

Will Dockless Bike Sharing System Alter the Subway Price Premium in Rental Market?
Evidence from Beijing

By

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Abstract

The dockless bike-sharing system emerged in 2016 in China. It achieves door-to-door connection and is thus regarded as an efficient solution to the urban last mile problem. Empirical studies have found that the entry of dockless bikes can flatten the rent price gradient for subway accessibility for 10 Chinese cities on average, yet haven't discussed if this effect also exists in a single city where subway accessibility varies across locations. This study uses difference-in-differences (DID) empirical design to analyze the impact of dockless bike-sharing on Beijing's rental market, and further explores the spatial heterogeneity of such impact. Results show that the rental price gradient flattens slightly for apartments within the 3km radius from a subway station in Beijing. Taking the heterogeneity of development in Beijing into account, the study further finds that the rental price gradient becomes slightly steeper in more developed areas such as North Beijing or Beijing within the 4th Ring Road, and flattens by up to 16% in less developed areas such as South Beijing and Beijing outside the 4th Ring Road. Such impact on rental price gradient is not linear within the 3km radius, where in more developed areas the largest reduction in gradient happens at 1000-2000m, and in less developed areas at 0-500m. The entry of dockless bike-sharing system can generate great social benefits. Switching from walking to biking from homes to subway stations saves about 8.3 minutes of commuting time per trip on average in Beijing, where the most developed area saves 7.24 minutes and the least developed saves 11.8 minutes. Allowing for a 10-min commuting time from homes to subway stations, a tenant would be able to choose from apartments within 800m to subway stations to up to 3km to subway stations. This study contributes to the nascent literature on dockless bike-sharing systems and its impacts on housing rental market, and also yields policy implications for better integrating the bike-sharing system and the existing public transit systems, and the resulted benefit of enhancing housing supply in public transit accessible locations.

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Chapter 1

Introduction

1.1 Introduction

The last mile problem in transportation network refers to the difficulty in transferring people from origins (homes, offices, etc.) to public transportation hubs (subway stations, bus stops, etc.), or from public transportation hubs to their final destinations. This adds to substantial commuting costs. Policy makers have initiated many programs to solve this problem; the public bike-sharing system is one among the solutions. The first generation of bike-sharing system was proposed in Amsterdam, Netherlands, in 1965, providing transiting services to citizens free of charge. In the 1970s to 1990s, as technologies became more advanced and affordable, many bike-sharing systems were initiated in many European cities (Shaheen et al., 2010). In the early 2000s, China started to support public bike-sharing systems in big cities such as Beijing, Shanghai, Hangzhou and Wuhan. These bike-sharing systems place bike stations in certain areas in cities; users need to pick up the bikes at stations, make payment with coins or smart cards, and return the bikes to any station after the trip.

The dock-based bike-sharing system plays an important role in solving urban last mile problem. Until 2016 October, there were up to 1,700 public bike stations and more than 55,000 dock-based bikes serving 380,000 registered users. The daily use of dock-based bikes in Beijing is around 200,000. Studies have found that bus stops and subway stations

are popular destinations of public bike trips, indicating that public bike-sharing systems integrate into city's public transportation infrastructure (Zhao and Li, 2017).

However, public bike-sharing systems remain an inefficient solution to the urban last mile problem. First, the bike stations which are usually located at populated places are still beyond reach of citizens who live far from them. Second, users may not be able to return the bikes to stations that are closest to their destinations due to limited number of docks at each station. Third, such system is often not profitable due to low charge. Last, the budget for maintaining or expanding the bike-sharing system often comes from government, which is always limited.

In 2016, the new dockless bike-sharing system was initiated in Beijing, China, and the market has rapidly expanded across the country. Fundamentally different from the traditional bike-sharing programs which place bikes at fixed stations, the dockless bike-sharing system does not place docking facilities. Each bike is installed with smart lockers; users can unlock the bikes and pay for the trips with smart phones, and lock the bikes and leave them almost anywhere at their convenience. The major dockless bike operators such as *Ofo* and *Mobike* also developed smart phone applications for their bikes. Users are able to view the locations of bikes near them and book them in advance. Compared to the traditional bike-sharing systems, dockless bike-sharing systems have made it possible for users to travel from their actual origins to their final destinations, achieving door-to-door connection and reducing travel costs significantly. From a user behavior study report released by *Mobike* in mid-2017, public transit nodes are the most popular destinations. Taking Beijing as an example, nearly 90% of *Mobike* users' destinations are public transit nodes; around 44% of the destinations are subway stations, and the rest of the destinations are bus stops. This indicates that the dockless bike-sharing system works as an integration of public transport mode. Dockless bikes have outnumbered traditional dock-based bikes, too. It is reported that more than 25 dockless bike operators have put more than 2 million dockless bikes in Beijing, where 700 thousand of them are from *Mobike*.

Empirical studies have found that proximity to public transit nodes can increase housing prices. Many studies found that the reduced commuting costs for houses near subway

stations have been capitalized into housing prices cities around the world such as Toronto (Bajic, 1983), Beijing (Xu et al., 2015) and Hangzhou (Wen et al., 2018). A study also find that after the introduction of dock-based public bikes in Shanghai and Houston, the role of the traditional urban center is weakened, indicating that urban rail systems can transform a traditional monocentric urban form to a polycentric urban form (Pan et al., 2014). Other studies also found that price premium exists when houses are close to bus stops (Cervero and Kang, 2011) and traditional docked bike stations (Pelechrinis et al., 2015).

Since dockless bike-sharing systems can reduce travel costs from homes to subway stations, can we expect that the houses which are farther from subway stations are now also appreciated? Chu et al. (n.d.) studied the impacts of dockless bike-sharing systems on housing prices using resale transaction data from 10 big cities in China. The study found that for each city, houses far from subway stations are also favored after the entry of dockless bikes, and the subway price premium of houses close to subway stations reduces. This study has provided us an answer that the dockless bike-sharing system has an impact on housing prices at municipal level. However, the pattern of bike usage and user behaviors may vary within each city, and Chu et al.'s study did not tell us if such variation can affect the subway price premium. Moreover, the study used generalized rental listings in the 10 cities, and found that rental price premium is also reduced. Similarly, the study did not tell us the impact on rental price premium in each city and within each city. It is important to study each city separately, for the socioeconomic factors and urban form differ greatly among cities, and rental price premium may be affected by these factors.

Most previous studies examined the price premium using sales prices, which is heavily reflected by speculative demand and affected expectation effect. To better examine the user value of a location, later literature should use rental prices. Among all cities in China, Beijing has the highest rental price. The average income in Beijing in 2017 was ¥8,467/month (\$1225/Month), while the average rental price for a 1B1B apartment in Beijing in 2017 August was ¥5,404/Month (\$803/Month), which is more than 60% of the average income. By the end of 2017, there were more than 7 million tenants in Beijing and around 80% of them were migrant workers without a Beijing Hukou. Studying the impact of dockless bikes on

rental price premium can help us understand both the economic and social benefits to this large population. Dockless bikes may generate economic benefits for tenants if they can reduce the capitalization effect of living close to subway stations. They can also generate social benefits. Jin et al. (2018) found that a combination of public transportation and dockless bikes can greatly reduce commuting time, and it is a preferable option to driving private cars when length of travel time or ease in finding parking are concerns. Social benefits may also include increased housing supply for tenants to choose from. Zheng, Xu, et al. (2016) found that new subway lines in Beijing have capitalization effect in home values, and the extent of such effect varies depending on the elasticity of housing supply market. Zheng, Sun, et al. (2014) also found the variation in capitalization effect of school quality and subway accessibility with land availability. The entry of dockless bikes may alter the capitalization effect of subway systems, resulting in changes in the housing supply market.

Moreover, understanding the heterogeneity effect within a city can help city governments with future policy-making. The development level within a city often differs from place to place. This is true in Beijing, where the north of Beijing (north beyond Chang'an Avenue) is more developed than the south, and regions within the 5th Ring road are more developed than areas outside the 5th Ring road. Understanding how the entry of dockless bikes can affect different areas in Beijing can help us better understand the potential benefits and costs to citizens.

1.2 Research questions and hypotheses

This study aims to quantify the impact of dockless bike-sharing system on rental market in Beijing and examine how such impact differs across Beijing. To do this, this study asks the following research questions and make the following hypotheses.

1. How much does subway price premium in rental market in Beijing change due to the entry of dockless bikes?

By asking this question, the study aims to quantify the rental price premium before and after the entry of dockless bike-sharing systems in Beijing. The hypothesis is that the

apartments closer to subway stations will be less appreciated, and the apartments farther from subway stations will be more appreciated. Thus, the rental price premium curve around subway stations is expected to be flatter after the entry of dockless bike-sharing system.

2. Is the change in rental price premium heterogeneous across Beijing?

By asking this question, this study aims to understand if the change in subway price premium in rental market differs spatially across Beijing. This question can be studied by partitioning Beijing into sub-areas, and examine the change in subway price premium separately. It is expected that the impact differs due to different development level in Beijing. The hypothesis is that the change in rental price premium will be larger in less developed areas.

3. What is the implication of such change in subway price premium in rental market in Beijing?

By asking this question, this study aims to discuss the benefits that dockless bike-sharing systems can generate. Potential benefits could be economic, such as savings on rentals and commuting costs. The benefits could also be social, such as improved accessibility and increased housing supply. Understanding and quantifying potential benefits may help us better understand the benefits of dockless bikes in the housing market other than their positive impacts on environment and human health.

1.3 Thesis structure

For the rest of this study, Chapter 2 reviews the recent literature on bike-sharing system's role as integration of public transportation infrastructure and its impact on subway price premium. Chapter 3 introduces the empirical strategy used to model the impact of entry of dockless bikes on rental price gradient, and introduces the data that are used in the study. Chapter 4 shows the major results and discusses the implications of the impact. Chapter 5 wraps up the study and discusses future work.

Chapter 2

Literature Review

This chapter reviews the relevant literature in three fields: bike-sharing as an integration to public transportation infrastructure, subway price premium, and bike-sharing's impact on subway price premium. By reviewing the literature I built up the theory that dockless bikes can flatten rental price gradient, yet such study is nascent and the heterogeneity of such effect within a city has not been examined.

2.1 Bike-sharing: integration of public transportation

Public bike-sharing systems are efficient to solve urban last mile transit problem by connecting users from their actual origins to public transit nodes (or from public transit nodes to their actual destinations), although traditional public bike-sharing systems place public bikes at certain locations, limiting the service to people around the docks. It has been widely cited that public bike-sharing systems can integrate to other public transportation modes such as trains and buses, and the bike-and-ride trips have become popular around the world as more public bike-sharing programs were initiated.

Bike-sharing programs first emerged in Amsterdam, Netherlands, in 1965. Through its long history in Europe, the programs were considered failures for the lack of payment scheme and stealing. In later generations of bike-sharing when payment systems (coin-deposit and smart card integration) were introduced, the programs became success and

have been operating until now. Some of the programs (i.e., the Yelo bike-sharing system launched in La Rochelle, France, in 2009) have seamlessly integrated with public transportation (Shaheen et al., 2010). The trend of bike-transit integration in North America came in much later than that in Europe, but witnessed a dramatic growth in U.S. and Canada. Pucher and Buehler (2009) reported a 38% growth in public transport trips between 1995 to 2008 and a 32% increase in total number of bike trips from 1990 to 2005-2007 in the U.S., which provided a rationale for more bike-transit integration. The authors argued that the bike-transit integration requires provision of infrastructures such as bike parking spaces and bike racks on transit vehicles.

Asia only started to introduce bike-sharing systems in 1990s, however is the fastest growing market. Taking China as an example, Hangzhou city launched its public bicycle system in 2008 and operated 40,000 bikes and 1,600 station in the city (Shaheen et al., 2010). Other cities such as Wuhan, Beijing and Tianjin all started their pilot public bike systems in the 2000s. The trend in bike-and-ride trips is also witnessed in China. Zhang and Huang (2012) evaluated the performance of bike-sharing system in Wuchang area in Wuhan, China, and found that 55% of the respondents use public bikes to integrate with bus, and 35% to integrate walking. However, the integration rate to subway system is less than 1% due to lack of development in subway system back in 2009. Zhao and Li (2017) randomly surveyed 739 passengers at 36 subway stations in Beijing on their travel behaviors and socioeconomic features to explore the determinants of bicycle use by commuters as transfer mode in Beijing. Among all the respondents, only 7% of them use bicycle as transfer mode to subway stations, and about 80% of them cycle for 1-4 km. The authors found that cycling is considered as a cheap travel mode to some extent, even compared with walking. The authors suggested that public bike-sharing initiatives could promote bike-and-ride integration.

Literature also reports the limitation of bike-and-ride integration and inefficiency of traditional docked bike-sharing systems, one of the major is the geographical mismatch between supply and demand. Liu et al. (2012) pointed out that some public bicycle stations are rarely used. What is more, public bicycle stations are located at relatively denser areas,

which are sometimes far from neighborhoods. Kabra et al. (2018) also argued that limited accessibility to public bikes making bike-sharing inefficient in solving urban last mile problems. They found every additional meter of walking to a dock decreases a user's likelihood of using a public bike from that dock by 0.194%, and this reduction is even more significant when the distance from homes to bike station is greater than 300 meters. This implies that the contribution of traditional docked bike-sharing system to urban accessibility can be limited by the locations of the docks.

The dockless bike-sharing system solves the limitation of accessibility to public bikes. Since these public bikes are "dockless", users can pick them up and leave them almost anywhere at their convenience. Since the dockless bike-sharing System only started to operate in 2016, and the trip data are difficult to acquire, only a few studies have looked at the user behaviors of dockless bike-sharing system. Deng, Xie, et al. (2017) analyzed the spatiotemporal patterns of dockless bike usage in Beijing. The study found that public transit nodes including bus stops and subway stations are popular origins and destinations. This popularity peaks during rush hours, and differs spatially across Beijing.

2.2 Housing price premium

Rich literature has investigated how proximity to public transit systems affect housing prices, and come to a general conclusion that houses that are close to public transit nodes enjoy higher prices. Such impact is called "housing price premium". Housing price premium due to proximity to public transit nodes reflects the trade-off between consumers' willingness to pay and commuting costs. Understanding the concept of housing price premium and quantifying such effect can provide numerous implications such as policy suggestions on housing price adjustment, grant adjustment and housing affordability policies.

Most of the literature focused on the impact of closeness to subway stations or to new subway lines on surrounding properties, and denote such impact as "subway price premium". Bajic (1983) used the modal choice model and hedonic price regression model to identify the effects of a new subway line on the values of housing units in Toronto, Canada.

The paper found that commuting costs can be saved for properties near the new subway line, yet the direct savings have been capitalized into the increased housing values. Bae et al. (2003) analyzed the impact of subway Line 5 in Seoul, Korea, on nearby residential areas. By using hedonic price model, the study found that the impact of Line 5 on housing value increase is statistically significant in year 1989, 1995 and 1997, when the line was announced, built and opened, respectively.

With the development of subway lines in many cities in China and drastic housing price increases in these years, it is worthwhile studying how the subway line can further affect housing prices in China. Wen et al. (2018) adopted hedonic price model and quantile regression model to investigate the capitalization effect of a new subway line on housing prices in Hangzhou. The study found that the average housing price within 2 km of the stations is 2.1% to 6.1% higher than those outside and the subway opening strengthens the capitalization effect of traffic accessibility. Other urban policies, although not directly relevant to subway, may also lead to impacts on changes in subway premium. Xu et al. (2015) studied how the subway demand would increase after the city government of Beijing imposed restriction on private driving in October, 2008. The paper made the hypothesis that the car restriction policy (one can only drive for 4 days in the weekdays) will increase subway demand in Beijing, which then lead to higher demand and appreciation on properties proximate to subway stations. By using pseudo-repeat sale regression model and hedonic regression model, the results were as expected. There is around 1.8 to 2.7 percentage of increase in people's willingness to pay for subway proximity, which is about 36% to 60% of the initial price premium. The study also found spatial heterogeneity of such impact in Beijing, where locations where subway travel time can better match that of car travel experience relatively higher housing price appreciation. Studies have also found that the capitalization effect of public transit systems may depend on land availability. In other words, the impact of public transit systems on housing price is heterogeneous depending on the elasticity of housing supply. Zheng, Xu, et al. (2016) found that new subway lines in Beijing have capitalization effect in home values, and the extent of such effect varies depending on the elasticity of housing supply market. Zheng, Sun, et al. (2014) also found

the variation in capitalization effect of school quality and subway accessibility with land availability.

