$\Omega \triangleq \frac{p^d}{p^m} \frac{\frac{1+\theta}{1+\theta(1-\beta)} - \frac{(1+\theta)(1-\alpha)}{2[1+\theta(1-\beta)]} - \frac{\theta\beta}{2[1+\theta(1-\beta)]}}{\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}} = \frac{\alpha(1+\theta)+(1+\theta)-\theta\beta}{\alpha[2(1+\theta)-\theta\beta]} > 1.$$

From equation (4) and (6), we derive

$$(\frac{v^d}{v^m})^{\gamma-1} = \left[2^{\frac{\theta\beta-(1+\theta)(1-\alpha)}{1+\theta(1-\beta)}} (\frac{1-p^d}{1-p^m})^{\frac{\theta\beta}{1+\theta(1-\beta)}} \Omega\right]^{\frac{\gamma-1}{\gamma-\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}}}.$$

Therefore, the comparison of $(\frac{v^d}{v^m})^{\gamma-1}$ and Ω is equivalent to the comparison of

$$\Gamma \triangleq \left[2^{\frac{\theta\beta-(1+\theta)(1-\alpha)}{1+\theta(1-\beta)}} (\frac{1-p^d}{1-p^m})^{\frac{\theta\beta}{1+\theta(1-\beta)}}\right]^{\frac{\gamma-1}{\gamma-\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}}}$$

and

$$\Omega^{1-\frac{\gamma-1}{\gamma-\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}}}.$$

Notice that whenever $\theta\beta-(1+\theta)(1-\alpha) \leq 0$, we must have

$$2^{\frac{\theta\beta-(1+\theta)(1-\alpha)}{1+\theta(1-\beta)}} \leq 1$$

and

$$\frac{\alpha(1+\theta)}{1+\theta(1-\beta)} = 1 + \frac{\theta\beta-(1+\theta)(1-\alpha)}{1+\theta(1-\beta)} \leq 1.$$

So it is straightforward to see that $\Gamma < 1$ since we have $1-p^d < 1-p^m$ from Proposition 1, and

$$\Omega^{1-\frac{\gamma-1}{\gamma-\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}}} \geq 1$$

since $\Omega > 1$ and $1-\frac{\gamma-1}{\gamma-\frac{\alpha(1+\theta)}{1+\theta(1-\beta)}} \geq 0$. As a result, whenever $\theta\beta-(1+\theta)(1-\alpha) \leq 0$, we should get $(\frac{v^d}{v^m})^{\gamma-1} < \Omega$, which implies that $r^d < r^m$. □

Condition (9) in the above proposition gives the condition under which the equilibrium investments satisfy $v^d > v^m$. Intuitively, the term $2^{\frac{\theta\beta-(1+\theta)(1-\alpha)}{1+\theta(1-\beta)}}$ in condition (9) measures the joint effects of the market expansion and business stealing effects. From the expressions of the firms' profit functions, it is easy to see that in the symmetric equilibrium, the business stealing effect is proportional to $2^{-\frac{(1+\theta)(1-\alpha)}{1+\theta(1-\beta)}}$ while the market expansion effect is proportional to $2^{\frac{\theta\beta}{1+\theta(1-\beta)}}$. So the term $2^{\frac{\theta\beta-(1+\theta)(1-\alpha)}{1+\theta(1-\beta)}}$ measures the joint effect. And this term becomes larger as the market expansion effect becomes stronger than the business stealing effect. The second part of Proposition 3 implies that when the business stealing effect dominates the market expansion effect ($\frac{\theta\beta-(1+\theta)(1-\alpha)}{1+\theta(1-\beta)} \leq 0$), it is impossible to achieve a higher utilization rate in the duopoly case. Therefore, we need to further consider the case of a sufficiently degree of increasing return to scale $\alpha+\beta > 1+\frac{1-\alpha}{\theta}$ to satisfy $\theta\beta-(1+\theta)(1-\alpha) > 0$. Notice that this condition rules out the case of constant return to scale: $\alpha+\beta = 1$. In other words, we should always get a lower utilization rate under constant return to scale.

Our last observation claims that it is possible to generate both $v^d > v^m$ and $r^d > r^m$ when both $\alpha+\beta$ and θ are sufficiently large.

Proposition 4 *Suppose that both α and β go to one, and θ goes to infinity. Then we must have both $v^d > v^m$ and $r^d > r^m$.*

Proof Consider the extreme case of $\alpha = \beta = 1$. In this case, the left-hand side of condition (9) is 2^θ while the right-hand side is $\frac{2(1+\theta)}{(1+\theta)+1} \frac{(1-p^m)^{\frac{\theta\beta}{1+\theta(1-\beta)}} p^m}{(1-p^d)^{\frac{\theta\beta}{1+\theta(1-\beta)}} p^d}$. Clearly, when θ goes to infinity, the left-hand side goes to infinity as well while the right-hand side stays bounded. As a result, condition (9) is satisfied. Moreover, from the proof of Proposition 2, $r^d > r^m$ if $(\frac{v^d}{v^m})^{\gamma-1} > \frac{\alpha(1+\theta)+(1+\theta)-\theta\beta}{\alpha[2(1+\theta)-\theta\beta]}$. Notice that the right-hand-side of the above inequality is one when $\alpha = 1$, while the left-hand-side goes to infinity as θ goes to infinity. Therefore, we must have both $v^d > v^m$ and $r^d > r^m$.$\square$

Figure 4 illustrates how the parameter values α and β affect the comparison of r^d and r^m when we fix $\theta = \gamma = 2$. We can see several interesting features from Figure 4. First of all, the dashed line in Figure 4 is an upper bound on the value of β. This comes from the requirement $\frac{\alpha(1+\theta)}{1+\theta(1-\beta)} < \gamma$. Second, the region between the solid line and the dashed line represents the parameter values of α and β under which we have $r^d > r^m$. From Proposition 2, in this region we have $v^d > v^m$, which also implies $TV^d = v^d r^d > TV^m = v^m r^m$. Notice that there is a sufficient degree of increasing return to scale in this region: $\alpha+\beta > 1$. In particular, this region exists only when $\alpha > 0.5$. This is because from Proposition 3, we require $\theta\beta > (1+\theta)(1-\alpha)$. So α cannot be too low such that the above inequality is satisfied for some $\beta \leq 1$. Finally, as α goes to one, $\alpha+\beta$ on the solid cutoff line decreases to be lower than 1.2, which implies that a small degree of increasing return to scale is enough to generate $v^d > v^m$.

Although it is difficult to conduct theoretical comparative static analyses, Figures 5 and 6 numerically investigate how the change in parameters affects the equilibrium outcomes in monopoly and duopoly cases. Figure 5 compares the equilibrium outcomes in monopoly and duopoly cases when we change parameter $z = \alpha+\beta$ while keeping the ratio $\frac{\alpha}{\beta}$ to be a constant. So in this numerical exercise, α and β changes with z at the same rate. Consistent with Proposition 1, we always have $p^d > p^m$ as seen in Figure 5a. Figure 5b plots how v^m and v^d change with z, and shows that $v^m > v^d$ when z is low and vice versa. This is consistent with our discussion of condition (9). Figures 5c and 5d show that both trade volumes and utilization rates follow similar patterns: they are higher in the duopoly case only when z is sufficiently large. This is also consistent with Figure 4: we need the degree of increasing return to scale to be sufficiently large to guarantee $r^d > r^m$, $v^d > v^m$ and $TV^d > TV^m$.

