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MARKET EXPANDING OR MARKET STEALING? COMPETITION WITH NETWORK EFFECTS IN BIKESHARING

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ABSTRACT

Using staggered entry of two dockless bikesharing firms, we find the entrant expands the market for the incumbent. The entry helps the incumbent to serve a greater number of trips, make more bike investment, 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 marketstealing effect on 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 winnertakesall, especially when users multihome across compatible networks.

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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 competing firms find it difficult to enter and survive even if they are more efficient than the incumbent.[2] In the meantime, multi-homing and compatibility could alleviate 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 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 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. This shift accounts for a major difference between bike-sharing and ride-sharing as of today, but research advance on autonomous vehicles could motivate ride-sharing platforms (e.g. Uber or Lyft) to move towards a one-sided network similar to that of bike-sharing. In this sense, what we observe in bike-sharing today could have important implications for the future market of other transportation means.

As documented by a burgeoning literature[5], bike-sharing solves the "last-mile" problem

[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 (2019) suggests that competition equilibrium depends on whether multi-homing occurs on one or two sides of ride-sharing 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 et al. (2018), 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.

of local transportation.[6] 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. Such "consumption-as-supply" is particularly attractive in dockless bike-sharing. It no longer requires fixed docks at the origin and destination of a trip, which mitigates the potential imbalance of demand and supply in different locations at different times.[7] 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.[8] Thanks to these positive network effects, ofo grew exponentially from a college campus to more than 250 cities in 20 countries by January 2018.[9]

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[10], making many cities a *de facto* monopoly or duopoly. If both entered the city, most consumers multi-home because the two bikes are almost perfect substitutes at the same time and location.[11] 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[12] 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.[13] 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."

[6]Most Chinese use bike for regular commute instead of leisure or entertainment. See more details in Section I.

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

[8]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.

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

[10]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%.

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

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

[13]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 II.D.

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 (listing price is 1 RMB per trip). 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 IV is the projected Mobike's entry date in a city, where the projection uses the timing of Mobike's venture capital funding (eight 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 expansion in new users. Unlike other markets with positive network effects, bike-sharing firms can 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 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 didn't the incumbent expand the network as much by itself before the second firm entered? Third, why does the incumbent choose its post-entry investment such that the bike utilization rate is higher after the entry than before the entry?

To answer these questions, 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 derive how firm(s) choose price and bike investment in a subgame perfect equilibrium.[14]

Under weak conditions, the model predicts higher price in duopoly than in monopoly but the comparison on trade volume, bike investment and bike utilization rate depends on a few

[14] We only consider symmetric equilibrium in duopoly, given the similarity between ofo and Mobike.

factors. The first factor is positive network effects modeled as a matching technology with increasing return to scale. When there is 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 large and 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 terms of 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 the cost might be too convex to justify the investment.[15] Towards the end of the paper, we articulate why alternative stories – such as advertising, price war, investment war, and cost of the outside good – do not explain why a competitive entry can expand the market and enhance the incumbent's investment efficiency at the same time. Moreover, these alternative explanations are less consistent with the facts, when we conduct further analyses in light of our model predictions.

Our work is closest to the literature of network economy. By focusing on a market with potentially positive network effects, we show that competition expands the overall market. 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 concern 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 setting the cost of operation independent of network size (Katz and Shapiro 1985).[16] 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 esti-

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

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

mating how the number of users affects user evaluation[17], 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 geographic 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 (2019), 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.[18] Because of positive spillovers between bike-sharing firms, our work contrasts the market stealing effect documented in other network markets (Seamans and Zhu 2013; Angelucci and Cagé forthcoming).

The rest of the article is organized as follows. Section I describes the background. Section II summarizes the data. Section III describes our main econometric specifications. Section IV reports the baseline empirical results. Section V presents a theoretical model that highlights consumer search and network effects. The model also clarifies how positive network effects differ from alternative explanations. Section VI reports further data analysis in light of the model. Section VII concludes with policy implications.

I. Background

Public transit and bicycle were the primary transportation means in China before private ownership of automobile took off in 1990s. As a result, major city roads include dedicated bike lanes and there is no requirement for bike helmet.[19] Traditional bike-sharing systems provide bike rental service through stations, which means that each bike is docked at a station,

[17]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 et al. 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 et al. 2010; Kim et al. 2014; Angelucci and Cagé forthcoming).

[18]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 et al. 2010).

[19]Bike-sharing systems have gone through a few generations, mostly driven by technological development in electronically-locking racks, telecommunication systems, smartcards and fobs, mobile phone access, and on-board computers (DeMaio 2003; DeMaio and Gifford 2004; DeMaio 2009; Zhang et al. 2015).

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 can use smart phones to scan the QR code on the bike lock 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 absorbed venture investment up to 4 billion USD and accumulatively placed more than 25 million bikes in hundreds of Chinese cities. Anecdotes suggest that, in the cities with high penetration, most bike riders use dockless bike-sharing rather than private bikes. From ofo's transactional data, we observe two distinct spikes of bike usage, one at 8am and the other at 6pm throughout a day. This pattern confirms that bike-sharing is largely used for daily commute rather than leisure or entertainment. 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 VI. 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 more entry.[20] However, various industry reports conclude that ofo and Mobike account for 90% to 95% of the bike-sharing markets from the very beginning.[21] That is why we focus on the competition between ofo and Mobike, especially how the new entrant (Mobike) affects the incumbent

[20] Some estimates suggest that nearly 30 new bike-sharing platforms were established in 2016 alone. See the report from National Business Daily: http://www.nbd.com.cn/articles/2017-01-05/1067671.html.

[21] 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).

A few bike-sharing studies have examined the network feature of docked bikes [22] and the problem of bike rebalance.[23] Our paper focuses 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 of these features, 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.