A number of studies also looked at how other public transportation modes—bus and bike-sharing—can lead to housing price premium. Cervero and Kang (2011) examined the land-market effects of converting regular bus operations to Bus rapid transit (BRT) services in Seoul, Korea, and found that residences within 300m of BRT stops enjoy up to 10% land price increase. Moreover, the multimodel revealed the tendency of property owners to convert from single-family residences to higher density apartments and condominiums. Pelechrinis et al. (2015) looked at the docked bike-sharing system in Pittsburg, U.S. The authors applied difference-in-differences method to estimate the installation of public bike stations on the housing prices in the zipcode zone the station locates, and found around 2.5% of increase on both sales and rental prices at its surrounding neighborhood.

The traditional docked bike-sharing systems leads to housing price premium, because the bikes are stored at fixed locations, and only surrounding houses can be benefited. The dockless bike-sharing system is fundamentally different with the traditional docked ones. Traditional public bike docks are usually located at populated areas, while dockless bikes can appear anywhere as long as someone cycled them there. Therefore, it is likely that communities that were far from subway stations may also enjoy a house price premium, because the commuting costs are reduced. Only one unpublished study started to look at the impact of dockless bikes on housing price premium. Chu et al. (n.d.) has been working on a working paper on the impacts of dockless bike-sharing systems subway premium in 10 big cities in China by applying difference-in-differences model on housing resale prices in each city. The team has found that the introduction of dockless bike-sharing system reduces the housing price premium in all cities. For example, the subway price premium shrinks by 53% per km and by 57% in Shanghai and Beijing, respectively. Although the study also found the entry of dockless bikes reduces rental price premium by 18.2%, the authors used rental listings from all 10 cities and reported the aggregated effect.

Chu et.al's study was the first one trying to investigate the impact of dockless bike-sharing on the housing market. The study provided a good background that the entry of

dockless bikes can flatten the housing price premium at municipal level, yet failed to understand how such impact differs within cities. Moreover, the study used all rental listings in the 10 cities and found that rental price premium is also reduced, yet failed to specify the impact on rental price premium in each city and within each city. It is important to study each city respectively, for the socioeconomic factors and urban form differ greatly among cities, and rental price premium may be affected by these factors.

The development within Beijing has been varied historically. In the past, the north part of the inner city (areas within the 2nd Ring road) was places for the wealth, and the south part was for sales and manufacturing. Even since the establish of modern China, most development happened in the north of Beijing, such as founding of universities, industrial parks and business centers, while the south part continued to develop with agriculture and sales of groceries. Zhang (2004) has found that the distribution of cultural sites such as libraries and museums is uneven between the north and the south of Beijing. Deng, Cai, et al. (2012) studied the accessibility with highway and subway network in Beijing, and found the accessible areas in north of Beijing is significantly larger than those in the south. The authors also found that the road density and accessibility decreases from the center of Beijing to the outskirts. Land use patterns, road network and cultural sites can all affect rental prices. Therefore, it is worth studying how do dockless bike-sharing system affects different regions of Beijing.

2.3 Gaps in the literature

Since dockless bike-sharing has just been introduced for less than three years and is mainly popular in China, Chu et al.'s study is currently the only one looking at the relationship between dockless bike-sharing usage and housing prices. The study has provided a general and good image of the relationship between dockless bike-sharing and subway premium in the big cities in China at city level. However, there are still research gaps that are worth exploring:

- **The spatial heterogeneity of the impact of dockless bikes on housing price pre-**

mium within a city. It is important to look into the within-city spatial differences of such impact because of the complexity of urban forms and heterogeneous development of Chinese cities. Understanding the spatial heterogeneity within cities can also contribute to policy implications on city governance, housing supply, and transportation policies.

- **The impact of dockless bikes on rental prices at city scale or within cities.** The impact on rental market is worth examining, for the rental market reflects the use value, while resale prices incorporates investment intention. Moreover, among over 7 million tenants in Beijing, more than 80% of them are migrant workers without Beijing Hukou. Quantifying the impact of dockless bikes on rental market also provides a picture of benefits to tenants.

Chapter 3

Methods and Data

This chapter introduces the method and data that are used in this study. A difference-in-differences (DID) quasi-experiment is designed to quantify the change in subway price premium due to the entry of dockless bikes and test the spatial heterogeneity of such impact. The method section describes the specification of DID models. The data section introduces the data that are used in this study, the collection methods, and descriptive analysis.

3.1 Empirical strategy

The change in subway price premium is modelled with difference-in-differences hedonic regression model. The specification is:

$$\begin{aligned} \log(price_{ij}) = & \beta_0 + \beta_1 X_{ij} + \beta_2 L_{ij} + \beta_3 Y M_{ij} + \beta_4 Subway_j + \\ & \beta_5 d_subway_j + \beta_6 d_subway_j \times BIKE + u_{ij} \end{aligned} \quad (3.1)$$

where $price_{ij}$ represents the rental price of observation i in complex j . X_{ij} is the vector of a apartment/room physical attributes including size, whether the building has a lift, the decoration status, the approximate level of the apartment/room, the heating supply method, the age of the building, and the facing direction of the apartment/room. L_{ij} is the vector of a complex's location attributes including the number of convenient stores within 500

meters, network-based distance to the closest shopping mall, grade AAA hospital and university. Note that the distance to a complex's closest subway station is not included in L_{ij} but separately listed in the model. YM_{ij} is the year and month dummy indicating when the transaction happened; it works as time fixed effect to control for other policies and inflation that may happened during the study period. $Subway_j$ is the closest subway station to complex j ; the inclusion of it works as the location fixed effect, accounting for the surrounding conditions of complex j . It also reflects the uneven distribution of dockless bikes around subway stations in Beijing. d_subway is the network-based distance from complex j to its closest subway station. $BIKE$ is a binary dummy indicating the entry of dockless bike-sharing program. Mobike entered Beijing on September 1, 2016; so, $BIKE = 0$ for all transactions happened before August 31, 2016, and $BIKE = 1$ for all transactions happened on and after September 1, 2016. This is the entry date of *Mobike*, a major and the largest dockless bikes operator in China. Although *Ofo*, another operator, entered in Beijing around 4 months earlier than *Mobike*, it did not create much impact in affecting people's travelling behaviors. From the dockless bikes penetration index provided by Baidu, only until late 2016 did dockless bikes penetrated to people's daily lives. Moreover, DID method estimates the average treatment effect after the entry date, so it is reasonable to use the entry date of *Mobike* instead of a date when dockless bikes have highly penetrated into daily life. β_0 is the constant; β_1 and β_2 are estimated coefficient vectors that quantify the impact of room attributes, complex location attributes on rental prices. β_5 measures the impact of subway proximity on rentals and is expected to be significantly negative, meaning that the average rental price will reduce by $100\beta_5\%$ when the room/apartment is 1km away from subway stations. β_6 measures the impact of entry of dockless bikes on housing price gradient. After the entry of dockless bike-sharing, the subway price premium gradient is $100(\beta_5 + \beta_6)\%$. β_6 is expected to be positive and significant, meaning that the entry of dockless bikes flattens the overall gradient.

However, the gradient may not be linear, and the impact of dockless bikes on subway price premium may not be constant over distances. To better model the subway price premium and its change due to entry of dockless bikes, I replaced the continuous variable

d_{subway_j} in Model 3.1 with discrete variables indicating the locations of complexes around subway stations. The model is specified as followed:

$$\begin{aligned}
\log(price_{ij}) = & \beta_0 + \beta_1 X_{ij} + \beta_2 L_{ij} + \beta_3 Y M_{ij} + \beta_4 Subway_j + \\
& \beta_5 subway500_j + \beta_6 subway500_j \times BIKE + \\
& \beta_7 subway1000_j + \beta_8 subway1000_j \times BIKE + \\
& \beta_9 subway1500_j + \beta_{10} subway1500_j \times BIKE + \\
& \beta_{11} subway2000_j + \beta_{12} subway2000_j \times BIKE + \\
& \beta_{13} subway2500_j + \beta_{14} subway2500_j \times BIKE + u_{ij}
\end{aligned} \tag{3.2}$$

where $subway500_j, subway1000_j, subway1500_j, subway2000_j$ and $subway2500_j$ are binary variables indicating if complex j falls in to the region within 0-500m, 500-1000m, 1000-1500m, 1500-2000m and 2000-2500m of its closest subway station; 2500-3000m is the control group, and is dropped in the regression model. I expect $\beta_5, \beta_7, \beta_9, \beta_{11}$ and β_{13} to be significantly positive, meaning that apartments located within 0-2500m are more appreciated than those located in 2500-3000m region. $\beta_6, \beta_8, \beta_{10}, \beta_{12}$ and β_{14} measures the impact of entry of dockless bikes on the appreciation of apartments located in 0-2500m region, and I expect them to be negative and significant.

3.2 Data

This study uses a series sets of data to study the impacts of dockless bike-sharing system on subway premium on rentals. This section introduces the data, how they are collected and processed, and the descriptive statistics.

3.2.1 Rental transactions

This study focuses on the subway premium in rental market in Beijing and how is the subway price premium affected by the integration of dockless bike-sharing and the existing

subway infrastructure. Among all major real estate brokers in China, only Lianjia - which accounts for about 50% of the market - preserved and provided the historical rent transactions dated back to 2002 through its mobile app. The transactions were thus collected from Lianjia.

Collecting the full records of rent transactions from Lianjia requires two major steps. First, I scraped the full list of complexes (xiaoqu) including complex ID, complex name, business circle, district, latitude and longitude. Then, for each complex, I scraped all of its rent transactions; each transaction contains rich information including rent price, room size, floor, heating status, decoration status, etc. Fiddler was used to acquire the web addresses of list of complexes and rent transactions from Lianjia mobile app. Web scraping codes were written in Python.

The dataset of rent transactions in Beijing stores more than 880,000 records; 209,214 happened during the study period (May 1st, 2016, to May 31st, 2017). A valid complex should meet the following criteria. First, transactions in a complex must happen both before and after the entry date of dockless bikes (September 1st, 2016). Second, a complex must locates within 3 km of network distance to its closest subway station, for it is unlikely that tenants will cycle for more than 3 km to transfer for subway. Third, the distance to the complex's closest subway station should be time-invariant. Based on these criteria, the number of transactions has reduced to 191,414, happened in 4,365 complexes.

Table 3.1 provides the descriptive statistics of the house attributes. A tenant can either rent for the whole apartment or a single room, and Lianjia provides the rental price and size accordingly. That is to say, if a tenant rented for a single room, the record reflects the price and size of the single room; if a tenant rented for the full house, the record reflects the price and size of the full house. The mean rental prices during the study period are ¥5,605/Month (\$834/Month), ¥2,372/Month (\$353/Month) and ¥5,344/Month (\$795/Month) for a full house, a single room and others, respectively. The average sizes are $69.55 m^2$, $13.51 m^2$ and $72.33 m^2$ for a full house, a single room and others, respectively. Other attributes such as age of the building, whether there is lift in the building, the decoration status, height, heating supply and direction of the room can be found in the

table. Below shows the locations of complexes, the average rental prices for a whole apartment and a single room. Figure 3-1 shows that most complexes cluster in within the 4th Ring road; complexes in the outskirts mostly locate around subway stations. Figure 3-2 and Figure 3-3 shows the average unit rental price (measured in $\text{¥}/m^2$) for a whole apartment and a single room, respectively. From both plots can we find that apartments/rooms in major districts (Dongcheng, Xicheng, Haidian and Chaoyang) are more expensive to rent than those in other districts. This four districts belong to the north of Beijing. This indicates uneven appreciation of living locations between the north and the south of Beijing.

3.2.2 Dockless bike usage

To study the heterogeneity of impacts of dockless bike-sharing on rentals and to fill the gap identified in Literature Review, I used the records of bike usage provided by Mobike, a major dockless bike operating company that occupies about 50% of the market. It is also the only public dockless bike usage dataset online.

The original dataset contains 3,205,329 records from May 10th-16th and 18th-23rd, 2017, generated by 349,373 users using 484,580 bikes. Each record contains basic information including order ID, user ID, bike ID, bike type, start time, start location and end location; the locations are encoded in geohash format with precision of 7. Figure 3-4 shows the daily and hourly usage of bikes. The first 9 days indicates the periodic patterns, where the demand peaks in the morning and evening rush hours and noon in workdays, and relatively steady during weekends. The last 5 days show irregular patterns which may be due to reduced sampling size.

To best represent the bike demand as integration of current public transport, I only kept the weekdays in the first 9 days (May 10th-16th, 18th-19th, 2017) as the final bike usage. The final dataset contains 1,999,682 records (62.39% of the original dataset), generating by 320,148 (91.71% of the original dataset) users using 451,051 (93.08% of the original dataset) bikes.

I counted the number of dockless bike trips started within 150m around each complex

Table 3.1: Summary statistics of variables.

Variable	Definition	Unit	Obs.	Mean	Std.	Min	Max
Rented room attributes							
rental	Rental price for a full apartment	RMB Yuan/month	50,227	5,605	2,169.033	500	15,000
	Rental price for a single room	RMB Yuan/month	75,953	2,372	692.52	660	14,000
	Others (not reported)	RMB Yuan/month	51,169	5344	2388.591	400	15,000
size	Size of a full apartment	m^2	50,227	69.55	26.95	6.00	350.03
	Size of a single room	m^2	75,953	13.51	6.98	2.70	229.18
	Others (not reported)	m^2	50,227	72.33	72.33	5.00	894.73
lift	Whether the building has lift (1 = yes, 0 = no/data unavailable)	Binary	191,414	0.61	0.49	0	1
decoration	Decoration status (2 = well decorated, 1 = simple decoration, 0 = no decoration/others)	Indicator	191,414	1.35	0.90	0	2
height	Level of room (3 = high level, 2 = mid level, 1 = low level, 0 = basement/data unavailable)	Indicator	191,414	2.03	0.80	0	3
heating	Heating status (1 = centralized heating, 0 = self-provided heating/data unavailable)	Binary	191,414	0.83	0.38	0	1
age	House age	Year	191,414	20.34	13.41	0	113
direction	Room facing direction (1 = south-facing, 0 = other directions)	Binary	191,414	0.63	0.48	0	1
Location attributes							
n_store	Number of convenient stores within 500 meters	Count	4,331	29.36	16.81	1.00	158.00
d.bizCircle	Network-based distance to the closest big shopping mall	Meier	4,331	1,008.14	661.32	1.04	4,304.49
d.hospital	Network-based distance to the closest Grade AAA hospital	Meier	4,331	2,425.98	2,018.16	0.44	14,794.30
d.subway	Network-based distance to the closest subway station	Meier	4,331	1,144.48	599.30	9.70	2,994.15
d.university	Network-based distance to the closest university	Meier	4,331	893.93	636.12	0.11	4,921.13
d.CBD	Euclidean distance to the City Center (Tiananmen Square)	Meier	4,331	12,713.4	6,972.80	974.3	38,543.8
l.walk	Walking time to the closest subway station	Second	4,331	802.88	437.03	7	2,921
l.bike	Cycling time to the closest subway station	Second	4,331	271.57	155.01	2	1,092
bike_intensity	Average number of dockless bike demand during morning rush hour (06:00-8:00) in each complex	Count/Complex	4,331	10.01	10.26	0	123
Other attributes							
BIKE	Dummy indicating if dockless bike-sharing has been introduced	Binary	191,414	0.69	0.46	0	1
Subway	Dummy indicating which subway station the complex is closest to	Binary	273	0.69	0.46	0	1