Figure 6 compares the equilibrium outcomes in monopoly and duopoly cases when we change the distribution parameter θ. The findings are similar to the ones in Figure 5. In particular, we find that when we fix other parameters, it is also possible to have $r^d > r^m$, $v^d > v^m$ and $TV^d > TV^m$ when θ is sufficiently large. Moreover, although sufficiently high θ and sufficiently high z are both consistent with our baseline results, an increase in θ always decreases bike investment in the monopoly case while an increase in z always increases bike investment in the monopoly case. This is very intuitive. An increase in θ implies a smaller measure of consumers with high cost c and hence makes the market unattractive. A monopoly firm will optimally respond by lowering its bike investment. On the contrary, an increase in z implies a larger degree of increasing return to scale and hence makes the market more unattractive. A monopoly firm will optimally respond by increasing its bike investment.

To summarize, we find that it is possible that investment, trade volume and utilization rate all increase in the duopoly case when θ or z are sufficiently large. A high z can be interpreted as a large enough increasing return to scale in the matching function. A high θ can be interpreted as the density of the private cost of the outside good (c) decreasing at a sufficiently high speed as c increases. In both situations, the market expansion effect is sufficiently large to dominate the business stealing effect, which implies the following testable implications:

1. After the entrant's entry, the incumbent's price goes up;
2. After the entrant's entry, some of the incumbent's old customers are stolen by the entrant while the incumbent can get new customers due to market expansion;
3. After the entrant's entry, the incumbent's bike investment may increase when θ is sufficiently high or $z = \alpha + \beta$ is sufficiently high;
4. After the entrant's entry, both the incumbent's trade volume and utilization rate can also go up when θ is sufficiently high or $z = \alpha + \beta$ is sufficiently high.

6.4 Discussion of the model

The model highlights a few important features of bike-sharing: consumer search, matching technology, investment cost and the outside good. We now discuss each respectively.

6.4.1 Consumer search

Using bike-sharing requires the consumer to initiate a bike search. Assuming the search is random and once-for-all, we downplay competition *within* the search process. As a result, competition only affects the search result through bike investment (which affects the matching probability), and the number of consumers that decide to search (which depends on the expected matching rate, consumer's private cost of using the outside good, and the price of each bike-sharing firm). Because of these assumptions, competition tends to reduce the demand elasticity facing *each* firm, which naturally leads to our Proposition 1: entry increases the equilibrium price.

The assumption that search is once-for-all might seem strong at the first glance. It nonetheless reflects an important feature at the current stage of bike sharing: the scarcity margin is more important than price margin. That is to say, most consumers use bike-sharing for commute (rather than recreation) and they care more about finding a bike than the relatively small price differential. Therefore, they will not continue searching as in standard search models. Our model remains appropriate as long as there is a keen concern of not finding a bike in time. It is also possible to develop a more complete model incorporating search cost, but we choose not to do so for two reasons. On the one hand, the results in such a full-fledged model is likely similar to those in the current model.[31] On the other hand, a very detailed model of consumer search might blur the main purpose of our model, which is to explain the bigger puzzle in higher utilization rate post entry. We do not even need a complicated search model to explain why price and investment increase after entry (e.g. Mobike's marketing campaign alone could achieve it), but the real challenge is explaining the increase in utilization rate while keeping the changes in price and investment consistent with the facts. For this purpose, we believe our current model of consumer search provides the simplest way to illustrate the main driving force behind the data.

6.4.2 Network effects in the matching technology versus investment cost

The second key feature is network effects. Given a fixed supply of bikes, the more consumers search for a bike, the less likely each consumer gets matched to a bike. This is a negative network effect of congestion. However, if bikes and searchers increase proportionally, the matching rate will increase or decrease depending on the matching technology. When the matching technology has increasing return to scale ($z = \alpha + \beta > 1$), two million consumers searching for $2N$ bikes will have a higher matching rate than the first million consumers searching for N bikes, and the improved matching efficiency will encourage more consumers to join the search. This creates a positive network effect. Furthermore, because matching rate improves by scale, each bike has a higher rate of utilization as the numbers of consumers and bikes increase. If investment cost per bike does not increase as fast as the utilization rate, firm(s) has incentive to invest in more bikes. This creates a second positive feedback in the system, similar to what we have seen on two-sided platforms (e.g. more sellers attract buyers, and more buyers attracts sellers).

If the network effect is positive, it could have an important impact on market structure. For instance, if the positive network effects are always large enough to swamp any increase in investment cost, the market is winner-takes-all, because the monopolist has incentive to invest in infinite bikes, leaving no room for other firms to enter. This possibility is ruled out in our model when we impose the assumption $\frac{\alpha(1+\theta)}{1+\theta(1-\beta)} < \gamma$. Under this assumption, the cost of investment will eventually dominate the expanding incentive driven by the positive network effects.

When the positive network effects are sufficiently large but not too large to trigger winner-takes-all, each duopolist will engage in more bike investment than the monopolist. This is because each duopolist free rides on the competitor's investment. Every bike invested by firm 2 costs nothing to firm 1, but expands the overall market and benefits firm 1. In this sense, it is more cost-efficient than firm 1's own investment. While free-riding incentive often exists in duopoly, it is magnified when the market enjoys large, positive network effects. With such

[31] For example, due to positive search cost, the famous Diamond paradox claims that firms will charge monopoly price, which is quite close to the equilibrium price in our current model.

network effects, competitor's investment will make one's own investment more efficient in persuading more consumers to search and improving the matching rate. The monopolist alone cannot achieve the same efficiency, because the monopolist must invest at its own cost to get to the same scale and its cost function might be too convex to justify the investment. In that situation, we believe there is no first mover or second mover advantage, though the model has not addressed sequential entry explicitly. Since monopoly profit is greater than zero and duopoly profit is greater than monopoly profit, entry is always preferred to no entry.

In comparison, when the positive network effects are relatively small, the model predicts that each duopolist invests less than the monopolist. If all past investments are sunk, the monopolist may find it over-invested when the second firm enters. As a result, the entrant enjoys extra free ride from the monopolist's over-investment, which implies a first-mover disadvantage and a second-mover advantage. It is difficult to test whether this strategic concern applies to our data, but we have addressed the potential endogeneity of Mobike entry in the empirical analysis. The fact that we find ofo invests *more* after Mobike's entry suggests that this regrettable situation (for the monopolist) is unlikely in our setting.

6.4.3 Competition with the outside good

The extent to which competition expands the market also depends on the outside good, namely the distribution of consumers' private cost of using the outside good (c). The higher the private cost, the more attractive is bike-sharing relative to the outside good (private bike, private car, taxi, bus, etc.). Since the monopolist must first attract consumers of higher private cost, returns from the next batch of bike investment (which increases matching probability) will depend on the private cost of the next group of consumers. When the private cost distribution has a declining density ($\theta > 1$), the same improvement in matching probability will persuade more consumers to search for a bike, and this effect increases with the number of consumers already in bike-sharing. It amounts to a market expanding effect, which speeds up the incentive in bike investment as long as the extra return in such investment exceeds the extra cost of investment.