Although dockless bike-sharing facilitates "consumption-as-supply", the cost of bike maintenance and rebalance is non-trivial. According to ofo executives, average cost per bike is U-shaped. There is some economy of scale at the beginning, but two factors contribute to the turning point. The first one is geographic scope of bike rebalance. Imagine a circle city in which bikes are diffused from city center to the edge. The cost of rebalancing bikes to the center increase quadratically as the circle expands. On top of this, the cost of managing bicycle mechanics also increases with bike usage. On the one hand, it is more difficult to monitor mechanics as the number of mechanics increases, leading to an increase in moral hazard. On the other hand, mechanics are allocated by geographic grids. When bikes (and bike use) per grid rise rapidly, "effective intervention" of mechanics cannot catch up in the same speed. These managerial difficulties suggest that average cost per bike could increase

[22] Zheng et al. (2018) set up a structural demand model to estimate consumer preference for docked bikes in the London bike-sharing system. They demonstrate that the existing station network is far from ideal. Using data from a similar bike-sharing system in Paris, Kabra et al. (2018) stress that both station accessibility and bike availability are important for consumer demand. Dockless bike-sharing can mitigate accessibility and availability problems because it is possible to find a dockless bike near one's home or workplace. However, less constraint on parking location may also make bikes more dispersedly distributed and reduce 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.

[23] Both docked and dockless bike-sharing face the problem of bike rebalance, which has been the focus of a few studies (O'Mahony and Shmoys (2015), Pan et al. (2018))

with the number of bikes, even if firms may enjoy volume discount from bike manufacturers.

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 ofo data indicates that more than 99% of the trips end in less than 30 minutes. On top of the listing price, both firms engaged in aggressive marketing campaigns such as trip coupons, free riding day, and monthly card for 1 RMB. While some marketing campaigns target new users (e.g. the first three rides free), most promotional activities apply to both old and new users. Thanks to marketing, the average transaction price per trip can be significantly lower than the listing price. Probably because price per trip is low as compared to the average GDP per Capita (66990 RMB per year in our sample), ofo executives told us that users do not price shop at the time of consumption. More important are accessibility and availability (of any bike). For this reason, many users multi-home. Both publicly available reports[24] and internal evaluation from ofo estimate that 30-40% users simultaneously adopt ofo and Mobike. This number underestimates the degree of multi-homing, because it is derived from Android apps only and all smartphone users can access bike-sharing in many other ways (e.g. inside WeChat, Alipay, and Didi apps). Moreover, it is computed nationwide while obviously one does not need both apps if only one of them operates in a city.

II. 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.

A. *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 $(23.1632°\text{N}, 113.3578°\text{E})$ and $(23.1677°\text{N}, 113.3529°\text{E})$ will be counted as trips within the same grid

[24] See the "Industry Research Report on Bike-Sharing (2017)" released by QuestMobile and "Industry Research Report on Bike-Sharing Development (2017Q1&Q2)" issued by Trustdata.

(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 et al. (2016), we define the base as all grids that are ever covered by ofo within a city throughout our sample period. If at day *t* city *c* no trip occurs in grid *g*, then $q_{gct} = 0$. Assuming that there are *n* grids in the city and $g = 1$ to *n* are indexed in the non-decreasing order, we define the Gini Coverage Index as $Gini_{ct} = \frac{1}{n}\left[n + 1 - 2\frac{\sum_{g=1}^{n}(n+1-g)q_{gct}}{\sum_{g=1}^{n} q_{gct}}\right]$. Another way to define $Gini_{ct}$ is conditional on the grids that ofo has already covered in the city before Mobike's entry, which is a subset of the base used in the first version. We will report results on both measures of $Gini_{ct}$.

As detailed in Section I, 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 more than 99% of the trips end in less than 30 minutes. Since marketing campaigns led to fluctuations in price actually paid, we 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 I, 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.

B. *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.[25] 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.[26]

C. *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[27] 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[28]: 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

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

[26] 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.

[27] 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.

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

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.

D. *Sample Construction*

The original data extracted from ofo spans from September 7, 2015 to September 14, 2017. Besides, we collect Mobike's entry data from media reports, and cross-validate it with postings on Mobike's Weibo home page.[29] The data is further cleaned 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 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.

Cities in our sample could be further divided into three groups based on the sequence of ofo and Mobike's entry. 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*. Table A1 lists the names of cities in our sample. Figure A1 plots them on the map of China and depicts the expansion process of bike-sharing.

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

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

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.

III. 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 at city *c* and date *t*, such as $\log(Q_{ct})$, p_{ct}, $\%Free_{ct}$, and $Utilization_{ct}$; 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

$(f(t))$.[30] 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 et al. 1993; Autor 2003). Specifically, we use the following equation to test pre-treatment trends:

$$Y_{ct} = \alpha_c + \gamma_t + \sum_{k=2}^{14} \lambda_{-k} A_{ck} + X_{ct}^{'}\pi + (S_c \times f(t))^{'}\theta + \mu G_c \cdot t + \epsilon_{ct} \tag{2}$$

where A_{ck} is a set of dummies indicating that date *t* is $(2k-1)$ to $2k$ days before Mobike's entry into city *c*. Effectively, we define every two days as an interval and pool all days more than 4 weeks before Mobike's entry as $k = 14$, and choose the two days immediately before Mobike's entry (i.e., $k = 1$) as the omitted default category.[31] Thus, conditional on a sample of pre-entry observations, the coefficients $\{\lambda_{-k}\}_{k=2}^{k=14}$ test the comparability between *ofo First* and *ofo Alone* cities for every 2 days up to 4 weeks before Mobike's entry. If the two groups of cities are statistically comparable, each λ should be indistinguishable from zero. We will report the pre-treatment trend tests when we describe the baseline results.

