Examining Usage Patterns of Public Biking Behavior Based on IC Card Data: Comparison Before and After the Usage of Free-floating Shared Bikes

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***Abstract*—Construction and operation of public bike-sharing have played a central role in improving urban transportation system and facilitating residents' travel. This research examines usage patterns of biking behavior by analyzing extensive smart card data from public bike-sharing system in Ningbo, China. Existing studies consider usage patterns of a bike-sharing scheme mainly basing it on trip and weather data and therefore, few studies have taken into account how free-floating shared bikes affect public bicycles. Hypothesis testing and multinomial logistic regression model were adopted to examine trends and explore differences between the two datasets. This research found that trip frequency presents habitual patterns with an obvious morning and evening peak and that usage frequency of public bikes decreased after the emergence of free-floating shared bikes, especially in peak periods of weekdays. Concurrently, it's found that customers tend to spend significantly longer time on public bicycle trips than before emergence of free-floating shared bikes. Results indicate that free-floating shared bikes and public bicycles have competitive relationship in peak period. The findings of this research will therefore provide a good explanation of how bicycles serve residents and provide support for public bike system operational decisions.**

Keywords—Bike sharing, data mining, differences test, multinomial logit model

I. Introduction

Public bicycle system is the product of the city's promotion of "green transportation" and has the benefits such as energy saving and emission reduction, strengthening the body, improving the image of the city, and creates awareness of low-carbon and environmental protection to residents. It's noted that due to the convenience and low travel cost of public bike system, travelers had perceived these benefits and gradually more people chose bicycles to travel [1]. Public bike system does not only supply flexible and rapid mobility for short distance travelers, but also serves as a feeder mode to other public transport and improves accessibility [2]. However, in recent years, free-floating shared bikes came into existence under the "Internet +" and sharing economy concepts developed rapidly in metropolitans of China, which caused different degrees of impact on traditional public bike system. To promote the sound development of shared bicycle system in China is very crucial because it is challenging to comprehend how the dock-less shared bikes affect public bicycles. However, currently, finer grained insight into the changes the public bicycle system underwent as dock-less bicycles launched is lacking. Availability of trip data and a map indicating public bicycle stations make the analysis realizable.

The objective of this research is to examine the usage trends of the public bicycle system and explore how dock-less shared bikes affect public bicycles, and explain their mutual relationship extensively. This study, therefore, provides insights into coordinated and sustainable development of public bicycles and shared bicycles.

II. Literature of Review

With the increasing importance of green transportation, public bike system has become more and more popular around the world in recent years. Thus, a great number of studies on bike sharing have focused on researching spatial-temporal patterns based on station hire data as well as IC card data. In the beginning, by analyzing the frequency and turnover rate of public bike stations in different administrative districts, researchers divided bike stations into four several categories and calculated the service radius of bike stations by analyzing the relationship between public bicycle usage and travel distance to provide evidence for station optimization [3]. Station-based data could be applied to analyze the characteristics of bike stations, and it also provides insights for effective redistribution strategy and frequency. Temporal and spatial patterns of bike stations were explored by clustering massive station hire data to illustrate the patterns related to station location, neighborhood and time of day [4]. A further study on usage patterns and impact factors of public bicycle system was conducted. Previous studies have demonstrated that the public bicycle ridership is associated with the characteristics of surrounding built environment, such as job density, population, bicycle lanes, point of interest, and proximity to public transit [5][6][7]. According to the study of public bike system in Montreal, arrival and departure rate as the dependent variable are positively related to both population density and number of metro stations within a 250m buffer [8]. The results also show that the trip amount was highly correlated with the number of bike stations nearby rather than station capacity and trip activities were more frequent in regions with bus stations and universities [9]. Study also revealed that the variable of bicycle rentals has a negative relationship with job density in Minneapolis, Minnesota where public bike systems were competitors to bus and rails while neither population density nor bike lanes had a