To summarize, the model points out three potential explanations for the market expansion effects shown in Section 5: (1) an increasing-return matching technology that generates large enough positive network effects ($z = \alpha + \beta > 1$) but not large enough to dominate convex investment cost; (2) a declining density distribution of private cost that makes it easier to persuade the next batch of users to join bike-sharing ($\theta > 1$); and (3) an awareness marketing campaign that enhances the multiplier in the matching technology (A) while keeping the same return-to-scale. The last explanation is easy to rule out because in our model the utilization rate is independent of A hence an entry-motivated increase in A could lead to growth in bike investment but cannot explain the increase in bike utilization rate. The other two explanations works together to explain higher investment and higher utilization rate, if their combination satisfies the conditions laid out in the model.

Is there a way to further distinguish which of the two remaining explanations is the main driver of market expansion? We note that the two key parameters, z and θ, give us different comparative statistics. As shown in Figure 6 and Figure 5, the monopolist will invest more as z increases but invests less as θ increases. This is because higher θ means a steeper density function of private cost hence for a given threshold of private cost (above which consumers will search for bike) the monopolist can only attract a smaller fraction of the population. This reduces the investment incentive in monopoly. On the contrary, as z increases, the matching technology becomes more efficient, thus the monopolist can attract a higher fraction of consumers by investing more. This will increase the monopolist's investment incentive.

The differential comparative statistics offers an opportunity to test whether the observed variations in market expansion is mainly driven by variations in z or in θ. In particular, some ofo-first cities had more bikes on the road than other ofo-first cities, before Mobike entered. Assuming these cities are comparable in everything else, if the difference in θ drives this difference, the cities with a higher pre-entry ofo investment should have a lower θ, which implies that they should experience smaller market expansion effects upon Mobike's entry. On the contrary, if z drives the initial ofo investment, the first set of cities should have a higher zs, and therefore greater market expanding effects post entry. We will test this empirically.

7 Further Data Analysis Motivated by the Model

This section presents three sets of data analyses in light of the model.

First, the model suggests that market expands *because of* the competition. In particular, the entrant's bike investment enhances the matching rate and encourages more consumers to search for a generic bike once they start to search. This mechanism is most evident when ofo and Mobike bikes mingle together. Though we do not know exactly where Mobike puts its bikes within a city, the competition intensity between ofo and Mobike varies within *ofo-First* cities, because ofo had experienced a "campus period" when it restricted its operation within a college campus while Mobike always regards the whole city as the target market. Therefore, according to the model, the competition effects should be weaker if ofo was still in the "campus period" when Mobike entered the city. To test this prediction, we decompose $PostEntry_{ct}$ into $1_{campus} \cdot PostEntry_{ct}$ and $(1 - 1_{campus}) \cdot PostEntry_{ct}$, and estimate their coefficients separately. Table 6 shows the OLS and IV results on $\log(Q_{ct})$, p_{ct} and $\%Free_{ct}$. Compared with the baseline results, 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.

Our second set of analysis follows the comparative statistics implied by variations in z and θ. Greater market expansion effects could be driven by a higher θ, but higher θ implies greater reluctance to invest before the entry. This implies that we should observe greater market expansion in the *ofo-First* cities that had less bike investment before entry. In contrast, greater market expansion effects could be driven by a higher z and a higher z implies more investment before entry. This contrast leads us to include an interaction of pre-entry investment and the post entry dummy on the right hand side. Note that pre-entry investment only describes the cross-sectional variations across *ofo First* cities. To the extent that z and θ depends on pre-determined city attributes, pre-entry investment alone is absorbed by city fixed effects. As shown in Table 7, the positive price effect of entry is stronger when there had been more pre-entry investment in a city. The trade volume effect of entry goes the same direction, but the coefficient is only marginally significant. As articulated in the model, we need z and θ to work together to satisfy the conditions for higher investment and higher utilization rate post entry. Table 7 does not reject this interdependence. Rather, it shows that the differential market expansion effects (in price and trade volume) is more likely due to variations in the extent of increasing return of matching (z) rather than variations in the distribution of consumers' private cost (θ).

The third analysis explores detailed geographic information in our dataset. Although our model abstracts away from geography within a city, one can imagine that residents at different parts of the city have different costs of using alternative transportation. For example, living on a street right next to a bus or subway station may make bike-sharing unnecessary. In contrast, living one kilometer away from the station could make bike-sharing much more attractive. Similarly, people working at the city-center, where it is easy to call a taxi or walk to a bus station, could be more reluctant to use bike-sharing than those working at a less convenient location. These variations give us a geographic interpretation of the distribution of the private cost c. As shown in the model, the monopolist first attracts those with the highest c and stops at a threshold c that makes the marginal consumer indifferent between searching for a bike and taking alternative transportation. If the monopolist knows where the high-c people are, it will place bikes near them. When the entrant enters the market, it will place its bikes near the next batch of consumers that have the highest c among those that have not chosen bike-sharing yet. To the extent that c might vary across people even if they live at the same location (for example some residents in an apartment may have private cars while others do not), the entrant could also place some bikes close to where the incumbent's bikes have occupied before and enhance the probability of matching in the nearby area. Either way, entry could persuade people of lower c to join bike-sharing and these people may use either brand of bike depending on which is handy when they search. If they ride ofo bikes, these bikes will be available for the next rider at the destination. As a result, market expansion could geographically manifest in a network expansion of ofo bikes.

We use three variables to describe the geographic network of ofo bikes: $\#Grids_{ct}$ describes the total number of unique grids covered by (the origin) of any ofo bike trips in a city-day; $Gini_{ct}$ describes how evenly distributed the origin of ofo bike trips is in the city-day; and a second version of $Gini_{ct}$ is conditional on 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 first two variables, we use the same DID specification as Equation (1).

Table 8 reports the OLS and IV results for these three variables. 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. The network is also more evenly distributed within the grids that ofo has covered before the entry. Combined with other evidence, the geographic expansion confirms that Mobike's entry attracts more users, enhances the reach of the ofo bike network, and boosts the average bike utilization rate.

8 Conclusion

Using proprietary data from a major bike-sharing firm, we document how entry affects the market performance of the incumbent. Since bike-sharing features positive network effects but the market is city-specific, we have a rare opportunity to study competition with network effects. We find that the entrant expands the market, resulting in higher trade volume, higher price, higher bike investment, 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 in part justifies the entry decision.

Our findings challenge the classical "winner-takes-all" concern in a 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. In our context, entry creates positive spillovers on the incumbent, which helps the incumbent to better explore the positive network effects. This occurs for a couple of reasons: first, multi-homing consumers search for a generic bike, implying that one firm can motivate consumers to search but there is no guarantee that the search would lead to its own bike rather than the competitor's bike. Second, the cost of investing and maintaining a diverse network of bikes is convex, thus it is more cost-efficient to free ride on the competitor's investment than making all the investment on its own. In our model, the spillovers are mutual, which explains why the entrant finds it worthwhile to enter even if the incumbent has already operated in a market with positive network effects, and why the incumbent is willing to share the (expanded) market with the entrant. Furthermore, our work highlights the importance of the outside good in a network market. Since entry could generate market expansion, competition with the outside good is as important as within-market competition, for at least bike-sharing. These findings could have significant implications for policy makers, as they conduct merger reviews or consider entry policies in a market with positive network effects.