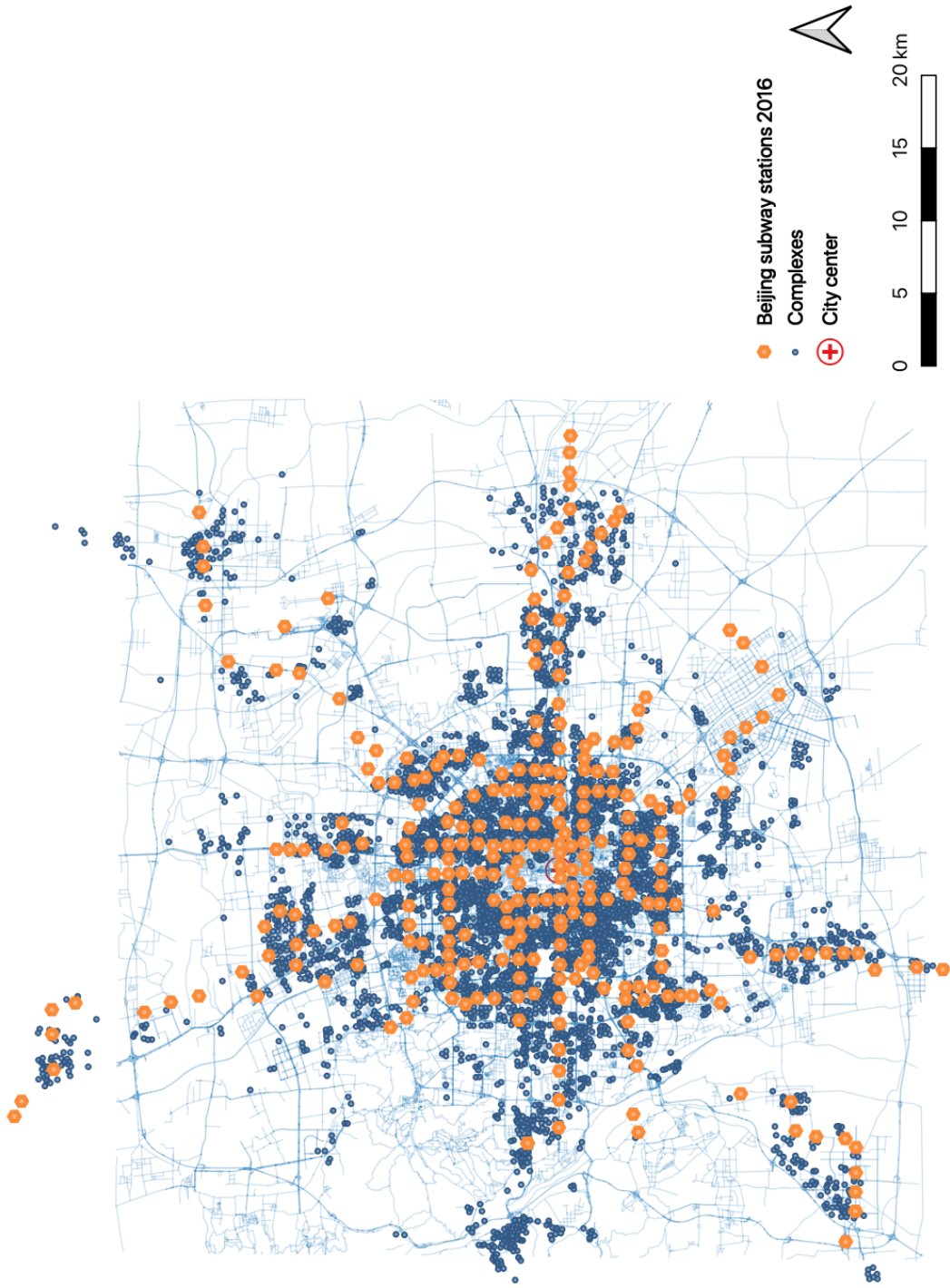


Figure 3-1-1: Locations of complexes and subway stations

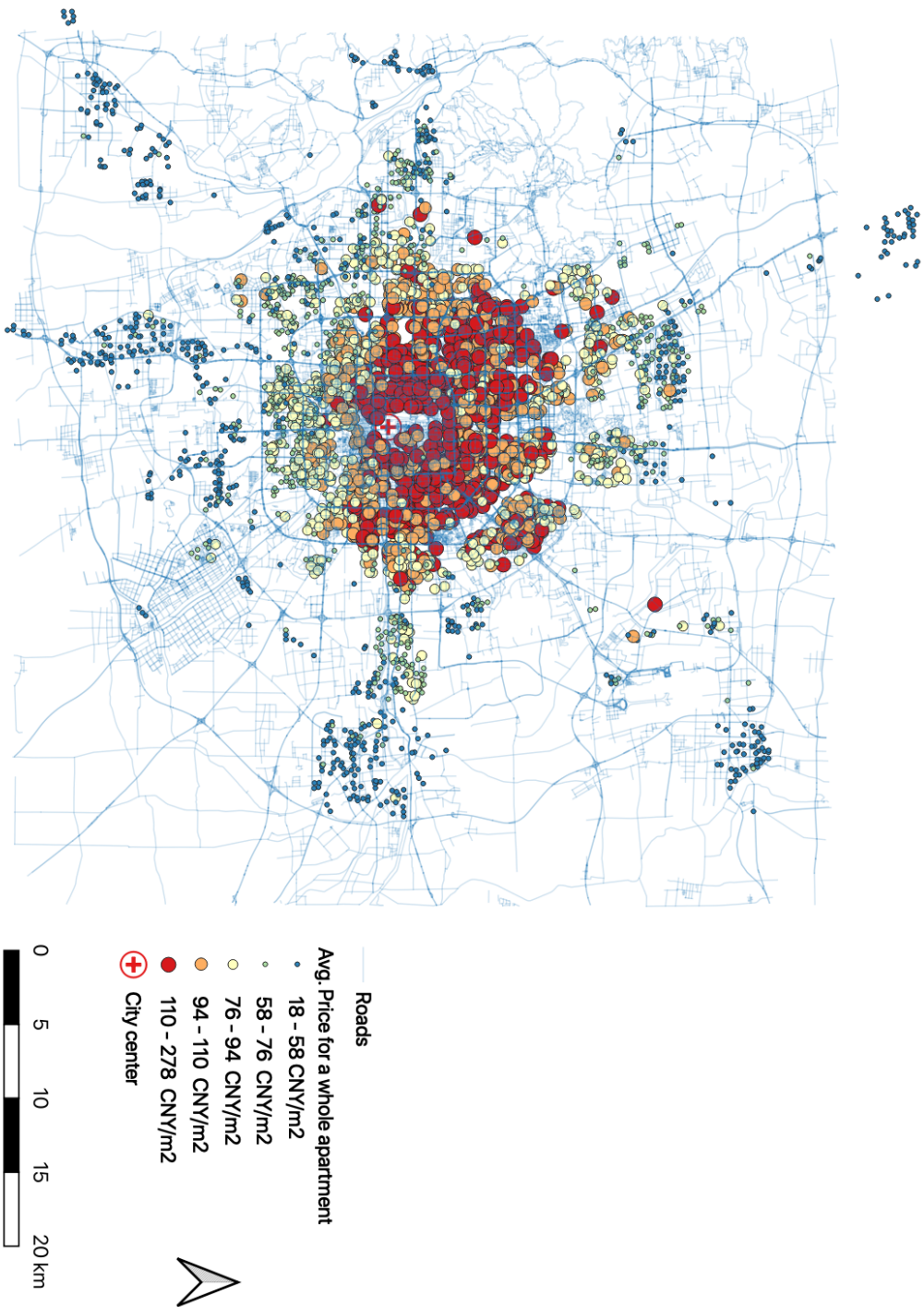


Figure 3-2: Average rental price for a whole apartment in each complex

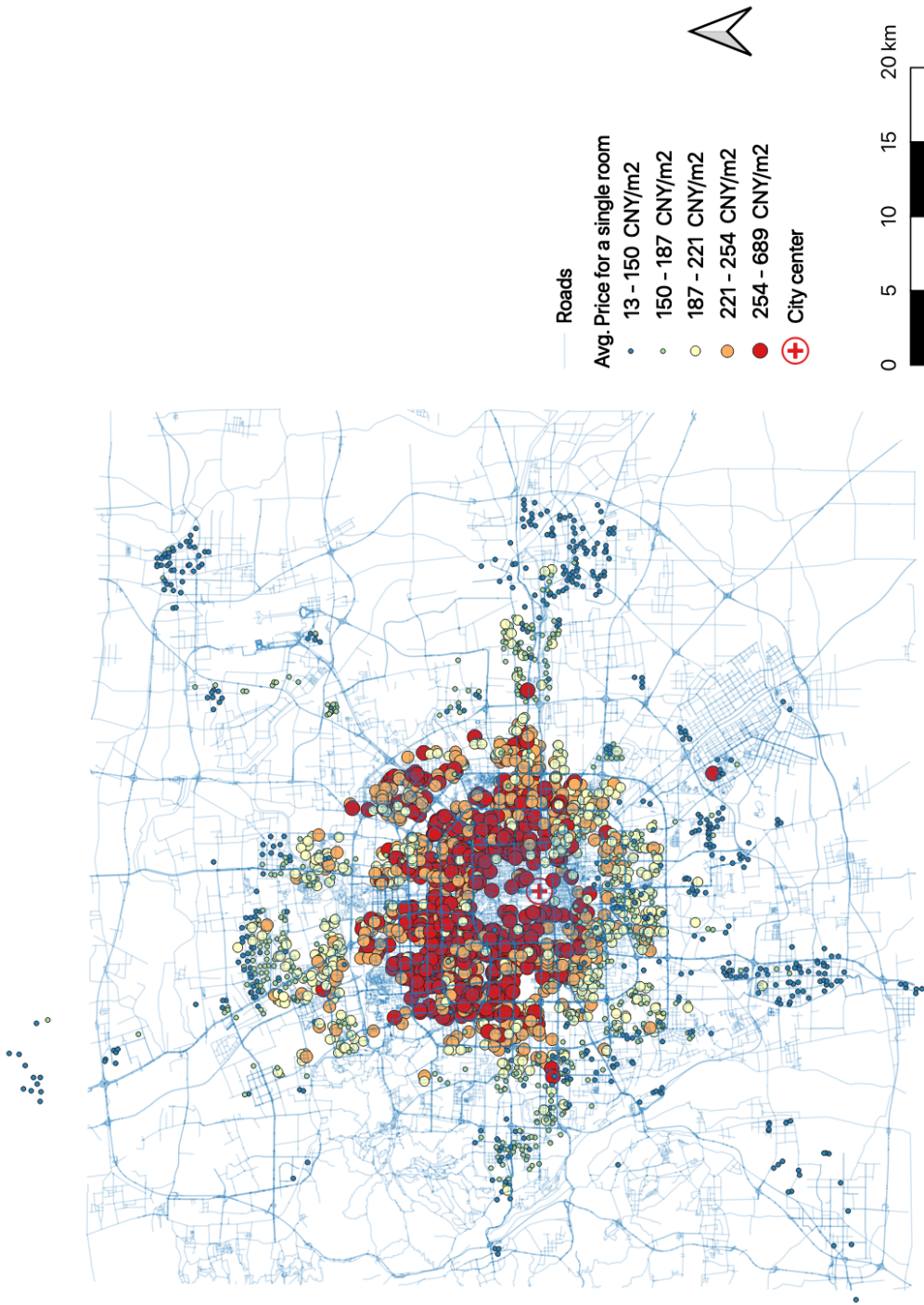


Figure 3-3: Average rental price for a single room in each complex

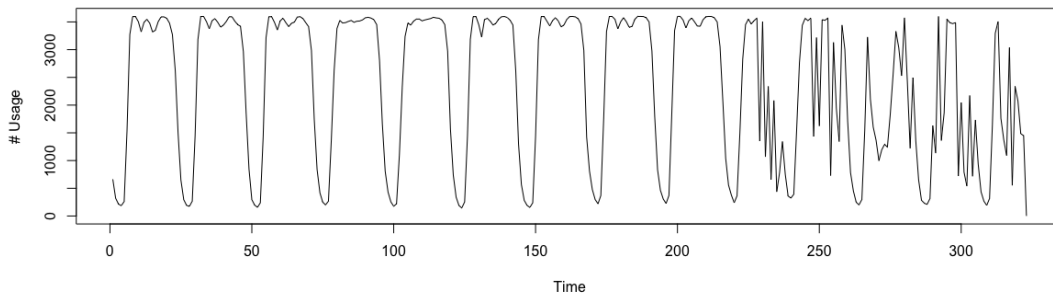


Figure 3-4: Hourly demand of dockless bikes in Beijing from May 10th-16th and 18th-23rd, 2017

during morning rush hours (6:00-08:00am) in the weekdays and divided that to daily demand. The descriptive statistics can be found in Table 3.1 Complex attributes. Some of the complexes use dockless bikes intensively, making more than 100 trips in the morning. Others do not use bikes, which may due to uneven distribution of bikes or proximity to transit nodes. The average rush hour demand in the morning is 10. Figure 3-5 and Figure 3-6 shows the heatmap of origins and destinations of morning rush hour trips. It is clear that the origins of rush hour trips are more dispersed, and the destinations are more concentrated around subway stations.

3.2.3 Points of Interest (POIs)

Not only the proximity to subway stations but also closeness to other amenities such as shopping malls, universities, hospitals and convenient stores can affect rental prices. To better model the price premium, I collected the locations of these amenities from Peking University Open Research Data. The locations of subway stations, grade AAA hospitals, universities, large shopping malls and convenient stores are shown in Figure 3-7, Figure 3-8 and Figure 3-9.

To remove the impact of newly built subway stations, I only kept the stations that have started operating before May 1st, 2016 (the start of the study period) so that all the distance from complexes to their closest facilities remain temporally unvaried. The locations of