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significant relationship with bike usage in California, Sacramento [10]. A study employed spatial multiple linear regression analysis to examine the impact of built environmental variables on trip demand found that the existing public transport station does not show a significant influence on public bike system usage, which indicates that the significant role of public bike system is not an intuitive feeder mode to exiting public transport facilities, but serves as a single mode for traveler to complete the total trips [11]. To sum up, studies mentioned above have adopted various statistical models to explore the factors affecting the usage patterns of public bike systems in different regions. The results of the present studies confirm that different conclusions drawn may be attributed to various urban characteristics and travel behavior.

Although there exist extensive studies that examine impacts of bicycle infrastructure, land use, built environment attributes and weather condition [9] on trip demand, very few explored how free-floating shared bikes affect public bikes based on massive trips data, and therefore this research aims in filling this void. Although studies exploring the influence of weather on public bicycle trip exist, research outcome has also indicated that weather influence is not as strong as one would originally assume for seasonal, social, economic, and infrastructure construction factors all playing their key roles appropriately. In the subsequent sections, the above factors remain as constant as possible, apart from the effects of free-floated shared bicycles.

III. Study area and Data

A. Study area

Ningbo, a coastal port city in southeastern China, is the economic center of the south wing of the Yangtze River Delta. High urban motorization is essential for economic development. While the use of motor vehicles as the primary transport mode contributes to a high level of air pollution, costly demand for fossil fuels, and harmful greenhouse gas emissions [12]. In 2013, the public bike system as a solution to the problem of the Last Kilometer of rail and bus transit was encouraged and officially opened for operation. This study mainly focuses on the Central Business District in Ningbo. The public bicycle station distribution in CBD and station capacity are illustrated in Fig.1.

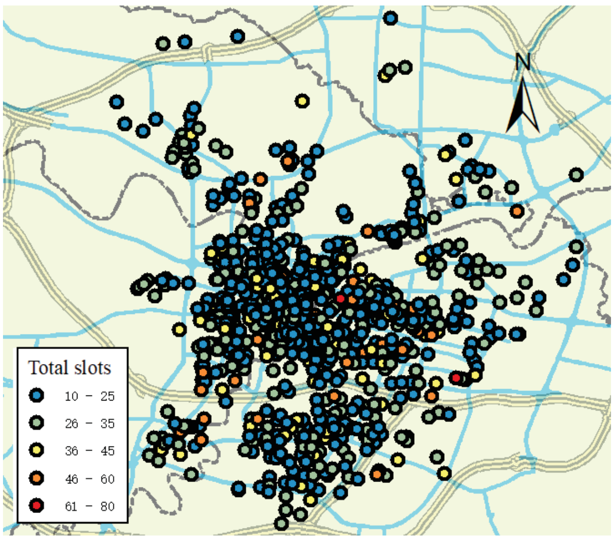

Fig. 1. Public bicycle station distribution

B. Data

The data used in this study including IC card data and location of the station were provided by the Ningbo University of Technology. IC card data span from June 2016 to June 2017 and indicates full year-round operation of the public bike system. During this period, the free-floating bike-sharing emerged in Ningbo in November 2016 and by making a comparison between dataset trends before and after usage of free-floating shared bikes, the impact of free-floating shared bikes on public bicycles usage can be quantified to a certain extent. The original dataset contains information of IC card number, trip origin, destination, trip start and end time, and station number. Station capacity is collected from Ningbo public bicycle official website and to provide an accurate comparison, datasets in June 2016 and June 2017 are used to make a comparative analysis, which alleviates the effects of varying seasons. The two datasets are clearly outlined as follows:

- The first dataset (we call it "Pre-Change" dataset) is in June 2016. Referring to the original trip dataset, there are 858966 records in June 2016. It covers 30 days, inclusive of 24 weekdays and eight weekend days. The average temperature in this month is 26 degrees with seven days of heavy rain, 13 days of light rain, and ten days of no rain.
- The second dataset (we call it "Post-Change" dataset) is in June 2017. In this case, free-floating shared bicycles were launched in November 2016 and so the selection of the second dataset avoids the bias of both the transition phase and varying seasons. The total number of valid days is similar to the pre-change dataset, with 668276 original records. The weather condition in this month is similar to the first dataset with 24 degrees of average temperature, seven days of heavy rain, ten days of light rain, and 13 days of no rain.