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

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

[31] We choose 28 days as the cutoff and pool all days more than 4 weeks before Mobike's entry together because the time gap between ofo entry and Mobike entry is less than 28 days in 20 of the 59 ofo first cities. This means that we have significantly less statistical power to look at specific days beyond the cutoff.

days between November 1, 2015 and September 14, 2017. We then fit the survival time in a proportional hazard duration model, where the explanatory variables are predetermined city attributes, the timing and amount of the 8-round Mobike financing from venture capital, and a new variable describing the cumulative number of days since Mobike's latest round of VC finance. From the estimates of the duration model, we then predict the median survival time for each city and add it to the starting date (November 1, 2015). This defines the predicted entry date of Mobike. From the predicted entry date, we can compute a new post-entry dummy ($\widehat{PostEntry_{ct}}$) as the IV for $PostEntry_{ct}$.

We argue that the predicted Mobike entry date is likely exogenous to city-specific unknowns, because city attributes are all pre-determined and Mobike's VC funding is not driven by a particular city. More specifically, Mobike's VC funding may depend on ofo's nationwide performance, which is controlled by calendar date fixed effects in the main specification, but we assume it is independent of ofo's performance in a particular city at a particular time. These assumptions are reasonable, because Mobike entered cities in a stunning speed, sometimes as fast as 10 cities on a single day. To the extent that VC investors demanded a plan of expansion before investment, it is conceivable that they care more about bigger cities. Thus in one robustness check, we classify the sampled Mobike entries by city size below or above median within each round of VC funding. By this definition, the effects of Mobike entry turn out to be more conspicuous in below-median cities , suggesting that the effects are unlikely driven by VC investors endogenously dictate which city to enter. We will report detailed 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.

IV. 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.

A. *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 pre-treatment trends, Figure 1 plots the point estimates of $\{\lambda_{-k}\}_{k=2}^{k=14}$ from Equation (2), along with the estimated 95% confidence intervals. The first three panels of Figure 1 correspond to the three key dependent variables ($\log(Q_{ct})$, p_{ct}, and $\%Free_{ct}$). All these estimates are statistically indistinguishable from zero.[32] This suggests that, after our control of observables, *ofo Alone* and *ofo First* cities follow statistically similar trend before Mobike's entry, although the two sets of cities differ in absolute population and other attributes.

To further address the concern of endogenous entry, we use the predicted entry date to construct an IV for $PostEntry_{ct}$. Table 3 first reports the first stage (Column 1) and then the IV results for $\log(Q_{ct})$, p_{ct}, and $\%Free_{ct}$ (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 3 Column 5-8 report 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 three robustness checks on the IV results in Appendix Table A3 and Appendix Table A4. 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

[32] If we test these coefficients jointly, they are not different from zero with 95% confidence.

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, 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. Third, one may still be concerned that VC investors may condition investment on the cities that Mobike would enter. If so, the plan to enter big cities should be more important than small cities, because the level of investment is likely dependent on city population. To address this, we use entry and finance dates to classify *ofo First* cities within each of the eight finance rounds of Mobike. In each round, we sort cities by population and divide them into above-median and below-median groups. We then pool all above-median cities and compare them to *ofo Alone* cites in OLS and 2SLS. In separate regressions, we also pool all below-median cities and compare them to *ofo Alone* cities. Results in Table A4 suggest that the effects of Mobike entry are more conspicuous in below-median cities than in above-median cities, which refutes the argument that the effects are driven by endogenous entry upon differential attention of VC investors.

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.

B. *New and Old Users*

If entry has led to an increase in revenue per trip 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 4. 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.[33] 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

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

Mobike. Conditional on active old users, Columns 5-6 show that the average number of trips they take on ofo does not change significantly post Mobike entry. This could happen even if Mobike's entry distracts some active old users from ofo, because users may increase the frequency of overall bike use, ofo has invested in more bikes post Mobike entry, or Mobike could differentiate its bike locations from those of ofo. 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.

V. 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 trip 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 trip 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.

A. *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, 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.[34] 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 using bike-sharing, 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 searches 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.[35]

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 choose between bike-sharing and their

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

[35] 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 $1 - c$.

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 $\psi(v)$.[36] In this case, the two duopoly firms simultaneously choose the measures of 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. Consistent with user pattern described by ofo executives, 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).

B. *Equilibrium Analysis*

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^*:

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

[36] In general, there is no need to assume that the firms have the same cost function. But the symmetric case is easy to solve theoretically. Moreover, in reality, the two leading bike-sharing firms, ofo and Mobike, are quite symmetric.

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 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 1 *Assume that* $\frac{\alpha(1+\theta)}{1+\theta(1-\beta)} < \gamma$*. Then, there exists a unique subgame perfect equilib-*

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

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 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

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

C. *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, trip volumes, and utilization rates in different cases. Trip 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

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

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 in terms of product quality or idiosyncratic consumer tastes, Cachon et al. (2008), Chen and Riordan (2008) and Kotowski and Zeckhauser (2017) all show that price may increase when market becomes more competitive. The reason can be due to sufficiently diverse and negatively correlated consumer preferences as in Chen and Riordan (2008) or a "market-expansion effect" tied to search activity as in Cachon et al. (2008) and Kotowski and Zeckhauser (2017). 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 imply 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).[37] 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 $v^d > v^m$. $\square$

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 $v^d > v^m$.

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 $r^d < r^m$.

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

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 effects. 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 2 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 2. First of all, the dashed line in Figure 2 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 3 and 4 numerically investigate how the change in parameters affects the equilibrium outcomes in monopoly and duopoly cases. Figure 3 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 change with z at the same rate. Consistent with Proposition 1, we always have $p^d > p^m$ as seen in Figure 3 Panel A. Figure 3 Panel B 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 3 Panel C and Panel D show that both trip 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 2: 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 4 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 3. 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, trip 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 trip volume and utilization rate can also go up when θ is sufficiently high or $z = \alpha + \beta$ is sufficiently high.

D. *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 the importance of each respectively.

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 three reasons. First and foremost, ofo executives confirm the modeled search pattern in today's world. Secondly, the results in a fully-fledged model allowing price shopping within search are likely similar to those in the current model.[38] Thirdly, 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 and most realistic way to illustrate the main driving force behind the data.