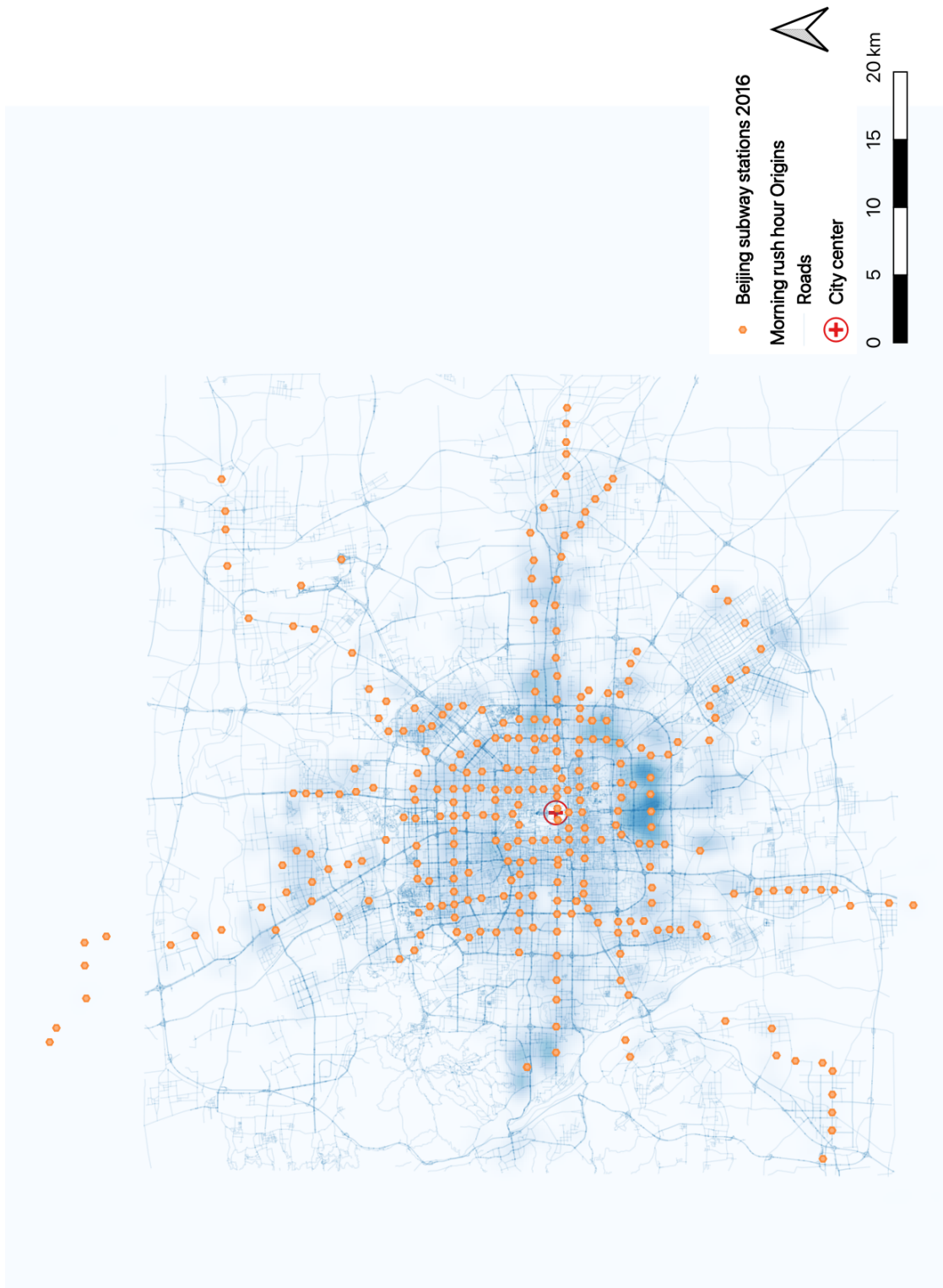


Figure 3-5: Origins of morning rush hours

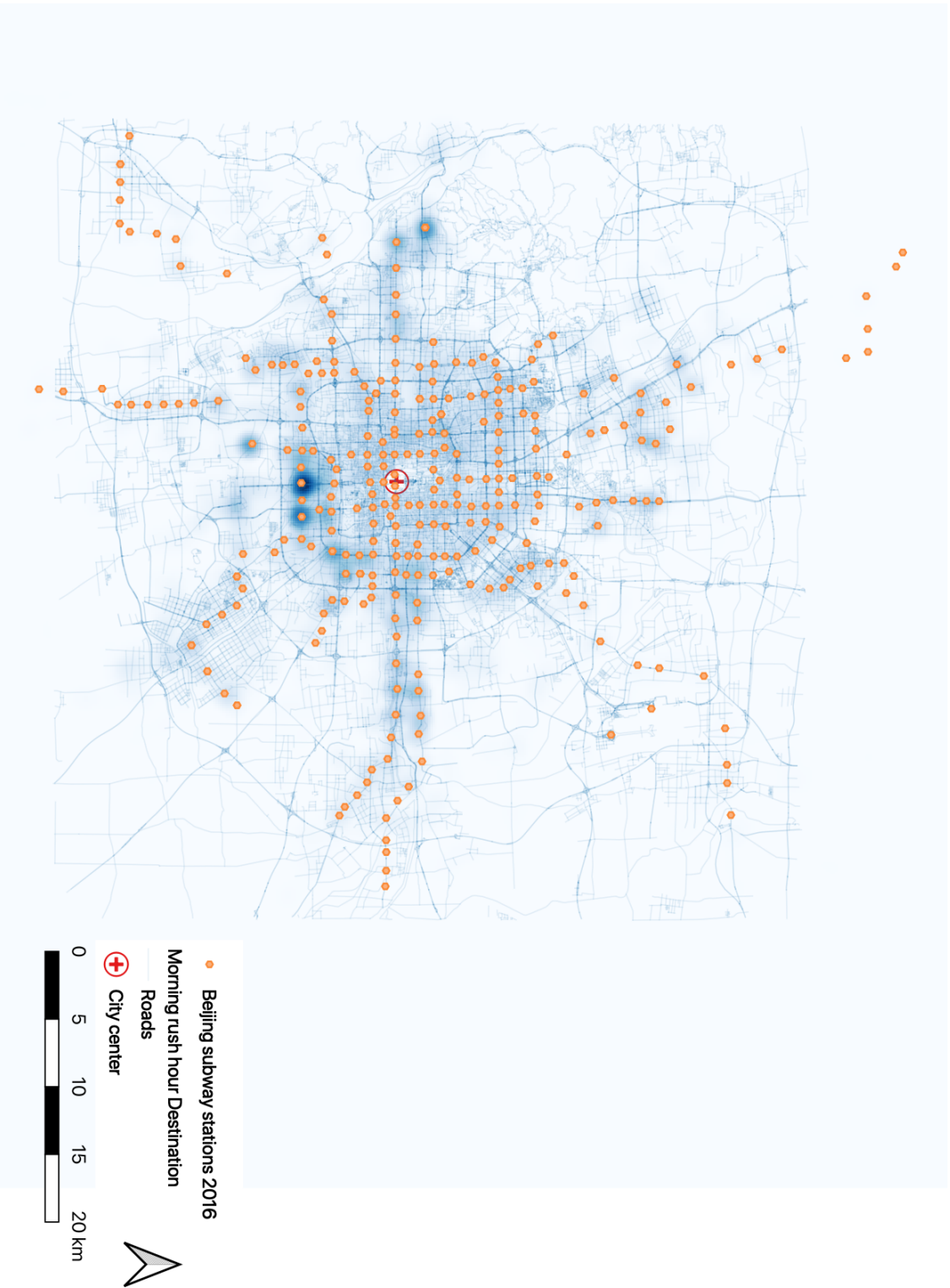


Figure 3-6: Destinations of morning rush hours

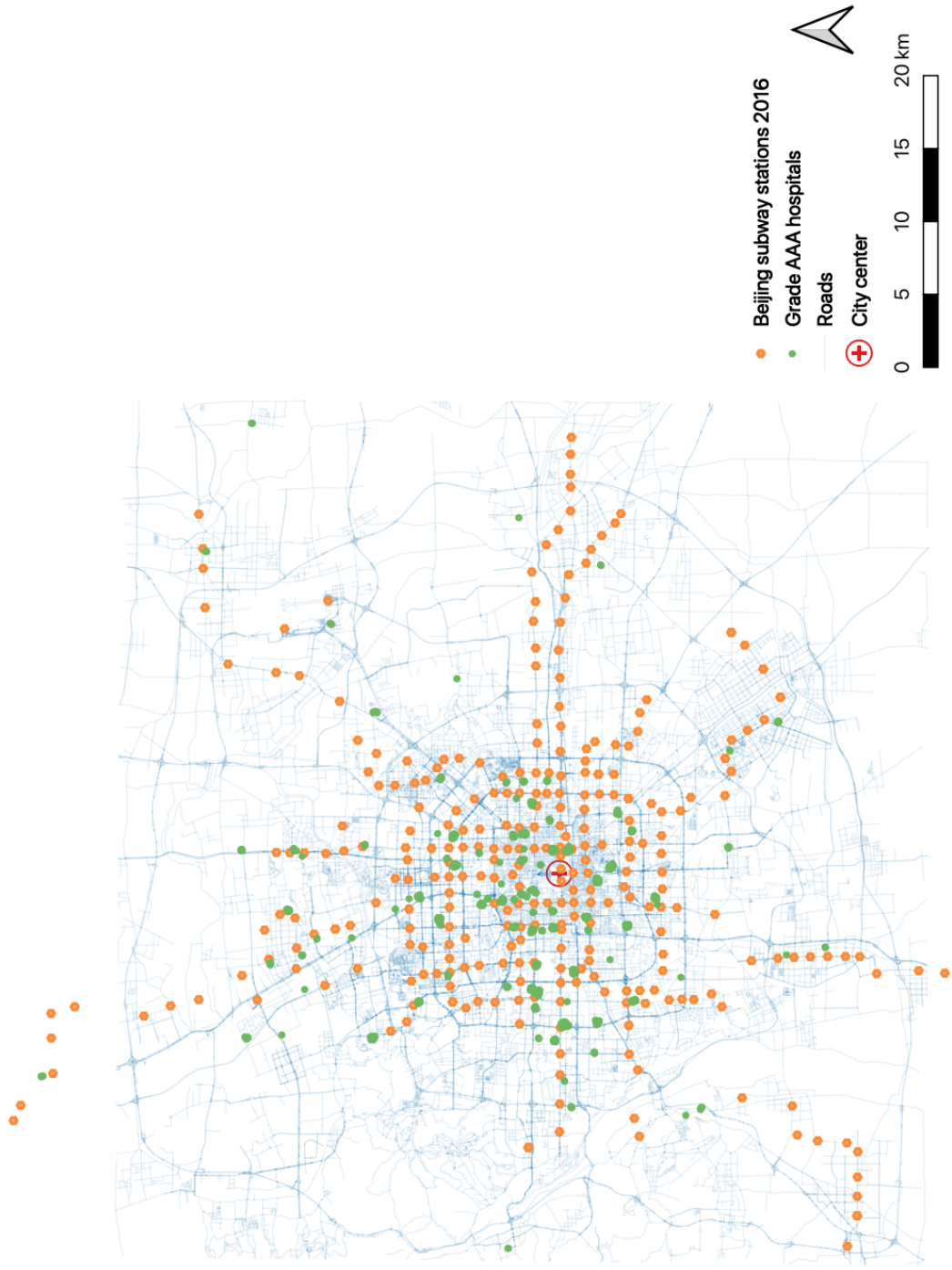


Figure 3-7: Locations of Grade AAA hospitals and subway stations

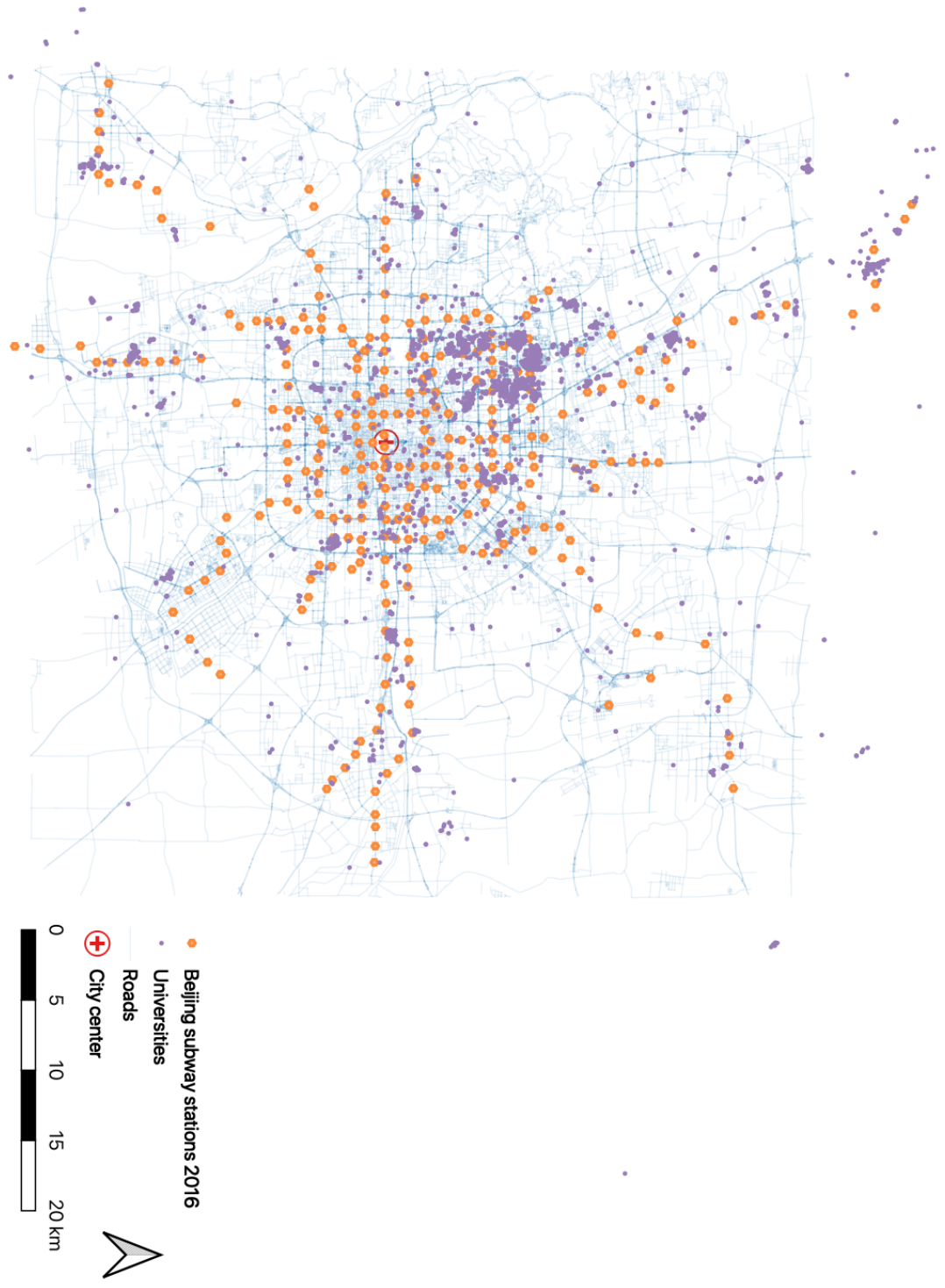


Figure 3-8: Locations of universities and subway stations



Figure 3-9: Locations of big shopping malls and subway stations

Grade AAA hospitals and universities rarely change with time. I also assume that shopping malls and convenient stores did not change in the study period.

From the plots we can find that good hospitals are mostly located in the city center. Universities are most clustered in Haidian district. Shopping malls are scattered in Beijing but mostly located around subway stations.

3.2.4 Beijing’s walkable road network and network-based distance to amenities

Past works uses Euclidean distances to measure proximity of houses to amenities. The euclidean distance are easy to compute and are good proxies to reflect the distance; however, this measurement ignores the spatial constraints of cities. This study uses network-based distance to avoid measurement errors.

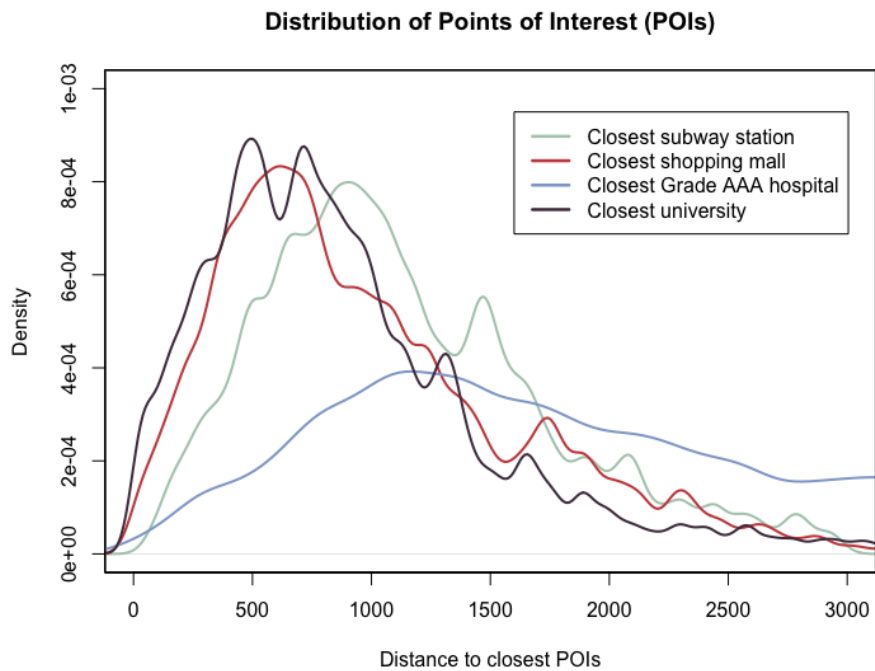


Figure 3-10: Distribution of POIs with respect to distance to complexes

Beijing’s walkable road network was downloaded from OpenStreetMap (OpenStreetMap, 2019) and transferred to ESRI shapefile format using Python. Assuming tenants prefer us-

ing the facilities that are closest to them, I used the “Find closest facility” from Network Analysis toolset in ArcGIS to find the closest subway stations, Grade AAA hospitals, universities and shopping malls for each complex and the network-based distances to these facilities. The distances to closest subway stations, hospitals, universities and shopping malls, and the distribution of number of nearby convenience stores are shown in Table 3.1 Complex attributes. The average distance from a complex to its closest subway station, shopping mall and university are around 1,000 meters, and the average distance to closest hospital is about 2,400 meters; the distribution of POIs to complexes is shown in Figure 3-10. I also counted the number of convenient stores within 500 meters around each complex as a proxy of convenience.