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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	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Panel A City-Day Level Variables								
Sample Size	19631		13560		2633		3438	
Dummy for Post-Entry Status	0.616	0.486	0.639	0.48	0	0	1	0
Log (Trip Volume)	NA	2.124	NA	2.074	NA	1.386	NA	1.968
Average Revenue per Trip (RMB)	NA	0.207	NA	0.195	NA	0.229	NA	0.23
Percent of Free Trips (0-100)	NA	22.774	NA	23.716	NA	19.869	NA	20.276
Log (# of New Users)	NA	1.997	NA	1.974	NA	1.789	NA	1.648
Percent of Active Old Users	NA	13.668	NA	12.955	NA	16.471	NA	13.905
Average # of Trips per Old User	NA	0.388	NA	0.41	NA	0.351	NA	0.305
Log (# of Grids Covered by ofo)	5.469	1.21	5.539	1.265	4.709	0.862	5.777	0.959
Gini Coverage Index	0.864	0.09	0.882	0.086	0.788	0.092	0.852	0.067
Dummy for ofo Operation within Campus	0.163	0.369	0.22	0.415	0	0	0.061	0.24
Speed of Wind	2.677	0.883	2.661	0.901	2.679	0.861	2.74	0.823
Temperature	21.276	7.69	20.167	8.164	23.515	5.708	23.935	5.838
Precipitation	0.171	0.486	0.152	0.455	0.208	0.519	0.219	0.567
Relative Humility	73.831	16.31	72.662	16.786	74.259	16.763	78.115	12.99
AQI (Air Quality Index)	84.196	47.688	87.795	51.345	77.956	37.909	74.782	36.304
Panel B City Level Variables								
Sample Size	104		59		23		22	
Logarithmic Population (10,000)	6.101	0.632	6.196	0.558	5.814	0.818	6.143	0.535
GDP per Capita (10,000 RMB)	6.699	3.356	6.94	3.254	5.981	3.118	6.804	3.885
Number of Taxis	5076.103	6903.375	6351.334	6265.299	2040.783	1951.386	4829.455	10325.5
Number of Buses	3029.936	4474.697	3774.835	4871.471	942.235	730.883	3214.847	5073.091
Road Surface (10,000 Square Meters)	3281.349	3189.038	3951.99	3476.455	1627.596	1267.843	3211.735	3248.628
Number of Mobile Phone Users (10,000)	688.125	585.702	806.576	603.333	366.957	217.516	706.227	689.128
Number of Internet Households (10,000)	142.173	159.78	170.593	184.558	70.609	44.449	140.773	145.571
Average Gradient (‰)	458.766	570.863	447.244	547.904	596.891	745.032	345.262	391.15

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	0.12	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	0.14	0.073	0.07	0.14	0.074	0.07
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 Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Calendar Date Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Relative Day Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Duopoly Group Trend					YES	YES	YES
Linear Time Trend		YES			YES		
City AttributesDate Fixed Effects			YES			YES	
City AttributesDay Fixed Effects				YES			YES
Number of Clusters	82	82	82	82	82	82	82
Number of 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 ofos 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 the linear time trend specific to the *ofo First* cites. The specification of Column 7 is taken as benchmark settings in the following analyses. Standard errors are in parentheses and 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 Fixed Effects	YES	YES	YES	YES
Calendar Date Fixed Effects	YES	YES	YES	YES
Relative Day Fixed Effects	YES	YES	YES	YES
Duopoly Group Trend	YES	YES	YES	YES
City AttributesDay Fixed Effects	YES	YES	YES	YES
Kleibergen-Paap F Test	8000.251	/	/	/
Number of Clusters	82	82	82	82
Number of 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 A3. Standard errors are in parentheses and clustered at the city level. *** Denotes significance at the 1%, ** 5%, and * 10% level.

Table 4: Competition Effects on Bike Utilization Rate and Bike Investment

	(1)	(2)	(3)	(4)
Dependent Variables	*Log (Bike Utilization Rate)*		*Bike Investment*	
Models	*OLS*	*2SLS*	*OLS*	*2SLS*
PostEntry	0.392**	0.457**		
	(0.185)	(0.198)		
Percent of Duopoly Days (1-100)			57.526**	58.384**
			(27.789)	(27.391)
Dummy for (Percent of) Operation within Campus	YES	YES	YES	YES
Weather Condition	YES	YES	YES	YES
Air Quality	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES
Calendar Date(Month) Fixed Effects	YES	YES	YES	YES
Relative Day(Month) Fixed Effects	YES	YES	YES	YES
Duopoly Group Trend	YES	YES	YES	YES
City AttributesDay(Month) Fixed Effects	YES	YES	YES	YES
Within Adjusted R^2	0.092	/	0.016	/
Number of Clusters	79	79	79	79
Number of Observations	15770	15770	616	616

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. Because of the lumpiness bike investment, we aggregate the investment data to month level, redefine *PostEntry* as the percent of days that Mobike operates in the city c and month m, reconstruct all weather and air variables as monthly average, and control for monthly time fixed effects instead of daily fixed effects. Standard errors are in parentheses and 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)	(7)	(8)	(9)	(10)
Dependent Variables	*Log (# of New Users)*		*Percent of Active Old Users*		*Average # of Trips per Old User*		*Average Revenue per Trip (New Users)*		*Average Revenue per Trip (Old Users)*	
Models	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*
PostEntry	0.652***	0.735***	-4.126***	-4.353***	-0.005	-0.003	0.029***	0.030***	0.032***	0.034***
	(0.228)	(0.243)	(1.446)	(1.551)	(0.036)	(0.039)	-0.007	-0.008	-0.008	-0.009
Dummy for Operation within Campus	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Weather Condition	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Air Quality	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Calendar Date Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Relative Day Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Duopoly Group Trend	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
City AttributesDay FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Within Adjusted R^2	0.265	/	0.075	/	0.006	/	0.007	/	0.041	/
Number of Clusters	82	82	82	82	82	82	82	82	82	82
Number of Observations	16193	16193	16193	16193	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 clustered at the city level. *** Denotes significance at the 1%, ** 5%, and * 10% level.

Table 6: 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*
PostEntryDummy 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)
PostEntryDummy 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 Fixed Effects	YES	YES	YES	YES	YES	YES
Calendar Date Fixed Effects	YES	YES	YES	YES	YES	YES
Relative Day Fixed Effects	YES	YES	YES	YES	YES	YES
Duopoly Group Trend	YES	YES	YES	YES	YES	YES
City AttributesDay Fixed Effects	YES	YES	YES	YES	YES	YES
Within Adjusted R^2	0.107	/	0.042	/	0.056	/
Number of Clusters	82	82	82	82	82	82
Number of 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 clustered at the city level. *** Denotes significance at the 1%, ** 5%, and * 10% level.