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

[38] 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.

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 attract 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 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.

Note that this can only occur when the investment cost is sufficiently convex. It is intuitive to conceive that market equilibrium only depends on the relative comparison between matching returns-to-scale and the curvature of investment cost. According to our model, when cost convexity dominates the increasing return-to-scale of the matching technology, we could observe higher price, volume, investment and utilization rate per firm in duopoly than in monopoly. Is it also possible to observe the same phenomena if the matching technology has a sufficiently decreasing return to scale but the investment cost is linear or concave? The answer is a sure no. If the cost is linear or concave ($\gamma \leq 1$), the condition $\frac{\alpha(1+\theta)}{1+\theta(1-\beta)} < \gamma$ implies $\theta\beta - (1+\theta)(1-\alpha) < 0$, which leads to lower utilization rate under duopoly ($r^d < r^m$) according to the second part of Proposition 3. In other words, both convex cost and sufficiently large increasing returns-to-scale are critical to support our empirical findings.

In contrast, when the network effects are positive but 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.

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.

E. *Alternative Explanations*

To summarize, the model points out a few potential explanations for market expansion: (1) an increasing-return matching technology that generates large enough positive network effects ($z = \alpha + \beta > 1$); (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 is equivalent to enhancing the multiplier in the matching technology (A) while keeping the same return-to-scale.

However, market expansion alone is not enough to explain the incumbent's increase in investment and utilization; we also need mechansims that make the incumbent's investment more efficient upon a competitive entry. An awareness marketing campaign cannot achieve this: in fact, bike utilization rate is independent of A, regardless whether the matching technology is increasing or decreasing return to scale. More specifically, while ad-driven expansion encourages the incumbent to invest in more bikes, more bikes and the improved matching efficiency (due to a higher A) also invite more users to adopt bike-sharing. In our model, the two forces cancel out each other, resulting in no change in bike utilization rate.

An even simpler explanation for volume expansion is price or investment war. By definition, price war should lead to lower price post entry, which contradicts our data. An investment war could lead to a higher price, as more bikes available make bike-sharing more attractive to consumers. But investment war alone – without other elements such as increasing return-to-scale in matching and convex investment cost – does not explain why the incumbent did not make that investment until the competitive entry, especially if that investment could benefit the incumbent in price, volume and utilization rate.

A more plausible explanation of market expansion lies in the outside good. If the density of the cost of using the outside good is downward sloping ($\theta > 1$), an increase in θ could make the next batch of investment (introduced by the entrant) more effective in persuading consumers to join bike-sharing than the existing batch invested by the monopolist, thus generating a market expansion effect.

Note that the two key parameters, θ for the distribution of the cost of the outside good and $z = \alpha + \beta$ for returns-to-scale of the matching technology, give us different comparative statistics. As shown in Figure 3 and Figure 4, 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 difference offers an opportunity to test whether the observed variations in market expansion is mainly driven by z or by 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.

VI. Further Data Analysis Motivated by the Model

It is difficult to estimate our model directly in the real data, due to lack of search information. Unlike ride-sharing (by Uber or Lyft), bike-sharing users often search for a bike first and then open the relevant app to unlock the bike. This is mostly because the GPS location on the phone screen is not accurate enough for consumers to find a specific bike. Given this user experience, it is difficult to measure how many users have searched for a bike but could not find one at any time of the day. This also prevents us from estimating the bike-user matching directly, even if ofo is the only bike-sharing platform in a city-day. To be more precise, a few recent papers overcome the lack of observability in potential users, but none of their techniques is applicable in our context. [39] In light of this difficulty, we explore three sets of reduce-form analyses to test model predictions.

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, we are fortunate to observe competition intensity variations within *ofo First* cities. This occurs 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 5 Panel A 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

[39] For instance, Buchholz (2019) estimates a matching function between taxi drivers and passengers. He identifies the matching function by mapping the observed spatial distribution of matches into optimal policy functions of vacant taxis across the day. In our case, there is no driver in bike-sharing. Bikes can move by consumption, maintenance or rebalancing. Using aggregate ofo data by grid-city-day, we cannot separate these factors, or model the "optimal" strategy of each bike mechanic. Alternatively, Brancaccio et al. (2019) propose a generic method to estimate the matching function between "buyers" and "sellers" when researchers observe only realized matches. To achieve identification, they assume (a) the number of buyers and sellers unchange over time, and (b) the distribution of buyers is known up to a parameter. These assumptions do not hold in bike-sharing: platforms' investment decision will endogenously change the number of "sellers", and it is crucial to account for changes in the number and types of searchers.

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 depend on pre-determined city attributes, pre-entry investment alone is absorbed by city fixed effects. As shown in Table 5 Panel B, the positive price effect of entry is stronger when there had been more pre-entry investment in a city. The trip 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 5 Panel B does not reject this interdependence. Rather, it shows that the differential market expansion effects (in price and trip 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 6 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.[40] 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.

VII. 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 trip 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

[40] Please note that the more evenly distributed network does not imply that the booming usage volume is purely driven by expansion to new grids. Table A5 provides further discussion.

reviews or consider entry policies in a market with positive network effects.