Changes between the two datasets are not only limited to the usage of free-floating shared bikes but also, the weather has an impact on cycling. To minimize the weather effect, both datasets are within the same months to ensure that there exist similar weather conditions. Comparative analysis of this study is mainly conducted at the aggregated level, and previous studies prove that biking is independent of the at the aggregated level [13]. Due to this, the limited effect of weather in the two datasets is minimized.

Before the evaluation, we conducted data cleaning whereby 15% and 9.5% of inaccurate records from the original trip dataset in June 2016 and 2017 were excluded separately. For the dataset in June 2016, only 36 of trip records were removed due to null return time while on the other hand, the rest of data removed were the trips that had the same origin and destination with a duration of less than 1 minute. For the dataset in June 2017, 1111 or 0.17% of trip records were excluded due to travel time being larger than 360 mins whereby 0.15% was due to null rental time, and 9.18% due to the same origin and destination with a duration of less than 1 minute.

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IV. Data Analysis

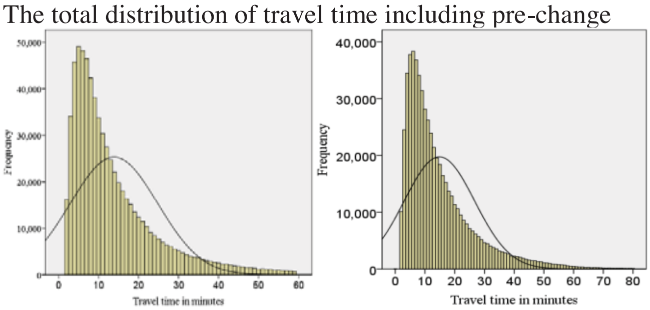
A. *Examining trends in the IC card data*

The IC card data of the public bicycles reflects clearly the usage patterns of the system. Statistical modeling analysis is an effective method used to explore the potential characteristics of the data. Table Ⅰ. Clearly demonstrates the variables employed in subsequent modelling sections in this research. Due to limited table space, the names of variables can't be displayed in the table and therefore they are listed in order of the table. That is, travel time, day of the week, time of day, usage of bike station, frequency of usage, distance travelled, station capacity, number of bike stations within 300m buffer, rainfall, number of bus station within 300m buffer in origin, and number of bus station within 300m buffer in destination. These explanatory variables are selected based on the characteristics of the public bike system and the data used and it is clear that the author was inspired by previous studies [14][15].