3.2.5 Time saving

To calculate the commuting time saving, I used Gaode Map (equivalent to Google Map) API to estimate the walking time and cycling time from complexes to the closest subway stations. The summary statistics of walking time and cycling time from complexes to subway stations are presented in Table 3.1. The weighted average time saving for a single trip in the morning rush hour can be calculated by the following equation:

$$Timesaving = \frac{\sum (t_walk_i - t_bike_i) \times (bike_intensity_i)}{\sum_{i=1}^n bike_intensity_i} \quad (3.3)$$

Chapter 4

Results and Discussion

4.1 Results

4.1.1 Baseline models - Impact of entry of dockless bike-sharing on rental prices

I first create 4 baseline models with Model 3.1 to find the impact of dockless bikes on rental price gradient for Beijing; the results are presented in Table 4.1. All of the transactions happened in complexes that are within 3km network-based radius from their closest subway stations. Column (1) regresses rental prices with room attributes, distance to CBD, and distance to its closest subway stations; the transaction time is fixed to capture the impact of any city-wide policy. The coefficient of $\log(d_subway)$ is -0.040 and statistically significant, indicating that the elasticity of distance to subway station of rental prices is -0.040. To capture the change on rental price gradient after the entry of dockless bikes, the interaction term $\log(d_subway) \times BIKE$ is added in the model and the result can be found in column (2). The positive coefficient of $\log(d_subway) \times BIKE$ indicates that dockless bikes flatten the rental price gradient; however, the estimation is not statistically significant and the magnitude of change is negligible (0.00003/0.040 is less than 0.1%). Other location attributes such as distance to business circles and number of convenient stores can also affect rental price gradients, and failing to include them may bias

the coefficient of $\log(d_{subway}) \times BIKE$. In column (3), I further add location attributes to the model. The price gradient becomes flatter compared to column (2) because other location attributes absorb the impact of proximity to subway stations, and the coefficient of $\log(d_{subway}) \times BIKE$ becomes larger (1.2%), yet still not significant. Lastly, being close to which subway station may also affect the rental prices gradient. For example, being close to Guomao - a subway station in CBD - is different with being close to Changyang - a subway station in the outskirts of Beijing. So, in column (4), I further add the closest subway stations as fixed effect. We can see that the effect of distance to CBD is partially absorbed by distance to closest subway stations. The change in rental price gradient is still small (0.62%) and not statistically significant. By adding more constraints to Baseline model 1 (column (1)), the adjusted R^2 increases from 0.784 to 0.880, meaning that the model is improved. Therefore, I will use the specifications in Baseline model 4 in the next sections.

4.1.2 Heterogeneity of the effect

The development level in a city can be heterogeneous. In Beijing, the north is more developed than the south, and the areas closer to the city center is more developed than the outskirts areas. The distribution of amenities and the density of transportation network can be different due to development levels, and thus can affect rental price gradient. To test if the rental price gradients and the change brought by dockless bikes are heterogeneous in Beijing, I applied Model 3.1 to sub areas in the city. The results are presented in Table 4.2.

North Beijing—area north to Chang’an Avenue—is generally more developed than South Beijing - the area that is south to Chang’an Avenue. The inner Beijing, which is defined as area within the 4th Ring Road, is more developed than the outer Beijing, area outside the 4th Ring Road. Therefore, to test if development level affects rental price gradients and changes brought by dockless bikes, I run Model 3.1 on North Beijing, South Beijing, Beijing within the 4th Ring Road and Beijing outside the 4th Ring Road. Column (2) to (5) shows the results. The rental price gradients in the four models are negative and significant.

Table 4.1: Baseline models

	Baseline 1	Baseline 2	Baseline 3	Baseline 4
	(1)	(2)	(3)	(4)
<u>Rented room attributes</u>				
log(size)	0.492*** (0.001)	0.492*** (0.001)	0.492*** (0.001)	0.488*** (0.001)
lift	0.072*** (0.001)	0.072*** (0.001)	0.070*** (0.001)	0.041*** (0.001)
decoration	0.051*** (0.001)	0.051*** (0.001)	0.051*** (0.001)	0.039*** (0.001)
height	-0.0004 (0.001)	-0.0004 (0.001)	-0.0001 (0.001)	0.004*** (0.001)
heating	0.013*** (0.002)	0.013*** (0.002)	0.014*** (0.002)	0.022*** (0.001)
age	-0.0004*** (0.0001)	-0.0004*** (0.0001)	-0.001*** (0.0001)	-0.003*** (0.0001)
direction	-0.008*** (0.001)	-0.008*** (0.001)	-0.008*** (0.001)	0.002** (0.001)
<u>Location attributes</u>				
log(n_store)			-0.035*** (0.001)	-0.002** (0.001)
log(d_bizCircle)			-0.019*** (0.001)	-0.015*** (0.001)
log(d_hospital)			-0.010*** (0.001)	-0.011*** (0.001)
log(d_university)			-0.028*** (0.001)	0.004*** (0.001)
log(d_CBD)	-0.351*** (0.001)	-0.351*** (0.001)	-0.355*** (0.001)	-0.178*** (0.008)
<u>Price gradient to distance to subway</u>				
log(d_subway)	-0.040*** (0.001)	-0.040*** (0.002)	-0.033*** (0.002)	-0.048*** (0.002)
log(d_subway)*BIKE		0.00003 (0.002)	0.0004 (0.002)	0.0003 (0.002)
Constant	9.835*** (0.014)	9.835*** (0.017)	10.313*** (0.020)	8.693*** (0.074)
Time fixed effect	Yes	Yes	Yes	Yes
Subway station fixed effect	No	No	No	Yes
Observations	191,414	191,414	191,414	191,414
No. of Complexes	4,331	4,331	4,331	4,331
Adj. R ²	0.784	0.784	0.788	0.880

Note:

This table reports the results of baseline models for all transactions happened in Beijing. From column (1) to (4) more explaining variables and fixed effects are added. Standard errors are in parentheses and are clustered at complex level.

*p<0.1; **p<0.05; ***p<0.01

We can see that the magnitude of coefficients of $\log(d_subway)$ in column (2) and (4) are smaller than those in column (3) and (5), meaning that with the increase of distance to subway stations, the rental prices drop much quicker in less developed areas than those in more developed areas. In more developed areas, the number as well as the density of amenities are larger, which can positively contribute to rental prices; as a result, being close to subway stations may have less an impact on rental prices. However, in less developed areas, there are fewer amenities which may also cluster around subway stations; as a result, proximity to subway stations may play a more important role in affecting rental prices in the less developed areas.

We can observe that the impact of entry of dockless bike-sharing systems is different in more/less developed areas. After the entry of dockless bike-sharing system, in more developed areas (column (2) and (4)), the coefficients of $\log(d_subway) \times BIKE$ are negative, meaning that the rental price gradients become steeper. This means that when the apartments being more distant from subway stations, their rentals decrease quicker in north Beijing, or areas within the 4th Ring Road of Beijing. The magnitude of change is small (7/5% and 3.6% for north Beijing and within the 4th Ring Road. We can see that the impacts are neither strong nor statistically significant in both models, and the signs are not as expected. The unexpected sign of $\log(d_subway) \times BIKE$ may due more appreciated apartments near subway stations or less favored apartments in distance areas, which is unable to tell by Model 3.1.

The rental price gradients and the impact of dockless bikes in less developed areas are different with those in more developed areas. In less developed areas, namely the south of Beijing and areas outside the 4th Ring Road (column (3) and (5)), we can see that the coefficients of $\log(d_subway) \times BIKE$ are all positive as expected, meaning that the entry of dockless bike-sharing system flattens the rental price gradients, making apartments distant to subway stations also favored by tenants. The largest impact happens in south of Beijing; the entry of dockless bike-sharing system brings down the original rental price premium by 13.85% in south of Beijing and highly significant at less than 1%. Areas outside the 4th Ring Road also witnesses 6.3% of decrease of its original rental price premium and

significant at 10%.

I further study the impact of dockless bike-sharing system in finer areas in Beijing, namely the North Beijing within the 4th Ring Road, North Beijing outside the 4th Ring Road, South Beijing within the 4th Ring Road, and South Beijing outside the 4th Ring Road. North Beijing within the 4th Ring Road is the most developed area, and South Beijing outside the 4th Ring Road is the least developed; the other two are mid-developed. The results are presented in Table 4.2. The coefficients of $\log(d_subway)$ for the four sub areas are all negative as expected. The coefficients for North Beijing outside the 4th Ring Road, South Beijing within the 4th Ring Road, and South Beijing outside the 4th Ring Road (column (2), (3) and (4)) have similar magnitude as Table 4.2 and are significant, while that for North Beijing within the 4th Ring Road is very small and not statistically significant. This is because that North Beijing within the 4th Ring Road is very developed where business, employment, education and entertainment cluster, and living close to subway stations may be less attractive than living close to other amenities, such as business circles. The coefficients of $\log(d_subway) \times BIKE$ are the impacts of dockless bikes on rental prices. The coefficient for North Beijing within the 4th Ring Road is negative and significant at 5%, indicating that dockless bikes lead to increased appreciation on apartments closer to subway stations. Similar with the finding in Table 4.2 column (2) and (4), a possible reason for the unexpected sign might be that apartments close to subway stations become more appreciated, or those distant from subway stations become less favored, yet we cannot tell from Model 3.1. The coefficients of $\log(d_subway) \times BIKE$ are positive for North Beijing outside the 4th Ring Road, South Beijing within the 4th Ring Road, and South Beijing outside the 4th Ring Road (column (2), (3) and (4)), while only that in model for South Beijing is significant. The positive coefficients imply that the rental price gradients become flatter in these three less developed areas; the magnitudes of reduction are 6.8%, 15.4% and 9.3% for North Beijing outside the 4th Ring Road, South Beijing within the 4th Ring Road, and South Beijing outside the 4th Ring Road, respectively.

The above results modelled the transactions happened within 3km radius from the closest subway stations. To test the robustness of the results, I also conducted two robustness

Table 4.2: Heterogeneity effect

	Full sample		North/South		Inner/Outer			Sub samples		
	Beijing (1)	North Beijing (2)	South Beijing (3)	within the 4 th Ring Road (4)	outside the 4 th Ring Road (5)	North within 4 th Ring Road (6)	North outside 4 th Ring Road (7)	South within 4 th Ring Road (8)	South outside 4 th Ring Road (9)	
Rented room attributes										
log(size)	0.488*** (0.001)	0.488*** (0.001)	0.489*** (0.001)	0.504*** (0.001)	0.478*** (0.001)	0.507*** (0.002)	0.478*** (0.001)	0.501*** (0.001)	0.479*** (0.002)	
lift	0.041*** (0.001)	0.043*** (0.001)	0.039*** (0.002)	0.032*** (0.002)	0.047*** (0.002)	0.034*** (0.002)	0.044*** (0.002)	0.027*** (0.002)	0.052*** (0.003)	
decoration	0.039*** (0.001)	0.038*** (0.001)	0.040*** (0.001)	0.041*** (0.001)	0.037*** (0.001)	0.045*** (0.001)	0.032*** (0.001)	0.037*** (0.001)	0.045*** (0.002)	
height	0.004*** (0.001)	0.003*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.003*** (0.001)	0.008*** (0.001)	0.00001 (0.001)	0.004*** (0.001)	0.008*** (0.002)	
heating	0.022*** (0.001)	0.022*** (0.002)	0.018*** (0.002)	0.018*** (0.002)	0.023*** (0.002)	0.013*** (0.004)	0.025*** (0.002)	0.020*** (0.003)	0.014*** (0.004)	
age	-0.003*** (0.0001)	-0.003*** (0.0001)	-0.004*** (0.0001)	-0.003*** (0.0001)	-0.004*** (0.0001)	-0.003*** (0.0001)	-0.004*** (0.0001)	-0.004*** (0.0001)	-0.003*** (0.0002)	
direction	0.002** (0.001)	-0.002* (0.001)	0.009*** (0.002)	-0.003*** (0.001)	0.006*** (0.001)	-0.016*** (0.002)	0.005*** (0.002)	0.010*** (0.002)	0.007*** (0.003)	
Location attributes										
log(n_store)	-0.002** (0.001)	-0.004*** (0.001)	-0.002 (0.002)	-0.004** (0.002)	-0.001 (0.001)	-0.008** (0.004)	-0.0002 (0.001)	-0.005** (0.002)	-0.001 (0.003)	
log(d.bizCircle)	-0.015*** (0.001)	-0.015*** (0.001)	-0.012*** (0.001)	-0.014*** (0.001)	-0.013*** (0.001)	-0.022*** (0.002)	-0.009*** (0.001)	-0.004** (0.002)	-0.019*** (0.002)	
log(d.hospital)	-0.011*** (0.001)	-0.007*** (0.002)	-0.020*** (0.002)	-0.004** (0.001)	-0.013*** (0.001)	-0.001 (0.002)	-0.015*** (0.002)	-0.011*** (0.002)	-0.020*** (0.004)	
log(d.university)	0.004*** (0.001)	0.003*** (0.001)	0.008*** (0.001)	-0.0002 (0.001)	0.009*** (0.001)	-0.003** (0.001)	0.008*** (0.001)	0.003** (0.002)	0.013*** (0.002)	
log(d.CBD)	-0.178*** (0.008)	-0.184*** (0.011)	-0.168*** (0.012)	-0.129*** (0.009)	-0.428*** (0.018)	-0.102*** (0.014)	-0.412*** (0.022)	-0.142*** (0.012)	-0.527*** (0.036)	
Price gradient to distance to subway										
log(d.subway)	-0.048*** (0.002)	-0.040*** (0.002)	-0.063*** (0.002)	-0.026*** (0.002)	-0.065*** (0.002)	-0.004 (0.004)	-0.061*** (0.003)	-0.047*** (0.003)	-0.076*** (0.004)	
log(d.subway)*BIKE	0.0003 (0.002)	-0.003 (0.002)	0.008*** (0.002)	-0.001 (0.003)	0.004 (0.002)	-0.008** (0.004)	0.004 (0.003)	0.008** (0.003)	0.007* (0.004)	
Constant	8.693*** (0.074)	8.715*** (0.104)	8.385*** (0.108)	8.054*** (0.084)	11.203*** (0.173)	7.725*** (0.130)	11.035*** (0.204)	7.958*** (0.115)	11.945*** (0.346)	
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Subway station fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	191,414	113,717	77,697	82,231	109,183	40,508	73,209	41,723	35,974	
No. of Complexes	4,331	2,606	1,725	2,511	1,820	1,391	1,215	1,120	605	
Adj. R ²	0.880	0.877	0.880	0.856	0.876	0.826	0.880	0.874	0.853	

Note:

This table reports the results of regressions with log-transaction prices with 3km from complexes to subway stations and other explaining variables as robustness check. All the complexes are located within 2km network-based distance to its closest subway station. North and south of Beijing are split by Chang'an Avenue. Time (year and month of the transaction) and subway stations are added as fixed effect. Standard errors are in parentheses and are clustered at complex level.

*p<0.1; **p<0.05; ***p<0.01

checks by limiting complexes to only 2km and 1.5km within their closest subway stations; results are presented in Table 4.3 and Table 4.4. Contrary to the results shown in Table 4.2 column (1), when we limit the complexes to those within 2km and 1.5km to their closest subway stations, the coefficients of $\log(d_subway)$ are negative and significant in both robustness checks. This means that the rental price gradients within 2km and 1.5km to subway stations become steeper in Beijing on average, that apartments closer to subway stations become more preferable.