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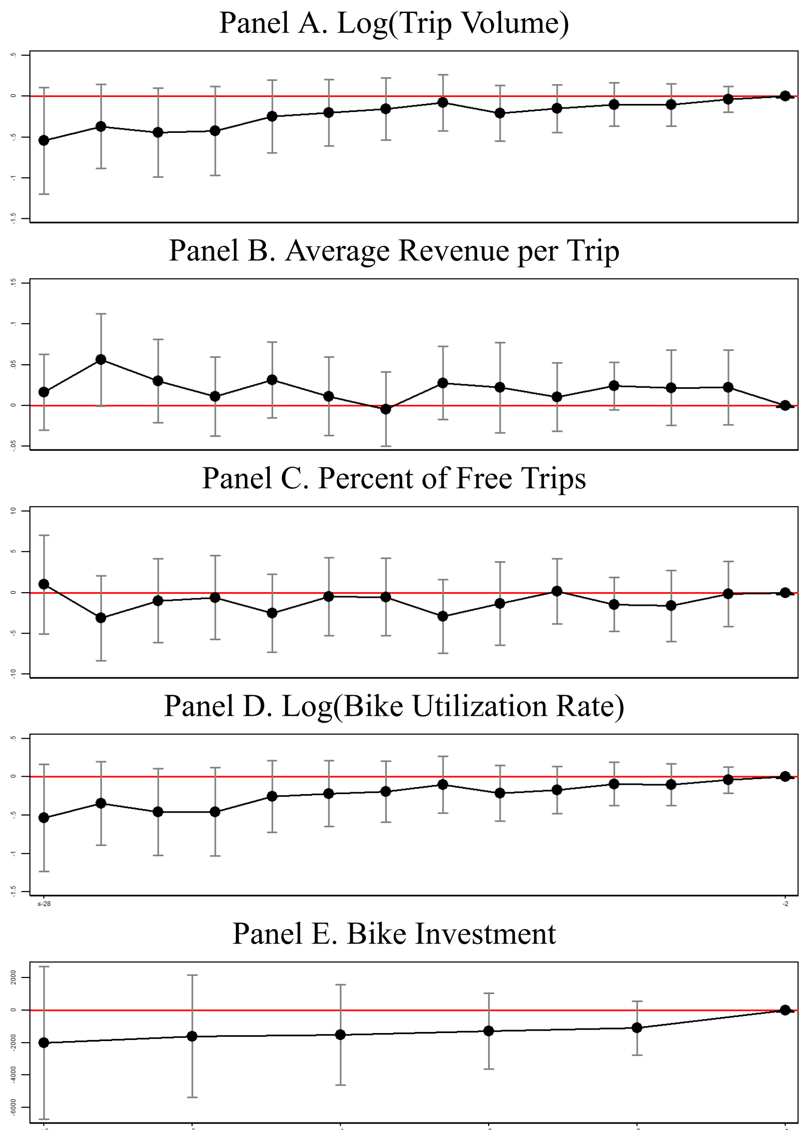

FIGURE 1. TEST OF COMMON PRE-TREND ASSUMPTION

Notes: Point estimates of $\{\lambda_{-k}\}_{k=2}^{k=14}$ in Equation (2) as well as corresponding 95% confidence intervals are plotted with relative days before Mobike's entry on the horizontal axis. The two days before Mobike's entry are omitted as base and days more than 4 weeks before the entry are all counted as $k = 14$. Similar notations apply to the last panel with time unit changed into month. All these estimates are statistically indistinguishable from zero. They are not different from zero with 95% confidence as well when tested jointly. Standard errors are clustered at the city level.

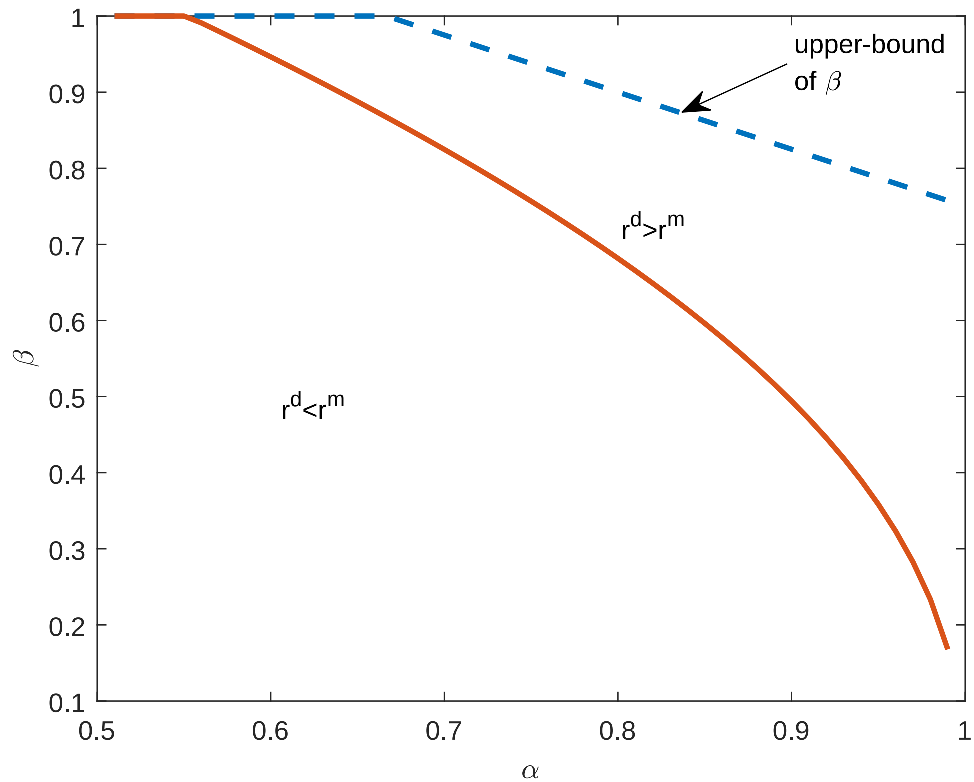

FIGURE 2. COMPARISON OF r^d AND r^m ($\theta = \gamma = 2$)