Table 7: Competition Effect Heterogeneity to Pre-Entry Bike Investment

	(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	0.121	0.198	0.017	0.021	-1.429	-1.765
	(0.216)	(0.233)	(0.013)	(0.014)	(1.500)	(1.625)
PostEntryPre-Entry Bike Investment	0.036*	0.034	0.003***	0.003***	-0.296*	-0.288*
	(0.021)	(0.021)	(0.001)	(0.001)	(0.149)	(0.149)
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 Fixed Effects	YES	YES	YES	YES	YES	YES
Calendar Date Fixed Effects	YES	YES	YES	YES	YES	YES
Relative Day Fixed Effects	YES	YES	YES	YES	YES	YES
Duopoly Group Trend	YES	YES	YES	YES	YES	YES
City AttributesDay Fixed Effects	YES	YES	YES	YES	YES	YES
Within Adjusted R^2	0.129	/	0.068	/	0.077	/
Number of Clusters	81	81	81	81	81	81
Number of Observations	16140	16140	16140	16140	16140	16140

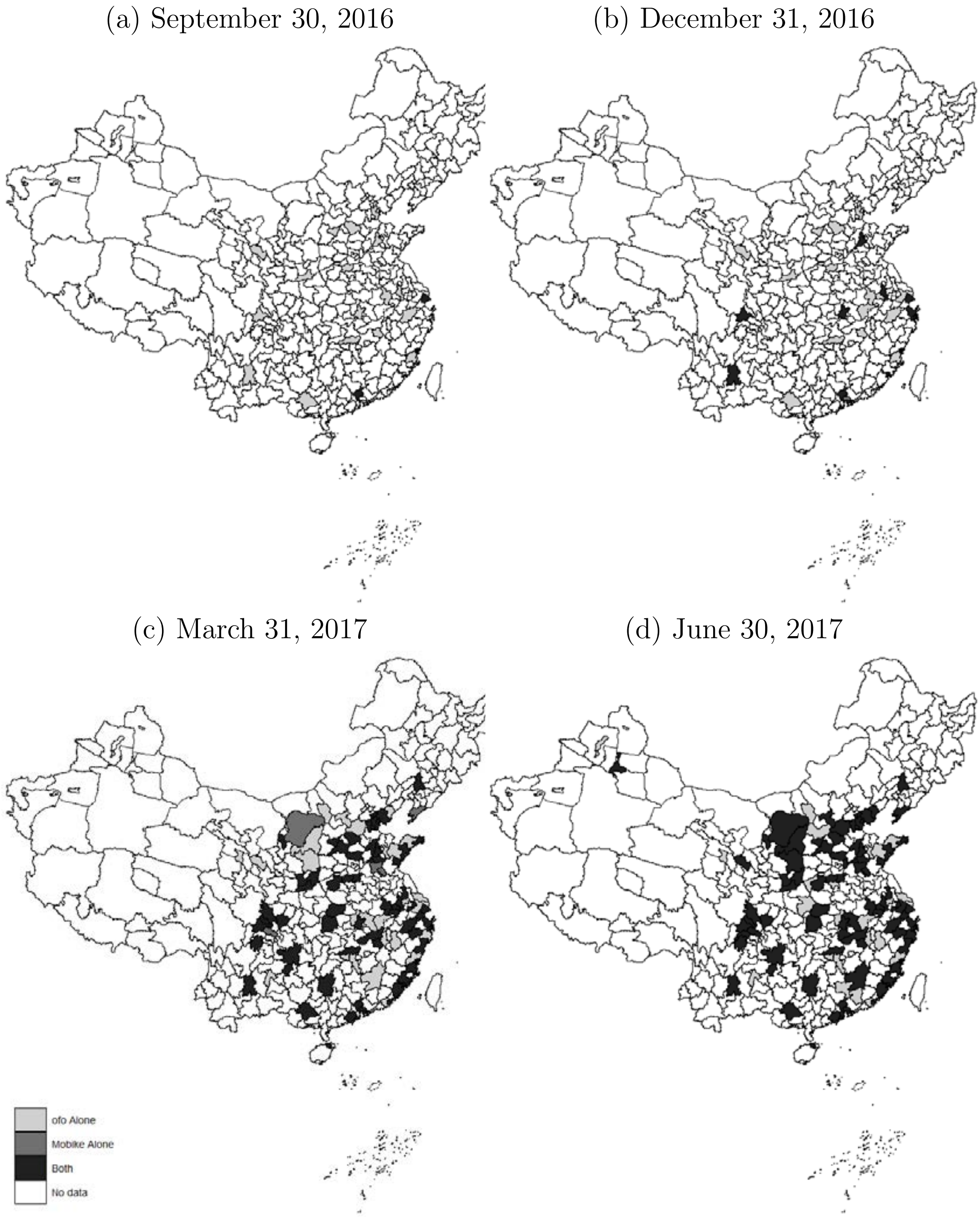
Notes: The *Pre-Entry Bike Investment* is calculated as the average number of accumulative bike investment over 10 days before Mobikes entry. If the time gap between the entry of ofo and Mobike is shorter than 10 days, this index is still constructed over all the gap days thought from less observations. To make the magnitude of coefficients suitable for understanding , we divide the number of pre-entry investment by 1,000. Bike investment data is missing for one of *ofo First* cities and the number of clusters thus decreases to 81. Standard errors are in parentheses and clustered at the city level. *** Denotes significance at the 1%, ** 5%, and * 10% level.

Table 8: Competition Effects on Geographical Reach of Bike-Sharing Network

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables	*Log (# of Grids covered by ofo)*		*Gini Coverage Index*		*Gini Coverage Index of Pre-Entry Grids*	
Models	*OLS*	*2SLS*	*OLS*	*OLS*	*2SLS*	*OLS*
PostEntry	0.195**	0.225**	-0.035***	-0.038***	-0.027**	-0.031***
	(0.081)	(0.086)	(0.007)	(0.008)	(0.010)	(0.011)
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 Fixed Effects	YES	YES	YES	YES	YES	YES
Calendar Date Fixed Effects	YES	YES	YES	YES	YES	YES
Relative Day Fixed Effects	YES	YES	YES	YES	YES	YES
City AttributesDay Fixed Effects	YES	YES	YES	YES	YES	YES
Duopoly Group Trend	YES	YES	YES	YES	NO	NO
Within Adjusted R^2	0.202	/	0.112	/	0.041	/
Number of Clusters	82	82	82	82	59	59
Number of Observations	16193	16193	16193	16193	13560	13560

Notes: "Pre-Entry Grids" could not be defined for *ofo Alone* group cities, which are excluded in Column 5 and 6 and the number of clusters decreases to 59 (i.e., the number of *ofo Frist* group cities). 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 clustered at the city level. *** Denotes significance at the 1%, ** 5%, and * 10% level.