Models presented in column (2) to (5) in both robustness checks show similar results with those in Table 4.2. For the more developed areas (column (2) and (4)) in both robustness checks, the coefficients of $\log(d_subway) \times BIKE$ are all negative, meaning that rental price gradients become steeper for apartments within 2km and 1.5km to their closest subway stations. The impacts are only significant in north Beijing in both robustness checks, and the magnitudes of change are around 30% (0.009/0.032 and 0.009/0.028 in 2km robustness check and 1.5km robustness check, respectively). For apartments within the 4th Ring Road, the change in rental price gradients are 12.5% (0.003/0.024) and 13.6% (0.003/0.022) for those within 2km and within 1.5km, respectively, yet not statistically significant. Change in rental price gradients for apartments within the 5th Ring Road are less than 1.5% in both models and not statistically significant, either. For the less developed areas (column (3) and (5)), only the signs of change in rental price gradient in south Beijing are as expected. The magnitude of change is 14.0% and significant for apartments within 2km to their closest subway stations, and 11.1% and not significant for those within 1.5km. The areas outside the 4th Ring Road, the rental price gradients for apartments within 2km and 1.5km become steeper, yet the magnitudes are small (3.7% and 6.2%, respectively) and not significant. It is interesting to find that the rental price premium for apartments outside the 5th Ring Road become larger; it increased by 20.9% and 28.9% for rooms within 2km and within 1.5km to subway stations, respectively. The changes are both statistically significant.

The results of sub-areas in Beijing are presented in column (6) to (9). The coefficients of $\log(d_subway)$ for all four sub-area models in both robustness checks are neg-

ative, and the magnitudes are similar with the results in Table 4.2. The coefficients of $\log(d_subway) \times BIKE$ for North Beijing within the 4th Ring Road are negative in both robustness checks, indicating that after the entry of dockless bikes the rental price gradients become steeper. The magnitudes of increase in gradients are also large, which triples the original magnitudes for apartments within 3km and 2km to subway stations, and doubles if only look at those in 1.5km radius. The differences in magnitude of increase also indicates that the impact of dockless bikes may not be linear in the 3km radius. The coefficients of $\log(d_subway) \times BIKE$ for North Beijing outside the 4th Ring Road become negative in both robustness checks. Comparing this finding to the result in Table 4.2, this may indicate that the rental price gradient is non-linear. The coefficients of $\log(d_subway) \times BIKE$ for South Beijing within and outside the 4th Ring Road are positive in both robustness checks, where only the one for South Beijing outside the 4th Ring Road is not significant. The gradients are reduced by 11.8% to 16.7%, indicating that dockless bikes have relatively consistent impacts in South Beijing.

From the results above, we can see that the entry of dockless bike-sharing system alters the rental price premium around subway stations. The impact is not uniform across the city. In more developed areas such as the North Beijing and areas within the 4th Ring Road, the rental price gradients become steeper, although the original rental price gradients are relatively flat. In less developed areas including South Beijing and areas outside the 4th Ring Road, the rental price gradients were steep, and have become flatter due to the entry of dockless bikes. Moreover, by conducting the robustness checks, I found that the changes on rental price gradients may not be linear. Therefore, I used Model 3.2 by replacing the continuous distance variable $\log(d_subway)$ with indicator dummies, allowing the gradient to be non-linear. Results are shown in Table 4.5.

Using transactions happened at 2500-3000m as the reference group, the coefficients of $subway500$, $subway1000$, $subway1500$, $subway2000$ and $subway2500$ are rental price premium before the entry of dockless bikes, and are expected to be positive and significant. Coefficients of $subway500 \times BIKE$, $subway1000 \times BIKE$, $subway1500 \times BIKE$, $subway2000 \times BIKE$ and $subway2500 \times BIKE$ are the impact of dockless bike-sharing

Table 4.3: Robustness check 1: Impact on rental price gradients using continuous distance. Limited to complexes that are within 2km to their closest subway stations

	Full sample		North/South		Inner/Outer		Sub samples		
	Beijing	North	South	within the 4 th Ring Road	outside the 4 th Ring Road	North within 4 th Ring Road	North outside 4 th Ring Road	South within 4 th Ring Road	South outside 4 th Ring Road
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rented room attributes									
log(size)	0.490** (0.001)	0.490** (0.001)	0.490** (0.001)	0.504*** (0.001)	0.479** (0.001)	0.509** (0.002)	0.479** (0.001)	0.499** (0.002)	0.476*** (0.002)
lift	0.039*** (0.001)	0.039*** (0.002)	0.039*** (0.002)	0.033*** (0.002)	0.043*** (0.002)	0.033*** (0.002)	0.039*** (0.002)	0.028*** (0.003)	0.056*** (0.004)
decoration	0.039*** (0.001)	0.038*** (0.001)	0.040*** (0.001)	0.041*** (0.001)	0.036*** (0.001)	0.046*** (0.001)	0.031*** (0.001)	0.037*** (0.002)	0.044*** (0.002)
height	0.005*** (0.001)	0.003*** (0.001)	0.007*** (0.001)	0.006*** (0.001)	0.003*** (0.001)	0.008*** (0.001)	0.002*** (0.001)	0.004*** (0.001)	0.009*** (0.002)
heating	0.018*** (0.002)	0.019*** (0.002)	0.014*** (0.002)	0.018*** (0.002)	0.018*** (0.002)	0.014*** (0.004)	0.022*** (0.002)	0.020*** (0.003)	0.014*** (0.005)
age	-0.003*** (0.0001)	-0.003*** (0.0001)	-0.004*** (0.0001)	-0.004*** (0.0001)	-0.003*** (0.0001)	-0.003*** (0.0001)	-0.004*** (0.0001)	-0.004*** (0.0001)	-0.003*** (0.0002)
direction	0.003*** (0.001)	-0.002 (0.001)	0.011*** (0.002)	-0.003* (0.002)	0.008*** (0.001)	-0.018*** (0.002)	0.007*** (0.002)	0.011*** (0.002)	0.006* (0.003)
Location attributes									
log(n_store)	-0.007** (0.001)	-0.006** (0.001)	-0.010** (0.002)	-0.013** (0.002)	-0.004** (0.001)	-0.007* (0.004)	-0.002 (0.002)	-0.006** (0.003)	0.0002 (0.003)
log(d_bizCircle)	-0.012*** (0.001)	-0.012*** (0.001)	-0.011*** (0.001)	-0.013*** (0.001)	-0.011*** (0.001)	-0.022*** (0.002)	-0.004*** (0.001)	-0.006*** (0.002)	-0.020*** (0.003)
log(d_hospital)	-0.009*** (0.001)	-0.006*** (0.001)	-0.016*** (0.002)	-0.004*** (0.001)	-0.012*** (0.002)	-0.001 (0.002)	-0.013*** (0.002)	-0.012*** (0.002)	-0.020*** (0.005)
log(d_university)	0.005*** (0.001)	0.004*** (0.001)	0.009*** (0.001)	-0.001 (0.001)	0.011*** (0.001)	-0.002 (0.001)	0.010*** (0.001)	0.004** (0.002)	0.012*** (0.003)
log(d_CBD)	-0.156*** (0.009)	-0.158*** (0.012)	-0.150*** (0.013)	-0.116*** (0.010)	-0.385*** (0.022)	-0.096** (0.014)	-0.372*** (0.026)	-0.138*** (0.015)	-0.542*** (0.046)
Price gradient to distance to subway									
log(d_subway)	-0.040** (0.002)	-0.032*** (0.003)	-0.055*** (0.003)	-0.023*** (0.003)	-0.055*** (0.003)	-0.005 (0.004)	-0.052*** (0.003)	-0.044*** (0.004)	-0.078*** (0.005)
log(d_subway)*BIKE	-0.004** (0.002)	-0.009*** (0.003)	0.007*** (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.008* (0.004)	-0.005 (0.003)	0.008* (0.004)	0.009* (0.005)
Constant	8.429*** (0.079)	8.393*** (0.111)	8.141*** (0.117)	7.945*** (0.088)	10.697*** (0.204)	7.667*** (0.133)	10.560*** (0.238)	7.924*** (0.142)	12.124*** (0.436)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subway station fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171,680	101,296	70,384	79,161	92,519	39,216	62,080	39,146	32,407
No. of Complexes	3957	2407	1550	2440	1517	1369	1038	1079	565
Adj. R ²	0.879	0.874	0.881	0.856	0.876	0.824	0.880	0.871	0.853

Note:

This table reports the results of regressions with log-transaction prices with distance from complexes to subway stations and other explaining variables as robustness check. All the complexes are located within 2km network-based distance to its closest subway station. North and south of Beijing are split by Chang'an Avenue. Time (year and month of the transaction) and subway stations are added as fixed effect. Standard errors are in parentheses and are clustered at complex level.

* p<0.1; ** p<0.05; *** p<0.01

Table 4.4: Robustness check 2: Impact on rental price gradients using continuous distance. Limited to complexes that are within 1.5km to their closest subway stations

	Full sample			North/South		Inner/Outer			Sub samples		
	Beijing (1)	North Beijing (2)	South Beijing (3)	within the 4 th Ring Road (4)	outside the 4 th Ring Road (5)	North within 4 th Ring Road (6)	North outside 4 th Ring Road (7)	South within 4 th Ring Road (8)	South outside 4 th Ring Road (9)		
Rented room attributes											
log(size)	0.490*** (0.001)	0.489*** (0.001)	0.490*** (0.001)	0.505*** (0.001)	0.477*** (0.001)	0.509*** (0.002)	0.476*** (0.001)	0.498*** (0.002)	0.477*** (0.002)		
lift	0.039*** (0.001)	0.040*** (0.002)	0.036*** (0.002)	0.033*** (0.002)	0.044*** (0.002)	0.034*** (0.002)	0.039*** (0.003)	0.029*** (0.003)	0.057*** (0.004)		
decoration	0.038*** (0.001)	0.038*** (0.001)	0.039*** (0.001)	0.041*** (0.001)	0.036*** (0.001)	0.045*** (0.001)	0.031*** (0.001)	0.039*** (0.002)	0.043*** (0.002)		
height	0.005*** (0.001)	0.003*** (0.001)	0.007*** (0.001)	0.005*** (0.001)	0.004*** (0.001)	0.007*** (0.001)	0.0003 (0.001)	0.004*** (0.002)	0.009*** (0.002)		
heating	0.019*** (0.002)	0.019*** (0.002)	0.018*** (0.003)	0.023*** (0.003)	0.014*** (0.002)	0.024*** (0.004)	0.014*** (0.003)	0.018*** (0.004)	0.017*** (0.005)		
age	-0.004*** (0.0001)	-0.004*** (0.0001)	-0.004*** (0.0001)	-0.003*** (0.0001)	-0.004*** (0.0001)	-0.003*** (0.0001)	-0.004*** (0.0001)	-0.004*** (0.0001)	-0.003*** (0.0002)		
direction	0.002 (0.001)	-0.003*** (0.001)	0.009*** (0.002)	-0.004*** (0.002)	0.007*** (0.002)	-0.021*** (0.003)	0.008*** (0.002)	0.011*** (0.003)	0.006 (0.004)		
Location attributes											
log(n_store)	-0.006*** (0.001)	-0.001 (0.002)	-0.014*** (0.002)	-0.017*** (0.002)	0.004** (0.002)	-0.003 (0.004)	0.005** (0.002)	0.001 (0.003)	-0.001 (0.004)		
log(d_bizCircle)	-0.009*** (0.001)	-0.011*** (0.001)	-0.006*** (0.001)	-0.014*** (0.001)	-0.001 (0.001)	-0.023*** (0.002)	-0.0001 (0.002)	-0.005** (0.003)	-0.020*** (0.003)		
log(d_hospital)	-0.006*** (0.001)	-0.002* (0.001)	-0.014*** (0.002)	-0.005*** (0.001)	-0.005** (0.002)	-0.00002 (0.002)	-0.006** (0.003)	-0.012*** (0.003)	-0.022*** (0.005)		
log(d_university)	0.005*** (0.001)	0.003*** (0.001)	0.010*** (0.001)	0.0002 (0.001)	0.011*** (0.001)	-0.001 (0.002)	0.009*** (0.002)	0.002 (0.002)	0.015*** (0.003)		
log(d CBD)	-0.164*** (0.010)	-0.160*** (0.014)	-0.167*** (0.014)	-0.124*** (0.011)	-0.494*** (0.029)	-0.092*** (0.016)	-0.527*** (0.034)	-0.077*** (0.017)	-0.545*** (0.050)		
Price gradient to distance to subway											
log(d_subway)	-0.033*** (0.002)	-0.028*** (0.003)	-0.043*** (0.003)	-0.021*** (0.003)	-0.048*** (0.003)	-0.008* (0.005)	-0.049*** (0.004)	-0.049*** (0.004)	-0.076*** (0.005)		
log(d_subway)*BKE	-0.004* (0.002)	-0.009*** (0.003)	0.005 (0.003)	-0.003 (0.003)	-0.003 (0.003)	-0.008 (0.005)	-0.005 (0.004)	0.006 (0.004)	0.009* (0.005)		
Constant	8.424*** (0.089)	8.365*** (0.128)	8.186*** (0.131)	8.015*** (0.097)	11.733*** (0.268)	7.637*** (0.148)	12.060*** (0.309)	7.362*** (0.158)	12.127*** (0.474)		
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Subway station fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Observations	144,191	83,261	60,930	71,797	72,394	34,874	48,387	32,496	28,034		
No. of Complexes	3337	2020	1317	2168	1169	1205	815	980	523		
Adj. R ²	0.879	0.872	0.884	0.857	0.879	0.824	0.881	0.870	0.854		

Note:

This table reports the results of regressions with log-transaction prices with 1.5km from complexes to subway stations and other explaining variables as robustness check. All the complexes are located within 2km network-based distance to its closest subway station. North and south of Beijing are split by Chang'an Avenue. Time (year and month of the transaction) and subway stations are added as fixed effect. Standard errors are in parentheses and are clustered at complex level.

*p<0.1; **p<0.05; ***p<0.01

Table 4.5: Impact on rental price gradients using distance dummies

	Full sample			Inner/Outer			Sub samples					
	North/South		South Beijing	within the 4 th Ring Road		outside the 4 th Ring Road	North within 4 th Ring Road		North outside 4 th Ring Road	South within 4 th Ring Road		South outside 4 th Ring Road
	Beijing	North		Beijing	(2)		(3)	(4)		(5)	(6)	
Price gradient to distance to subway	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)			
subway500	0.127*** (0.005)	0.111*** (0.007)	0.160*** (0.008)	0.107*** (0.011)	0.151*** (0.006)	-0.003 (0.011)	0.137*** (0.008)	0.148*** (0.012)	0.188*** (0.011)			
subway1000	0.110*** (0.005)	0.100*** (0.006)	0.131*** (0.007)	0.100*** (0.010)	0.122*** (0.006)	0.006 (0.010)	0.111*** (0.007)	0.126*** (0.011)	0.146*** (0.010)			
subway1500	0.078*** (0.005)	0.065*** (0.006)	0.102*** (0.007)	0.071*** (0.011)	0.084*** (0.005)	-0.023** (0.010)	0.068*** (0.007)	0.099*** (0.011)	0.115*** (0.009)			
subway2000	0.055*** (0.005)	0.059*** (0.007)	0.047*** (0.008)	0.067*** (0.011)	0.054*** (0.006)	-0.006 (0.011)	0.056*** (0.007)	0.065*** (0.012)	0.049*** (0.010)			
subway2500	0.025*** (0.005)	0.025*** (0.007)	0.021** (0.008)	0.035*** (0.013)	0.025*** (0.006)	0.011 (0.011)	0.017** (0.007)	0.006 (0.015)	0.042*** (0.010)			
subway500 × BIKE	-0.010* (0.006)	-0.009 (0.008)	-0.014* (0.008)	-0.002 (0.012)	-0.017** (0.007)	0.014 (0.012)	-0.013 (0.009)	0.002 (0.012)	-0.028** (0.011)			
subway1000 × BIKE	-0.011** (0.005)	-0.011 (0.007)	-0.013* (0.008)	-0.007 (0.011)	-0.013** (0.006)	0.016 (0.011)	-0.017** (0.008)	-0.006 (0.012)	-0.012 (0.010)			
subway1500 × BIKE	-0.013** (0.005)	-0.016** (0.007)	-0.010 (0.008)	-0.003 (0.011)	-0.020*** (0.006)	0.012 (0.011)	-0.020*** (0.007)	0.006 (0.012)	-0.022** (0.010)			
subway2000 × BIKE	-0.013** (0.006)	-0.020*** (0.008)	0.002 (0.008)	-0.007 (0.012)	-0.013** (0.006)	0.008 (0.012)	-0.019** (0.008)	0.011 (0.013)	-0.003 (0.011)			
subway2500 × BIKE	-0.003 (0.006)	-0.004 (0.008)	0.0002 (0.009)	-0.003 (0.014)	-0.003 (0.007)	0.012 (0.012)	-0.0005 (0.008)	0.023 (0.018)	-0.012 (0.011)			
Constant	8.244*** (0.073)	8.340*** (0.104)	7.793*** (0.109)	7.774*** (0.085)	10.674*** (0.171)	7.755*** (0.129)	10.459*** (0.202)	7.368*** (0.119)	11.800*** (0.350)			
Room attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subway station fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144,191	83,261	60,930	71,797	72,394	34,874	48,387	32,496	28,034			
No. of Complexes	3337	2020	1317	2168	1169	1205	815	980	523			
Adj. R ²	0.879	0.872	0.884	0.857	0.879	0.824	0.881	0.870	0.854			

Note:

This table reports the results of regressions with log-transaction prices with distance segment dummies 0-500m, 500-1000m, 1000-1500m, 1500-2000m, 2000-2500m and 2500-3000m. All complexes are located within 3km network-based distance to its closest subway station. Complexes in 2500-3000m are used as the reference group. Time (year and month of the transaction) and location (the closest subway stations) are added as fixed effect. Standard errors are in parentheses and are clustered at complex level.