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

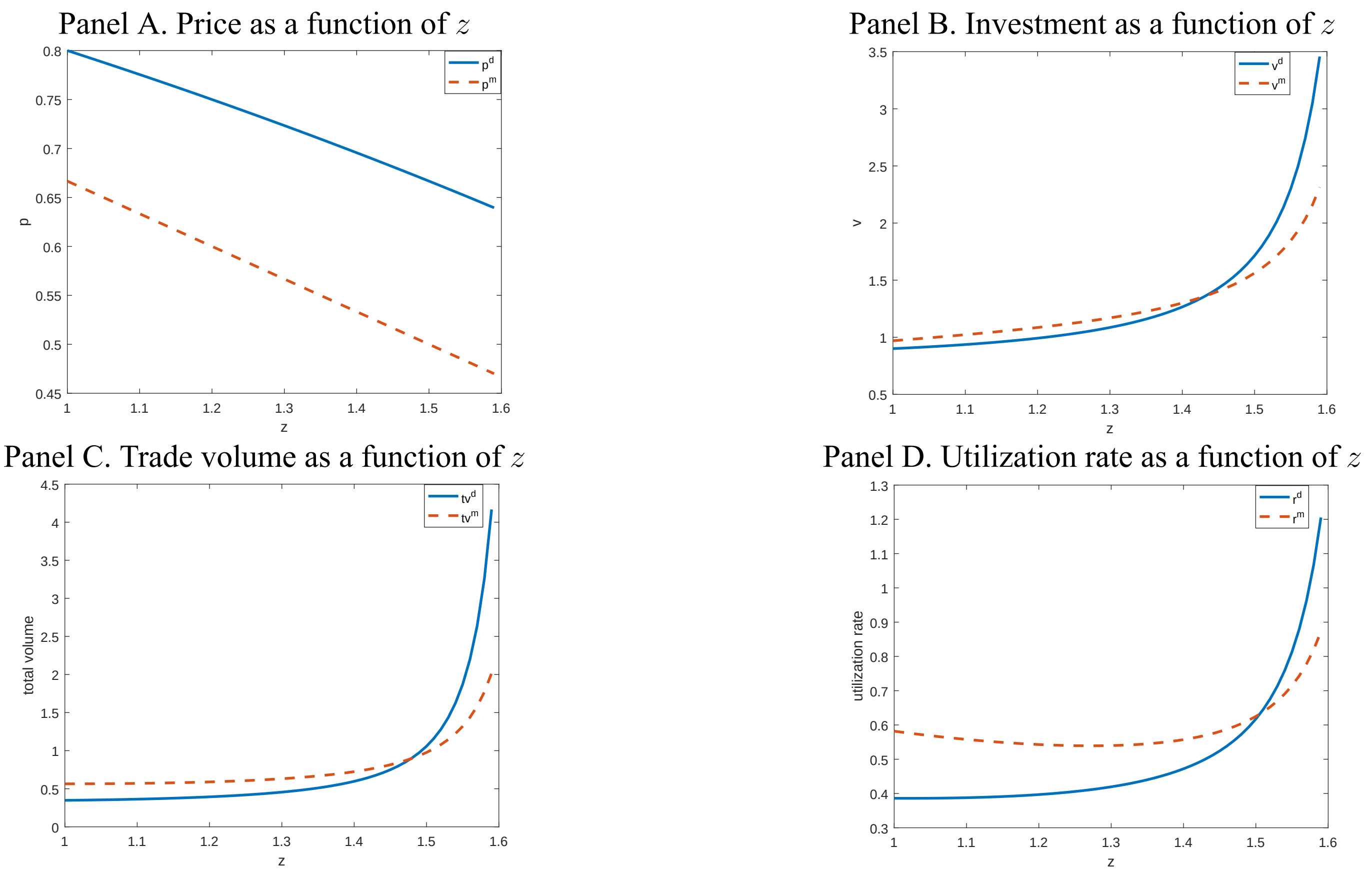

FIGURE 3. COMPARION OF MONOPOLY AND DUOPOLY EQUILIBRIUMS UNDER DIFFERENT $z = \alpha + \beta$

Notes: Panels in this graph plot how the equilibrium prices, investments, trade volumes and utilization rates change with $z = \alpha + \beta$ in both monopoly and duopoly cases.