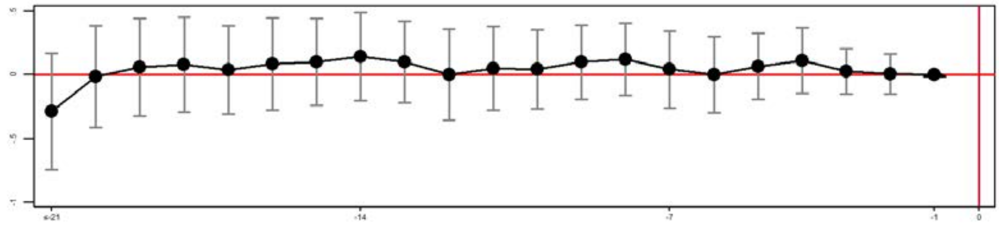
Figure 1: Expension Process of ofo and Mobike



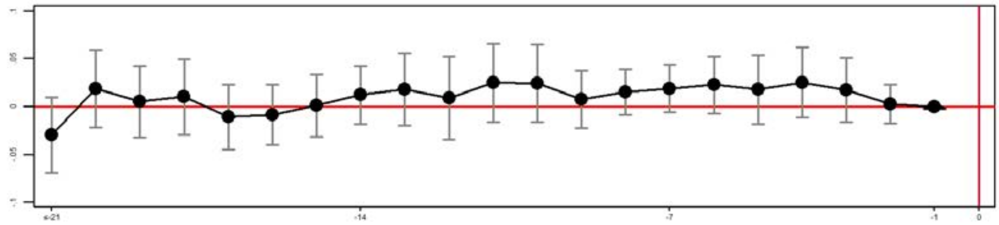
Notes: This figure depicts the expansion process of ofo and Mobike in our sample cities. Beijing and the 6 cities without detailed entry sequence are excluded. The base map of China comes from Resource and Environment Data Cloud Platform (http://www.resdc.cn).

Figure 2: Test of Common Pre-Trend Assumption

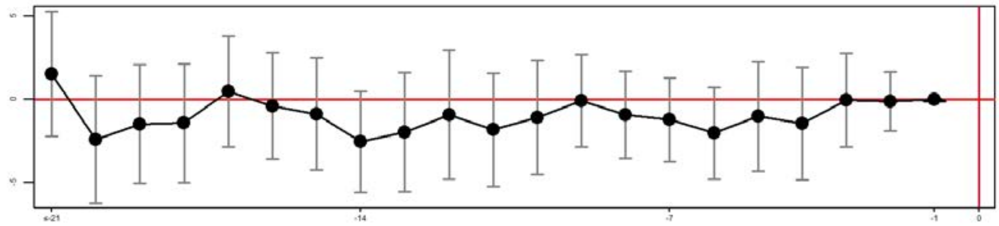
(a) Log(Trip Volume)



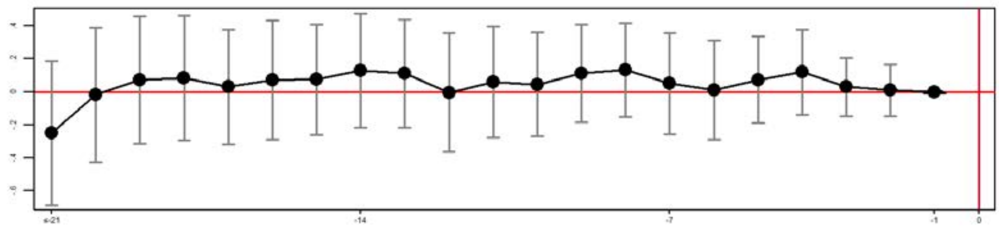
(b) Average Revenue per Trip



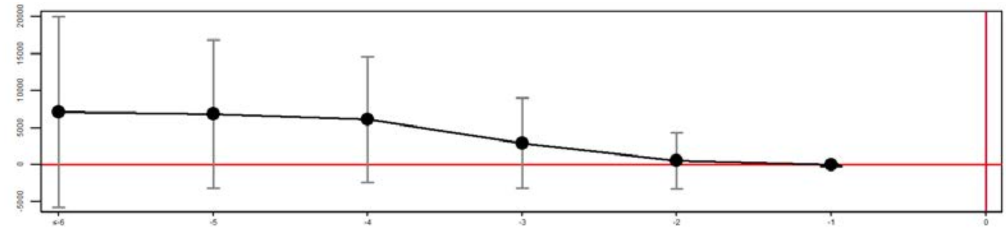
(c) Percent of Free Trips



(d) Log(Bike Utilization Rate)



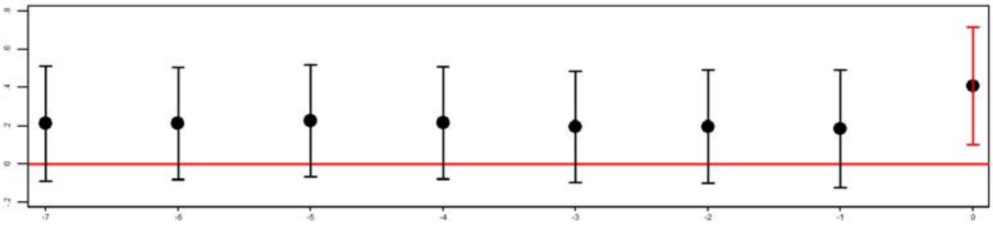
(e) Bike Investment



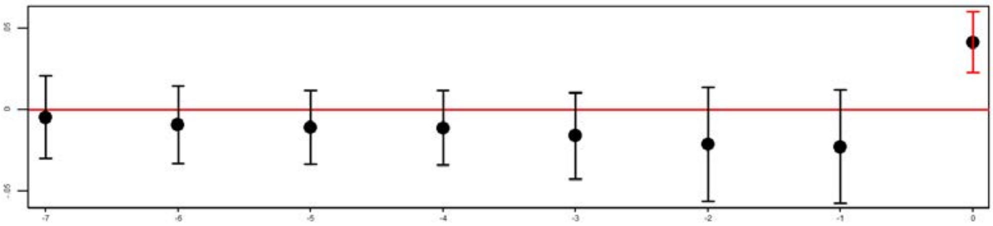
Notes: Point estimates of $\{\lambda_{-k}\}_{k=2}^{k=21}$ in Equation (2) as well as corresponding 95% confidence intervals are plotted with relative days before Mobike's entry on the horizontal axis. The day before Mobike's entry is omitted as base and days more than 3 weeks before the entry are all counted as 21. Similar notations apply to the last panel with time unit changed into month. 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 clustered at the city level.

Figure 3: Falsification Test of Forwards of *PostEntry*

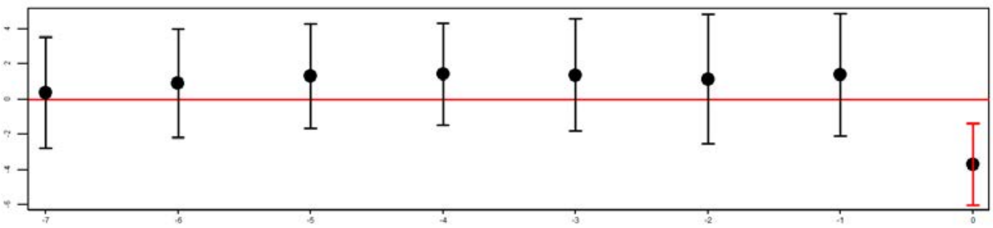
(a) Log(Trip Volume)