Note that in column (6) north of Beijing, the largest distance from a complex to subway station is less than 2500m. So in column (6) I use 2000-3000m as the reference group.

*p<0.1; **p<0.05; ***p<0.01

system on rental price premium in each distance segment. I expect them to be negative and significant. Moreover, I expect the impacts on complexes closer to subway stations are larger than those happen in farther complexes. Table 4.5 column (1) modelled all transactions happened within 3km to their closest subway stations in Beijing. We can see that the rental price premium at each segment decreases, where the largest drops happen at 1000-2000m, although the decrease in rental price premium at 0-1000m are also large. At 2000-2500m the magnitude of change in rental price premium is very small and not significant. The rental price premium before the entry and after the entry of dockless bikes are plotted in Figure 4-1. The solid lines shows the estimated price premium, and the shaded areas shows the standard errors. We can see from the plot that the gradient of rental price to distance to subway stations decreases slightly, which is in correspondence with the previous finding use continuous distance as the explaining variable.

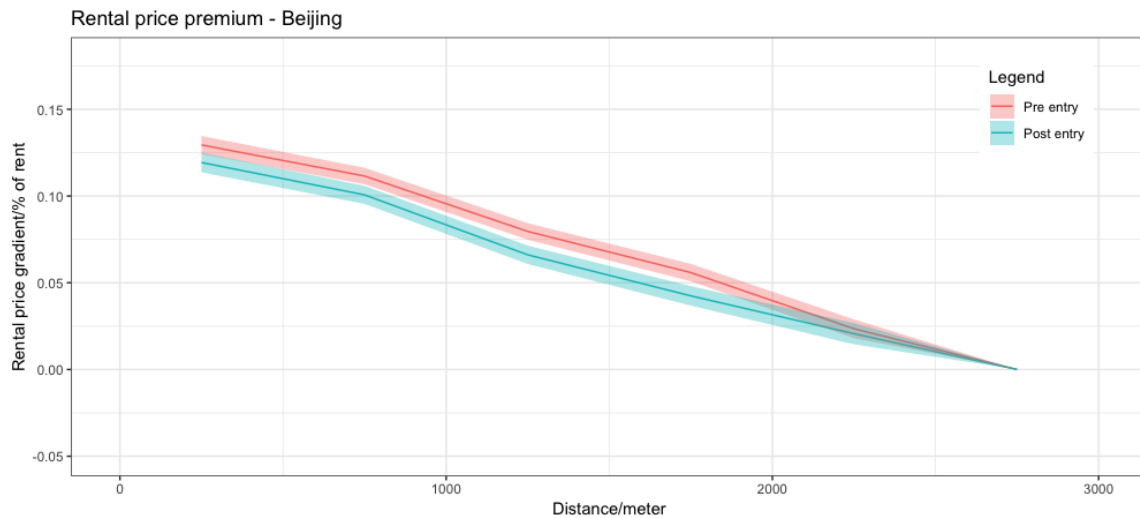


Figure 4-1: Average rental price premium in distance segments pre and post entry of dockless bikes in Beijing.

From the above results we know that the impacts of dockless bike-sharing system can be different within Beijing. Column (2) to (5) in Table 4.5 estimate the impacts of dockless bike-sharing systems in north and south Beijing and areas within and outside the 4th Ring Road; the results are plotted in Figure 4-2. From the Table 4.5 column (2) and (3) and Figure 4-2a and 4-2b we can see that the changes in rental price premium are non-linear

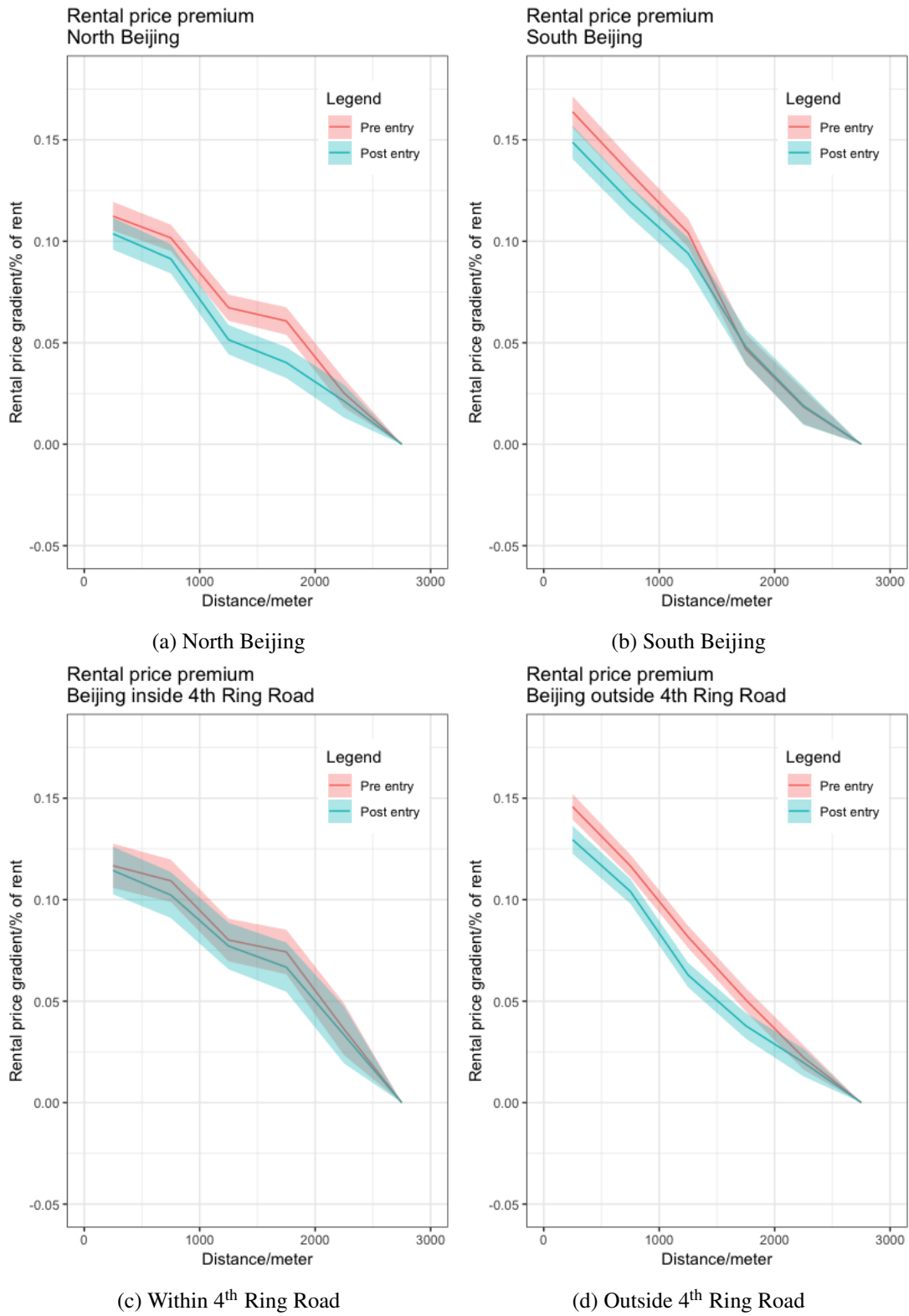
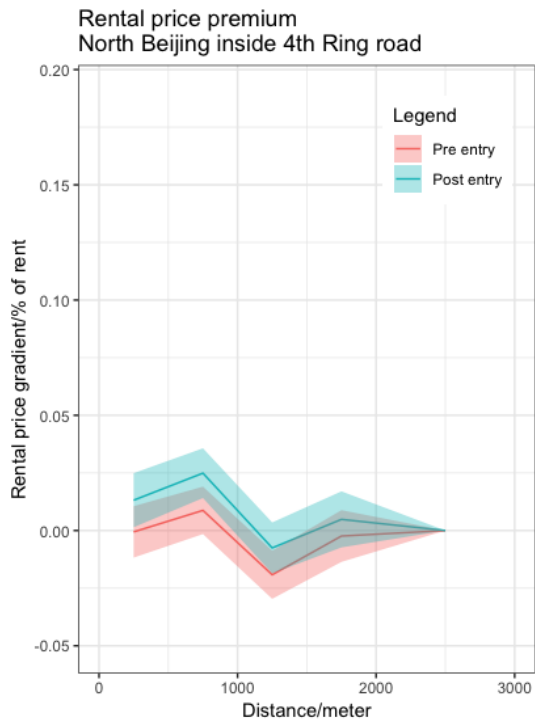


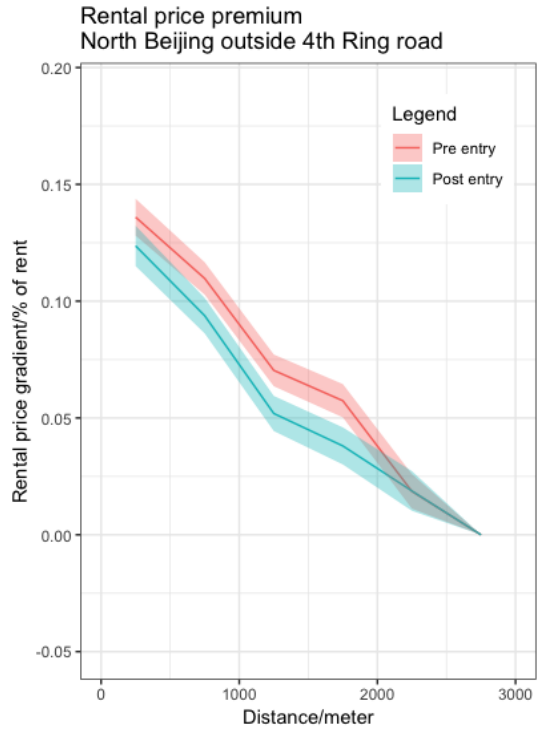
Figure 4-2: North/South and Inner/Outer of Beijing

in North and South Beijing. The largest drop in rental price premium happen at 1500-2000m, meaning that the dockless bikes making rooms at 1500-2000m less appreciated. The decrease in rental price premium at 0-1000m are smaller and not significant. The south of Beijing tells a different story. The rental price premium at 0-500m, 500-1000m and 1000-1500m in south Beijing before the entry of dockless bikes are greater than those in north Beijing, while price premium at 1500-2000m and 2000-2500m in south Beijing are smaller than those in north Beijing. This implies that tenants living in south Beijing favored complexes that are much closer to subway stations. The drop in rental price premium is largest at 0-500m as expected and statistically significant, and the magnitude of impact drops and even becomes zero as distance increases. This indicates that after the entry of dockless bikes, tenants live in the south favor less of rooms near subway stations. Figure 4-2c and 4-2d plotted results from Table 4.5 column (4) and (5) for areas within the 4th Ring Road and outside of it. For apartments locate within the 4th Ring Road, model estimates slight decrease at each distance segments, yet not statistically significant. The changes in rental price premium, compared with those before the entry of dockless bikes, are small, uncertain and not statistically significant. This implies that dockless bikes may not have much impact in reducing rental price premium within the 4th Ring Road. This may be due to the higher network density within the 4th Ring Road, where tenants can either choose to walk or bike. Figure 4-2d shows the change in rental price premium for apartments outside the 4th Ring Road. From Table 4.5 column (5) and plot, we can find significant reduction in rental price premium, where the largest drops happen at 1000-1500m and 0-500m.

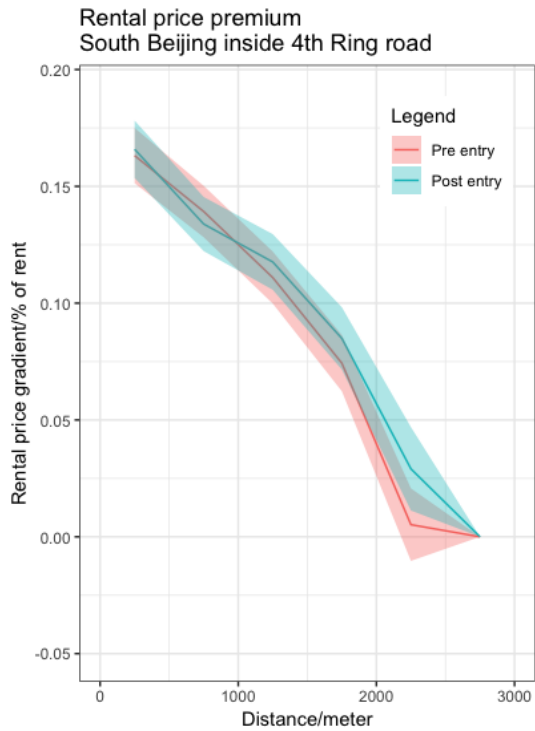
Table 4.5 column (6) to (9) and Figure 4-3 present the results for the sub-areas of Beijing, the North Beijing within the 4th Ring Road, North Beijing outside the 4th Ring Road, South Beijing within the 4th Ring Road, and South Beijing outside the 4th Ring Road. Note that for North Beijing within the 4th Ring Road, I used 2000m-3000m as the reference group, for the largest distance from a complex to its closest subway station is less than 2,500m. From Table 4.5 column (6) and Figure 4-3a we can see that the rental price gradient varies in each distance segment, and does not show a downward sloping trend. This is consistent with the model result in Table 4.2 column (1) that we have a



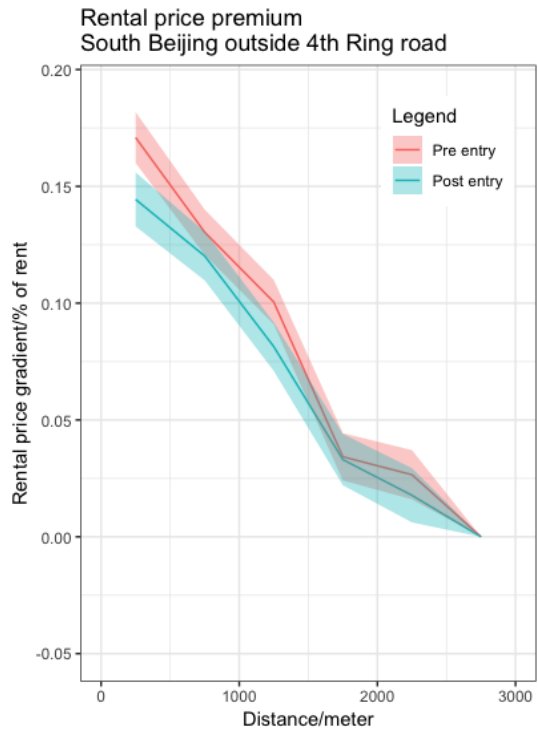
(a) North Beijing within the 4th Ring Road



(b) North Beijing outside the 4th Ring Road



(c) South Beijing within the 4th Ring Road



(d) South Beijing outside the 4th Ring Road

Figure 4-3: North/South Beijing within/outside the 4th Ring Road

very flat rental price gradient – nearly flat – in North Beijing. After the entry of dockless bikes, the rental price gradient at each segment increases, but the estimates of such increase are uncertain and not statistically significant. We can also observe increase in rental price gradients in each segments in South Beijing within the 4th Ring Road (column (3)), where the gradient only slightly drops at 500-1000m. However, the estimates for change in rental price gradients in this area are not statistically significant, either. For the outskirts of the city, we can find reduction in rental price gradient at most segments. In North Beijing outside the 4th Ring Road (column (7)), the largest drop happens at 1000-2000m. This explains why we find a steeper gradient in Table 4.3 and 4.4. In South Beijing outside the 4th Ring Road (column (7)), the reduction in rental price gradient at 0-500m and 1000-1500m are large and significant. This is consistent with the hypothesis that the rental price gradient drops the largest closer to subway stations.