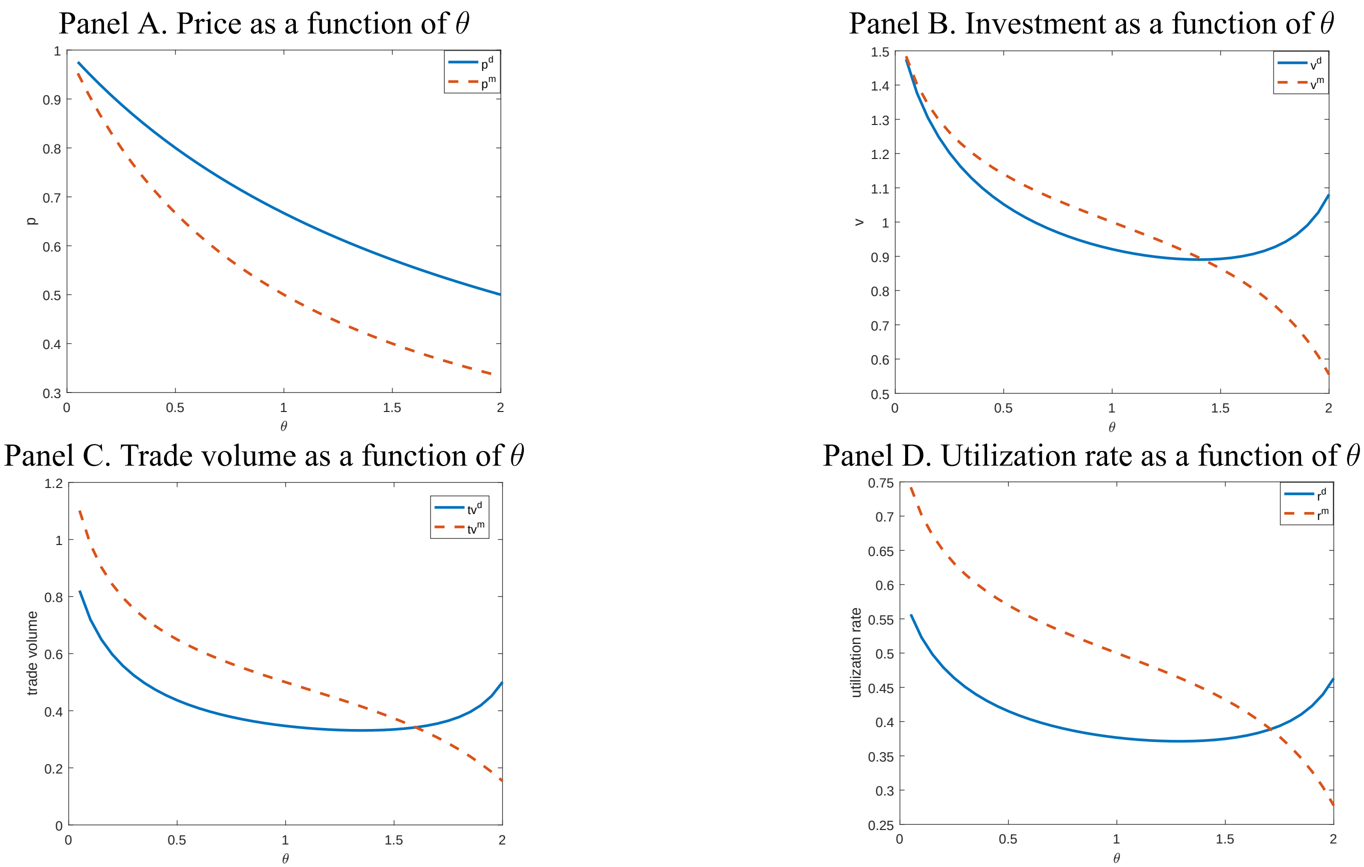

FIGURE 4. COMPARION OF MONOPOLY AND DUOPOLY EQUILIBRIUMS UNDER DIFFERENT θ

Notes: Panels in this graph plot how the equilibrium prices, investments, trade volumes and utilization rates change with θ in both monopoly and duopoly cases.

TABLE 1 – SUMMARY STATISTICS

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	6903	6351	6265	2041	1951	4829	10326
Number of Buses	3030	4475	3775	4871	942	731	3215	5073
Road Surface (10,000 Square Meters)	3281	3189	3952	3476	1628	1268	3212	3249
Number of Mobile Phone Users (10,000)	688	586	807	603	367	218	706	689
Number of Internet Households (10,000)	142	160	171	185	71	44	141	146
Average Gradient (‰)	459	571	447	548	597	745	345	391

Notes: Mean of key outcomes are masked by “NA” for confidentiality

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 Attributes×Date Fixed Effects			YES			YES	
City Attributes×Day 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 ofo's entry. Column 3 and 4 interact the city attributes with calendar date fixed effects and relative day fixed effects respectively. Column 5-7 further include the linear time trend specific to the *ofo First* cites. The specification of Column 7 is taken as benchmark setting in the following analyses. Standard errors in parentheses are clustered at the city level and ***, **, * denote significance at the 1%, 5%, 10% level respectively, the same hereinafter.

Table 3 – 2SLS Estimates and Competition Effects on Bike Utilization Rate and Bike Investment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variables	*PostEntry*	*Log (Trip Volume)*	*Average Revenue per Trip*	*Percent of Free Trips*	*Log (Bike Utilization Rate)*		*Bike Investment*	
Models	*First-Stage*	*2SLS*	*2SLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*
Predicted PostEntry	0.949***							
	(0.011)							
PostEntry		0.478**	0.045***	-3.999***	0.392**	0.457**	57.526**	58.384**
		(0.199)	(0.012)	(1.493)	(0.185)	(0.198)	(27.789)	(27.391)
Benchmark Setting	YES	YES	YES	YES	YES	YES	YES	YES
Kleibergen-Paap F Test	8000.251	/	/	/	/	/	/	/
Number of Clusters	82	82	82	82	79	79	79	79
Number of Observations	16193	16193	16193	16193	15770	15770	616	616

Notes: (1) 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. Further robustness checks of starting date choice and the assumption of baseline hazards are reported in Appendix Table A3. (2) Every two columns of Column 5-8 under the same outcome variable report OLS and 2SLS estimates separately which adopt the benchmark setting in Table 2 Column 7. Because of the lumpiness bike investment, we aggregate the investment data to month level and *PostEntry* is defined as the percent of days that Mobike operates in the city c and month m. We also reconstruct all weather and air variables as monthly average, and control for monthly time fixed effects instead of daily fixed effects.

TABLE 4 – 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
Benchmark Setting	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 setting in Table 2 Column 7. Standard errors are in parentheses and clustered at the city level.

TABLE 5 – FURTHER DATA ANALYSIS MOTIVATED BY THE MODEL

	(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*
Panel A Placebo Test Using ofo Campus Period						
PostEntry×Dummy for Operation within Campus	-0.176	-0.008	0.024	0.041	-1.795	-3.063
	(0.300)	(0.285)	(0.025)	(0.026)	(4.113)	(4.011)
PostEntry×Dummy for Operation in the Whole City	0.482**	0.533**	0.044***	0.045***	-3.935***	-4.105***
	(0.202)	(0.215)	(0.013)	(0.013)	(1.463)	(1.550)
Within Adjusted R2	0.122	/	0.060	/	0.070	/
Number of Clusters	82	82	82	82	82	82
Number of Observations	16193	16193	16193	16193	16193	16193
Panel B Competition Effect Heterogeneity to Pre-Entry Bike Investment						
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)
PostEntry×Pre-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)
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
Benchmark Setting	YES	YES	YES	YES	YES	YES

Notes: (1)In Panel A, 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 setting. Every two columns under the same outcome variable report OLS and 2SLS estimates separately. (2)In Panel B, the *Pre-Entry Bike Investment* is calculated as the average number of accumulative bike investment over 10 days before Mobike's 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.

Table 6 – 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
Duopoly Group Trend	YES	YES	YES	YES	NO	NO
City Attributes $\times$ Day Fixed Effects	YES	YES	YES	YES	YES	YES
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 setting in Table 2 Column 7.