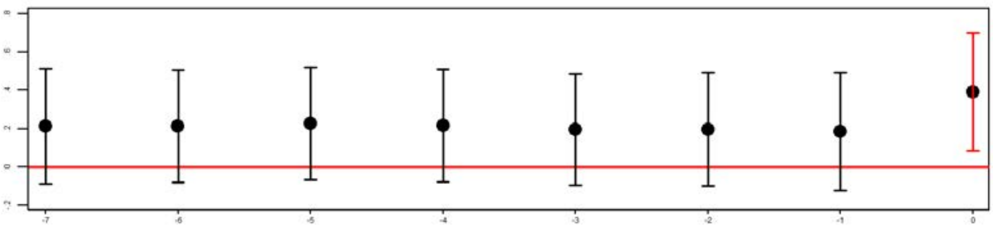
(b) Average Revenue per Trip



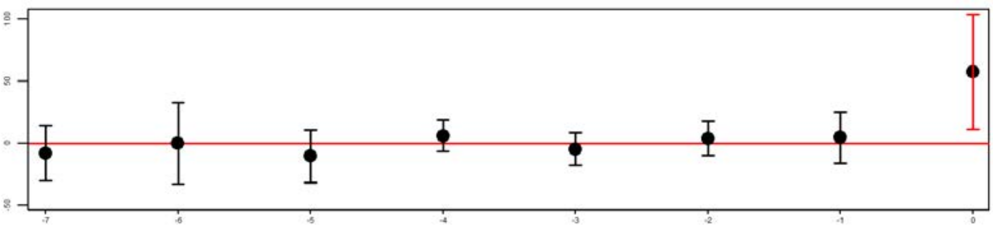
(c) Percent of Free Trips



(d) Log(Bike Utilization Rate)



(e) Bike Investment



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 intervals are depicted together with the baseline estimates from Table 2 Column 7 plotted on the very right. Similar notations apply to the last panel with time unit changed into month. Standard errors are clustered at the city level.

Figure 4: The graph plots how the parameter values α and β affect the comparison of r^d and r^m when we fix $\theta = \gamma = 2$.

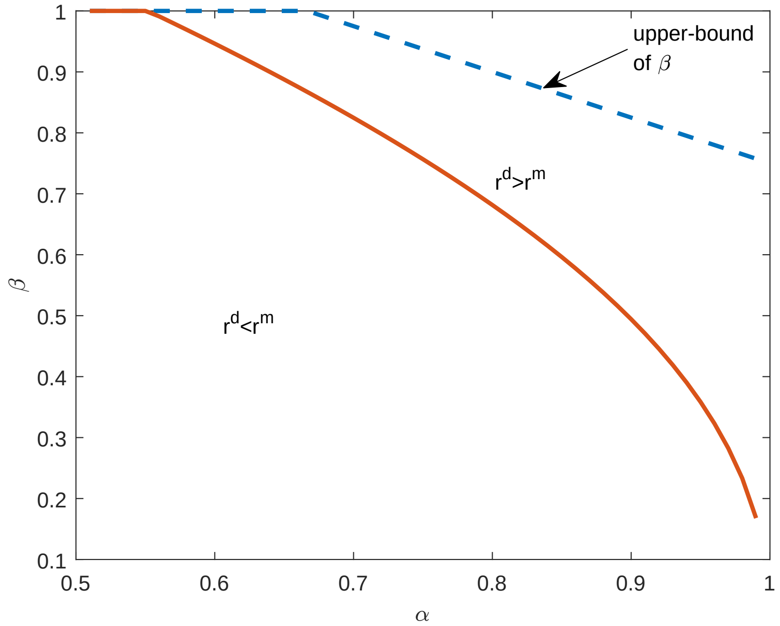
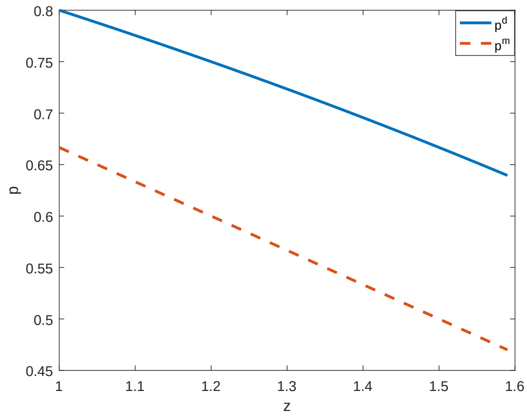
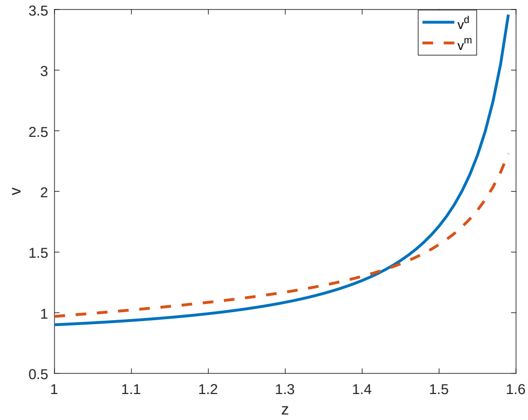


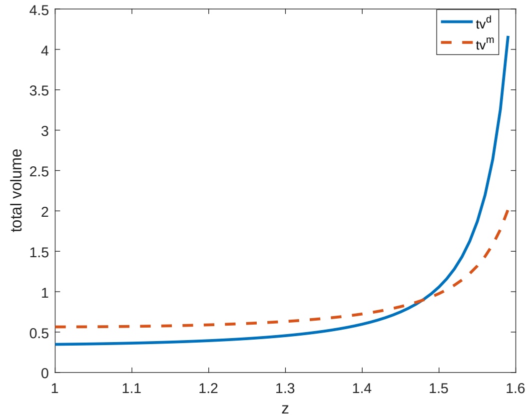
Figure 5: The graphs plot how the equilibrium prices, investments, trade volumes and utilization rates change with $z = \alpha + \beta$ in both monopoly and duopoly cases.