Based on the results of the distance segment models in different areas in Beijing, we can see that the rental price gradients as well as the changes of it due to dockless bikes vary at different distance segments. Generally, we can find that the dockless bikes can lead to greater impact on rental price gradients in less developed areas, namely South Beijing and Beijing outside the 4th Ring Road. Only in the South Beijing outside the 4th Ring Road do we observe the expected trend: rental price premium of apartments located within 0-500m reduces the most, and the reduction in rental price premium at each segment decreases as distance to subway stations increase. There are many forces that affect rental prices. One of the many forces is amenities. The distribution of amenities are usually heterogeneous across cities; moreover, such distribution may also be uneven with distance to subway stations. For example, in more developed areas, amenities such as parks and shopping malls are usually scattered, while in less developed areas they tend to be more clustered around subway stations. Other forces include the density of transportation network, new technology (i.e. dockless bikes) and policies that are specific based on counties. The interaction among different forces determine the changes in rental price gradients, resulting in different magnitudes of impacts around subway stations in the sub-areas in Beijing.

4.2 Discussion

4.2.1 Benefits of dockless bikes

The entry of dockless bike-sharing system can generate economic benefits by flattening the rental price gradient and social benefits by reducing commuting costs.

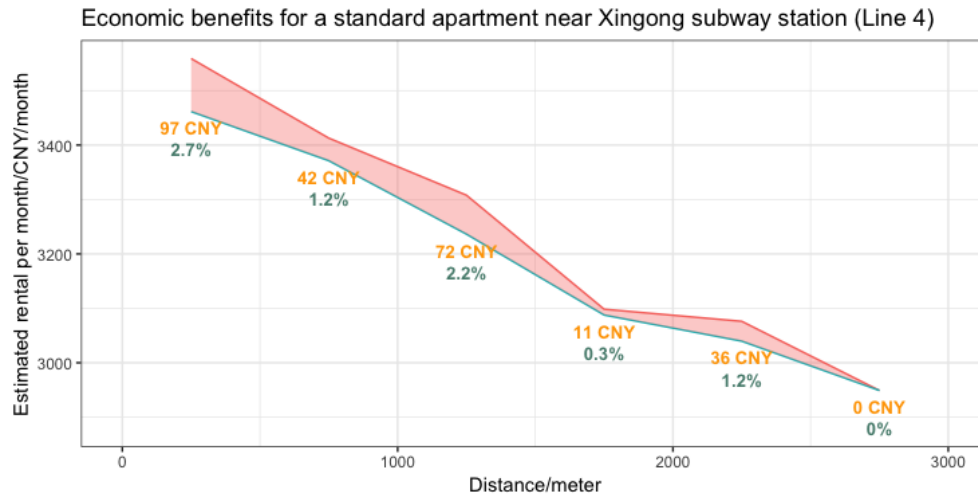


Figure 4-4: Economic benefits for a standardized hypothetical apartment near Xingong subway station

To estimate the economic benefits due to flattened rental price gradient, I select Xingong subway station as a case study. Xingong subway station locates in South Beijing outside the 4th Ring Road. It is one of the busiest subway station on Line 4. It is also one of the most popular dockless bike destinations in morning rush hours as shown in Figure 3-6. The calculation method is similar with (Chu et al., n.d.) proposed in their study. For a certain month after the entry of dockless bikes, I create a hypothesized standardized apartment with the mean values of room attributes. Then, assuming that the hypothesized apartment is located within one of the distance segment, I use the estimates in Table 4.5 column (9) to estimate the rental prices for it both before and after the dockless bikes. The difference of the two rental prices is thus the economic benefit that dockless bikes can bring to a standardized apartment. The estimated economic benefits for such a standardized apartment of 55m² near Xingong subway station is shown in Figure 4-4. The red line and

the blue line represent the estimated rental price before and after the entry of dockless bikes, respectively. The shade between two lines is the economic benefits, and the annotations in the figure shows the economic benefit at distance segments. We can see that tenants can save up to ¥97/Month if they were renting a standard apartment within 0-500m to Xingong subway station. The percentage under economic benefit measures the share of the benefit to the rental price before the entry of dockless bikes. Tenants who live close to subway stations may enjoy benefits of 2.7% of the rentals they pay. However, this magnitude of benefit may not be significant for tenants who live near Xingong subway station.

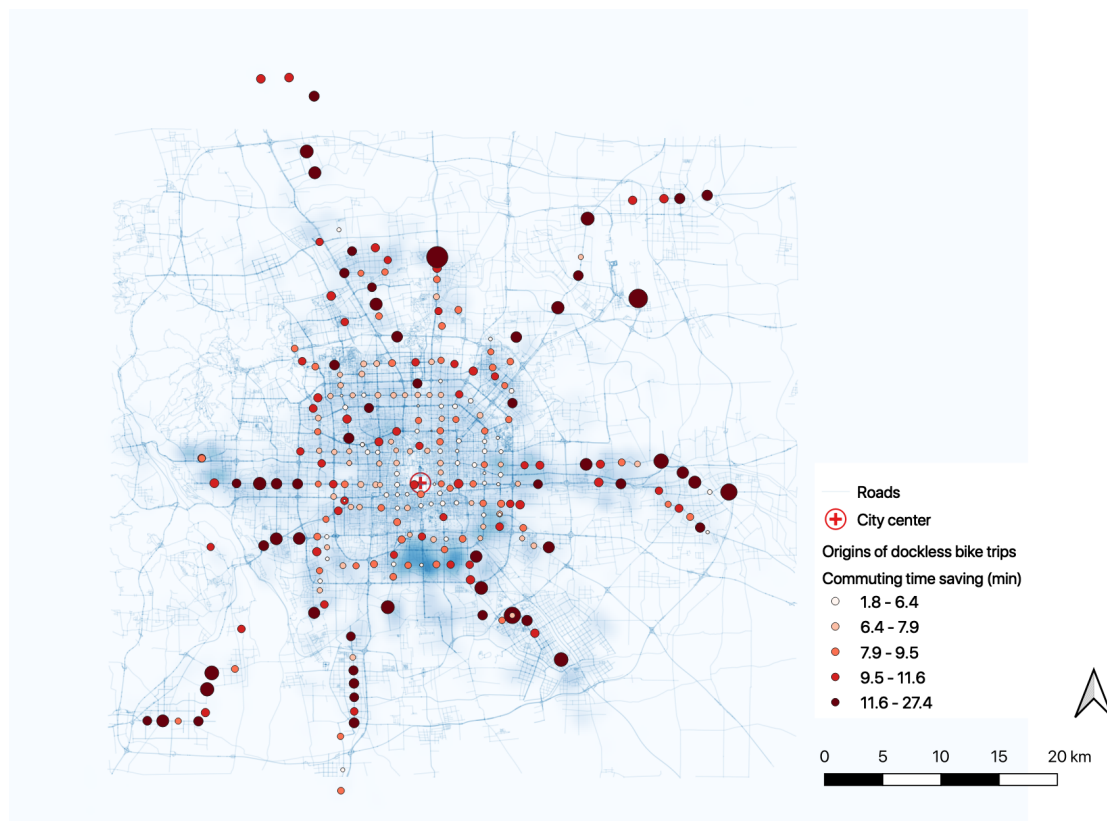


Figure 4-5: Time saving by switching from walk-and-ride to bike-and-ride

The entry of dockless bike-sharing system generates considerable benefits to tenants by improving the accessibility between homes and subway stations. Switching from walk-and-ride to bike-and-ride will save commuting time. By using Model 3.3, the time savings that one can enjoy per trip in each areas in Beijing are presented in Table 4.6, and the time that one can save if he/she lives around a specific subway station is presented in Figure

4-5. From the results we can find that dockless bike users in the inner city, i.e. within the 4th Ring Road saves less commuting time than those in the outskirts. This is because that the distances from homes to subway stations in the inner city are shorter than those in the outskirts. The time saving in North Beijing is only slightly shorter than that in South Beijing on average. The difference in time saving between North Beijing within the 4th Ring Road and South Beijing within the 4th Ring Road is also negligible. These may due to that complexes are closet to subway stations in inner Beijing, and the hotspots of dockless bike usage happen within the 4th Ring Road. It is worth noting that the difference of time saving between North Beijing outside the 4th Ring Road and South Beijing outside the 4th Ring Road become distinct. This indicates that complexes in South Beijing outside the 4th Ring Road are more distant from subway stations. By using dockless bikes, tenants in the outskirts of Beijing, especially in the South, can enjoy most benefits. Beijing citizens spend on average 52 minutes commuting. An average time saving of 8 minutes in Beijing can reduce the average commuting time by 15%.

Table 4.6: Time saving by using dockless bikes

Area	Time saving	No. of complex	No. of trips/hour
All Beijing	8min 18s	4,320	10,830
North Beijing	8min 16s	2,599	6,196
South Beijing	8min 20s	1,721	4,634
Within 4 th Ring Road	7min 21s	2,505	7,358
Outside 4 th Ring Road	10min 18s	1,815	3,472
North Beijing within 4 th Ring Road	7min 15s	1,388	3,662
North Beijing outside 4 th Ring Road	9min 25s	1,211	2,535
South Beijing within 4 th Ring Road	7min 27s	1,117	3,696
South Beijing outside 4 th Ring Road	11min 48s	604	937

Note:

This table presents the estimated time saving if one uses dockless bikes to travel from home to subway station

Dockless bikes can also increase the housing supply in the rental market in Beijing. Assuming that a tenant in Beijing is willing to spend 10 minutes to transfer to subway stations from his/her home. If the tenant chooses to walk, he/she would have to choose

apartments within 800m from a subway station. However, if the tenant chooses to use dockless bikes, he/she could choose apartments within 3km from a subway station. So, switching from walk-and-ride to bike-and-ride would give tenants more choices of housings to choose from, substantially increasing the supply in rental market.

4.2.2 Limitation of the study

This study can be improved in the following aspects to better understand the impact of dockless bike-sharing on rental prices.

In this study, I made a strong assumption that tenants will use the subway stations that are closest to them. However, in reality, people may live close to more than one subway stations, especially for those who live within a denser network. They may not choose to ride on the closest subway station but maybe the second closest, for the sake of reducing transfers underground. Some of the tenants may also rides buses instead of subway. Moreover, I also assumed that tenants will walk to the closest subway stations, as long as they live within 3km to them. However, according to (Zhao and Li, 2017), among all 749 people the researchers surveyed, around 73% of people transit from their homes to subway stations on foot, and around 17% of people take bus. The surveys were taken in 2015, at the time when the subway system can be considered as dense and provides good accessibility. Yet still, more than one sixth of people take bus to subway stations but not walk to there. Therefore, the assumptions that people will use the closest subway stations and only walk to there should be further justified.

To improve the justification, a survey on tenants should be helpful to understand their travel behaviors. The survey should cover questions including tenants' living locations, their commuting methods and routes, how they transfer to subway stations both before and after the entry of dockless bikes, and how often and for what purposes do they use the bikes.

If apartments far from subway stations are also appreciated after the entry of dockless bikes, tenants may have the incentives to move to farther complexes. The study period only

limits to May 1, 2016 to May 31, 2017, covering 13 full months, which is relatively a short period for tenants to relocate. If the study can cover a longer period, and if surveys were conducted to ask about relocation, tenants' decisions would be strong evidence to support that dockless bike-sharing system can improve accessibility and increase housing supply.

The dockless bikes usage data can be explored into more depth. I could further study how the frequency of bike usage at complex level affect rental prices. Since each of the transaction has origins and destinations, I could use routing services provided by Gaode Map to find the bike route. Some more advanced methodologies such as machine learning can also identify the home-subway trips, which is a more accurate estimation of demand and can improve the results of heterogeneity.

Chapter 5

Conclusion

Previous solutions to urban last mile problem such as traditional dock-based bike-sharing systems and shuttle bus services are not efficient enough, for the services are only provided at certain locations and users would have to walk to these sites. Dockless bike-sharing systems can be considered as a more efficient solution to the urban last mile problem, which reducing commuting costs and enabling door-to-door connection.

Literature has pointed out that dockless bike-sharing system can affect resale price premium of houses near subway stations and provide evidence at municipal level. However, whether the system can affect the rental market and if so, how such impact varies within a city remain unknown. It is important to understand the impact at these sub-areas, which can contribute to policy designs on bike-sharing management.

This study applies the difference-in-difference empirical design to understand the impact of dockless bike-sharing system on Beijing's rental market. Previous studies only examined the generalized impact of dockless bikes on rental prices, yet did not measure the effect for a single city or within a city. To fill the gaps identified in previous studies, I further investigated how such impact varies within a city by studying sub-areas of the city, with the help of rich rental and apartment data at transaction level. The results shows that the rental price gradient is flattened slightly in Beijing for apartments located within 3km from subway stations. Dividing Beijing into more developed and less developed regions by the Chang'an Avenue and the 4th Ring Road, I found that the reduction of rental price

gradient only becomes slightly steeper in more developed areas such as North Beijing or Beijing within the 4th Ring Road, and flattens by up to 16% in less developed areas such as South Beijing and Beijing outside the 4th Ring Road. The above results mean that the effect of dockless bikes on rental price gradient is heterogeneous within a city. By estimating the rental price gradient at different distance segments, I found that the impact on rental price gradient change is not linear within the 3km radius, where in more developed areas the largest reduction in gradient happens at 1000-2000m, and in less developed areas at 0-500m. These means that the uneven distribution of amenities around subway stations can affect the impact of dockless bikes.

The entry of dockless bike-sharing system can generate economic benefits for tenants. Taking Xingong subway station (Line 4) as an example, dockless bikes can bring about ¥97/Month of benefit to a standardized apartment of 55m², which is around 2.7% of the original rental price. Using dockless bikes can also bring great social benefits by saving commuting time. Switching from walking to biking from homes to subway stations saves about 8.3 minutes of commuting time per trip on average in Beijing, where the most developed area saves 7.24 minutes and the least developed saves 11.8 minutes. What is more, dockless bikes can dramatically increase housing supply in the rental market in Beijing. Allowing for a 10-min commuting time from homes to subway stations, a tenant would be able to choose from apartments within 800m to subway stations to up to 3km to subway stations. Thus, the entry of dockless bikes may also be able to adjust the housing supply in Beijing.

Admittedly, this study has limitations. I made strong assumptions on tenants' travel behaviors including assuming they will use the closest subway stations and will walk there. In reality this may not be true - tenants may choose to live close to multiple subway stations, and they may use bus or shuttle services to subway stations instead of walking there. The results would be more accurate and better justified if surveys were conducted on tenants' travel behaviors. Exploring more on the dockless bike usage data may also improve the results.

This study contributes to the current literature on how improved accessibility can affect

rental prices, and explores how the impact on rental prices varies within the city. This study also estimates both economic and social benefits that the entry of dockless bikes to a city can bring. These findings may be helpful for future policy design on bike-sharing management, such as moving bikes to outskirts of the city where they are needed.

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