For Online Publication

Appendix A:. Additional Figures and Tables

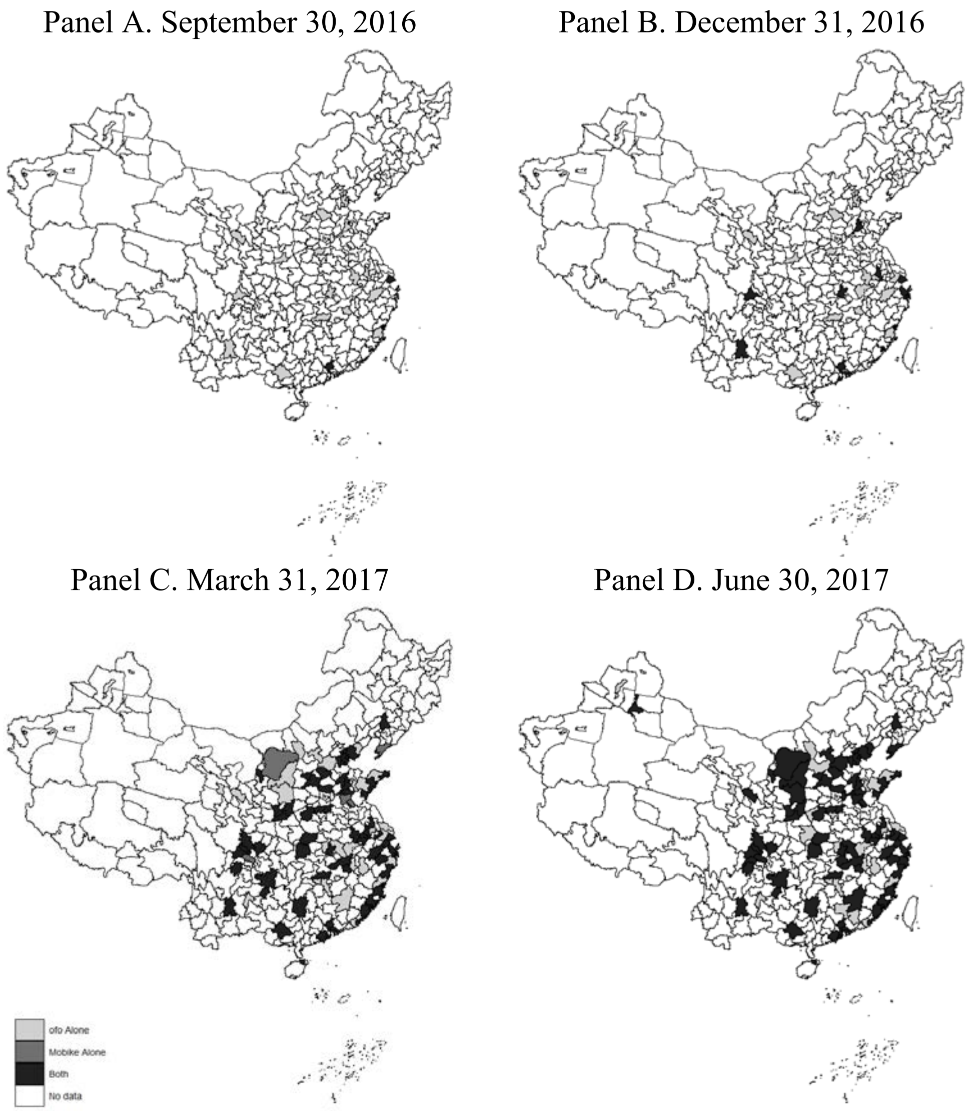

FIGURE A1. EXPENSION PROCESS OF OFO AND MOBIKE

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).

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 Attributes$\times$Day 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.

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 Attributes$\times$Day(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 5×3 = 15 estimates of β. This table provides further support to Table 3 in the sense that results are not driven by the choice of starting dates or distribution function.

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 – Subsample Regression for Test of IV Validity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variables	*Log (Trip Volume)*		*Average Revenue per Trip*		*Percent of Free Trips*		*Log (Bike Utilization Rate)*		*Bike Investment*	
Models	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*
Panel A *ofo Alone* and Above-Median *ofo First* Cities										
PostEntry	0.016	0.018	0.027**	0.026**	-1.913	-1.945	0.004	-0.001	82.709*	81.497*
	(0.154)	(0.164)	(0.010)	(0.011)	(1.405)	(1.489)	(0.159)	(0.167)	(43.572)	(42.634)
Within Adjusted R^2	0.1	/	0.059	/	0.065	/	0.062	/	0.091	/
Number of Clusters	54	54	54	54	54	54	51	51	51	51
Number of Observations	10159	10159	10159	10159	10159	10159	9736	9736	382	382
Panel B *ofo Alone* and Below-Median *ofo First* Cities										
PostEntry	0.627*	0.764**	0.053**	0.061***	-4.813*	-5.391*	0.544	0.682*	45.397**	45.868**
	(0.365)	(0.378)	(0.020)	(0.021)	(2.721)	(2.888)	(0.388)	(0.402)	(19.021)	(18.371)
Within Adjusted R^2	0.21	/	0.058	/	0.092	/	0.153	/	0.05	/
Number of Clusters	51	51	51	51	51	51	49	49	49	49
Number of Observations	8567	8567	8567	8567	8567	8567	8197	8197	331	331
Benchmark Setting	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: We use entry and finance dates to classify *ofo First* cities within each of the eight finance rounds of Mobike. In each round, we sort cities by population and divide them into above-median and below-median groups. We then compare above-median and below-median cities with *ofo Alone* cites in OLS and 2SLS, which are reported in Panel A and B respectively.

TABLE A5 – 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
Duopoly Group Trend	NO	NO	NO	NO
City Attributes$\times$Day Fixed Effects	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 Mobike's 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.

Appendix B:. Mathematical Appendix