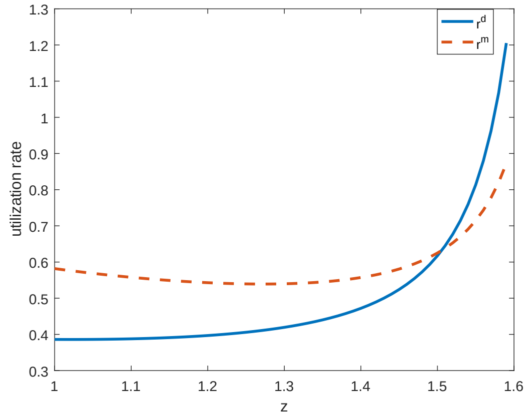
(a) Price as a function of z



(b) Investment as a function of z

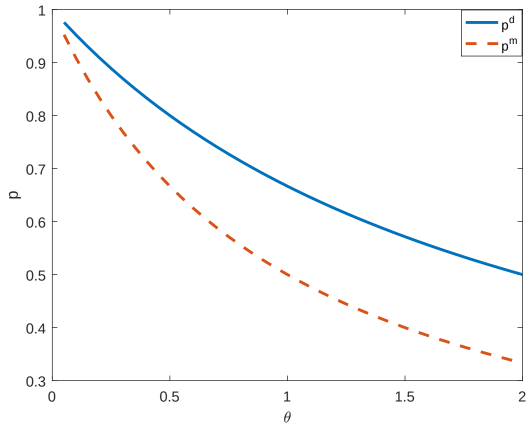


(c) Trade volume as a function of z

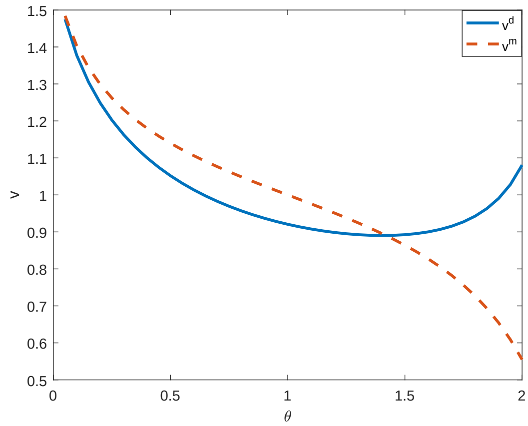


(d) Utilization rate as a function of z

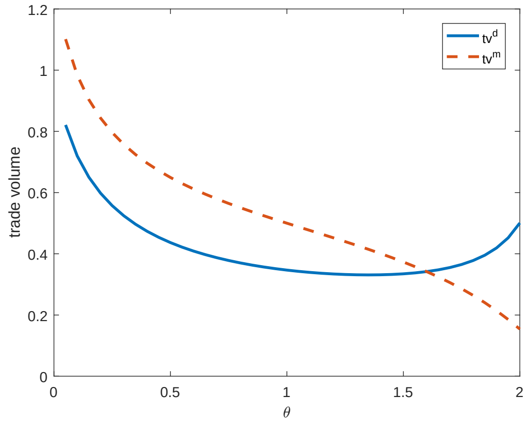
Figure 6: The graphs plot how the equilibrium prices, investments, trade volumes and utilization rates change with θ in both monopoly and duopoly cases.



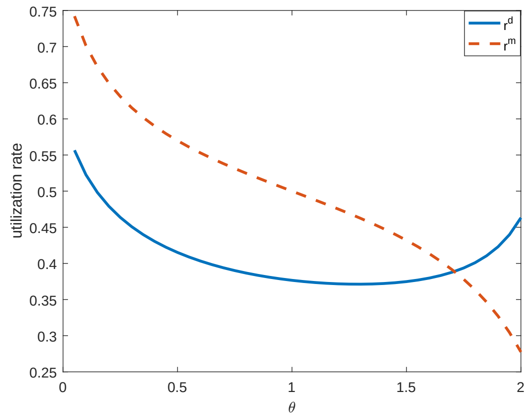
(a) Price as a function of θ



(b) Investment as a function of θ



(c) Trade volume as a function of θ



(d) Utilization rate as a function of θ

Appendix

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 Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Calendar Date Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Relative Day Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Duopoly Group Trend	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
City AttributesDay Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Within Adjusted R^2	0.103	/	0.133	/	0.074	/	0.053	/	0.079	/	0.061	/
Number of Clusters	59	59	104	104	59	59	104	104	59	59	104	104
Number of 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 clustered at the city level. *** Denotes significance at the 1%, ** 5%, and * 10% level.

Table A2: Robustness Check of Different Subsamples (*Continued*)

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Dependent Variables	*Log (Bike Utilization Rate)*				*Bike Investment*			
Subsamples	*ofo Alone Excluded*		*Mobike First Included*		*ofo Alone Excluded*		*Mobike First Included*	
Models	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*
PostEntry	0.397**	0.464**	0.357*	0.409**				
	-0.193	-0.206	-0.192	-0.202				
Percent of Duopoly Days (1-100)					51.669*	52.144*	40.842*	43.024*
					-30.894	-30.413	-21.713	-22.03
Dummy for (Percent of) 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 Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Calendar Date(Month) Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Relative Day(Month) Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Duopoly Group Trend	NO	NO	YES	YES	NO	NO	YES	YES
City AttributesDay(Month) Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Within Adjusted R^2	0.103	/	0.109	/	0.01	/	0.002	/
Number of Clusters	58	58	101	101	58	58	101	101
Number of Observations	13507	13507	19208	19208	515	515	754	754

Table A3: Robustness Check of 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)
Starting Dates / *Distribution*	12/1/15	1/1/16	2/1/16	3/1/16	4/1/16
Panel A Dependent Variables	*Log (Trip Volume)*				
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*				
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*				
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 five 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 53 = 15 estimates of β. This table provides further support to Table 3 and Table 4 in the sense that results are not driven by the choice of starting dates or distribution function. Standard errors are in parentheses and clustered at the city level. ***Denotes significance at the 1%, ** 5%, and * 10% level.

Table A3: Robustness Check of 2SLS Estimates (*Continued*)

	(1)	(2)	(3)	(4)	(5)
Starting Dates / *Distribution*	12/1/15	1/1/16	2/1/16	3/1/16	4/1/16
Panel D Dependent Variable	*Log (Bike Utilization Rate)*				
Weibull	0.461**	0.457**	0.463**	0.473**	0.480**
	(0.200)	(0.200)	(0.202)	(0.203)	(0.204)
Loglogistic	0.428**	0.434**	0.440**	0.445**	0.454**
	(0.196)	(0.198)	(0.198)	(0.200)	(0.202)
Lognormal	0.433**	0.436**	0.437**	0.444**	0.452**
	(0.198)	(0.200)	(0.200)	(0.202)	(0.205)
Panel E Dependent Variable	*Bike Investment*				
Weibull	52.342*	52.066*	51.285*	51.632*	51.866*
	(30.428)	(30.571)	(30.217)	(30.292)	(30.321)
Loglogistic	47.565	47.501	47.696	47.436	46.338
	(29.457)	(29.515)	(29.486)	(29.285)	46.338
Lognormal	48.052	47.765	46.609	47.315	46.894
	(29.610)	(29.754)	(29.490)	(29.435)	(29.289)

Table A4: Competition Effects on Usage Volume within Pre-Entry & Non-Campus Grids

	(1)	(2)	(3)	(4)
Dependent Variable		*Log (Trip Volume)*		
Models	*OLS*	*2SLS*	*OLS*	*2SLS*
PostEntry	0.386**	0.451**	0.440**	0.490**
	(0.190)	(0.205)	(0.194)	(0.210)
Dummy for Operation within Campus	YES	YES	YES	YES
Weather Condition	YES	YES	YES	YES
Air Quality	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES
Calendar Date Fixed Effects	YES	YES	YES	YES
Relative Day Fixed Effects	YES	YES	YES	YES
City AttributesDay Fixed Effects	YES	YES	YES	YES
Duopoly Group Trend	YES	YES	YES	YES
Within Adjusted R^2	0.101	/	0.045	/
Number of Clusters	59	59	53	53
Number of Observations	13560	13560	9170	9170

Notes: To investigate whether the booming usage is mainly driven by expansion to new grids, we first restrict to grids which are already covered by ofo before Mobikes entry and re-compute usage volume. *ofo Alone* and *Mobike First* cities are thus excluded and estimates are reported in Column 1 and 2. To eliminate potential effects from campus, we further restrict to non-campus grids among those old grids which are employed in the regression for Column 1 and 2. Please note that some cities of *ofo First* group have been covered by ofo completely during the campus period, i.e., ofo does not strictly enforce the within-campus strategy. We could not define non-campus grids for them and the number of clusters decreases to 53 in Column 3 and 4. Standard errors are in parentheses and clustered at the city level. ***Denotes significance at the 1%, ** 5%, and * 10% level.