TABLE I. Description of variables

Item list	Pre-Change		Post-Change	
	Frequency	*Percentage*	*Frequency*	*Percentage*
Less than 6 mins	145351	20.9%	107033	18.1%
6-11 mins	209333	30.1%	169124	28.6%
11-19 mins	174560	25.1%	154932	26.2%
Over 19 mins	166214	23.9%	160254	27.1%
Weekday	526579	75.7%	460079	77.8%
Weekend	168881	24.3%	131264	22.2%
AM Peak	149688	21.5%	119570	20.2%
Off Peak-Day	224909	32.3%	242208	41.0%
Off Peak-Night	180861	26.0%	121621	20.6%
PM Peak	140002	20.1%	107944	18.3%
Busiest stations	499132	71.8%	351897	59.5%
Busy stations	112230	16.1%	128616	21.7%
Less busy stations	67384	9.7%	87642	14.8%
Least busy stations	16714	2.4%	23188	3.9%
Every day	252589	36.3%	227594	38.5%
⩾ twice a week	251651	36.2%	202168	34.2%
⩾ once a week	93210	13.1%	76913	13.0%
< once a week	98010	14.1%	84668	14.3%
Less than 838m	220990	31.8%	166927	28.2%
838-1286m	158341	22.8%	128785	21.8%
1286-2000m	141280	20.3%	123307	20.9%
Greater than 2000	174849	25.1%	172324	29.1%
Less than 25	158647	22.8%	354878	60.0%
25-40	427392	61.5%	187715	31.7%
Greater than 40	109421	15.7%	48750	8.2%
Less than 2	89502	12.9%	71978	12.2%
2-4	284419	40.9%	381899	64.6%
Greater than 4	321539	46.2%	137466	23.2%
Heavy rain	148828	21.4%	37254	6.3%
Light rain	269143	38.7%	303950	51.4%
No rain	277489	39.9%	250138	42.3%
0	50446	7.3%	50907	8.6%
1-2 (Origin)	246312	35.4%	207469	35.1%
3-5	269856	38.8%	227373	38.5%
More than 5	128846	18.5%	105594	17.9%
0	70378	10.1%	69101	11.7%
1-2 (destination)	239060	34.4%	199822	33.8%
3-5	267785	38.5%	225863	38.2%
More than 5	118237	17.0%	96557	16.3%

These variables indicate some of the usage characteristics of the public bicycle system. As the first variable examined, travel time illustrated that almost half of the trips generated in the system were short trips with a travel time of fewer than 11 mins. Fig. 2(a) displays the distribution of travel time in June 2016, and it is seen that travel time ranges from 3 minutes to 60 minutes and mainly concentrates on short trips. In comparison to that, Fig. 2(b) shows that travel time distribution in June 2017 still focused on short trips, and despite that, the maximum value was longer than 60 minutes indicating a larger distribution span than that in June 2016. The total distribution of travel time including pre-change



(a) Pre-Change (b) Post-Change

Fig. 2. Distribution of travel time in (a) June 2016; (b) June 2017

indicates that travel times had a mean of 14.69 minutes and a standard deviation of 11.38 minutes. Travel time of lowest 25% of customers remained below 6 minutes, while above 19 minutes for the highest 25%. The former group used at least 13 minutes less than the latter one, which implied that a significant travel time difference. Therefore, riders were subsequently classified into four categories according to whether their travel times were between 0-25th, 25-50th, 50-75th, or 75-100th percentiles, and quartiles of travel time are taken as thresholds. The results for days of the week indicated that about 76% of trips were recorded on the weekend. During day time, results indicated that the majority of trips took place in off-peak periods from 9 am to 5 pm. Fig. 4 gives a comparison of the frequency of public

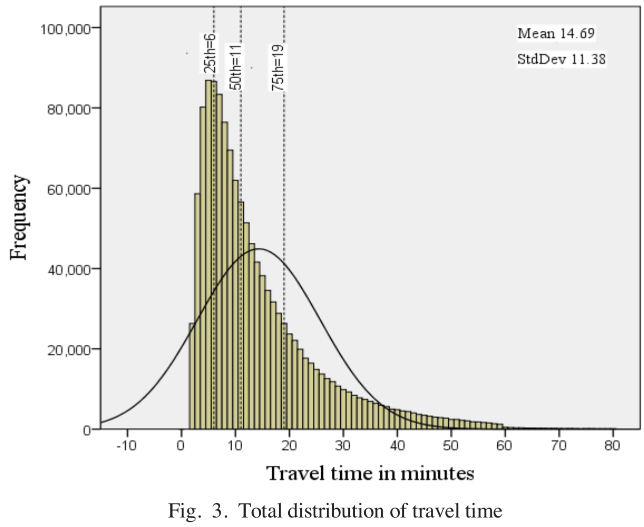


Fig. 3. Total distribution of travel time

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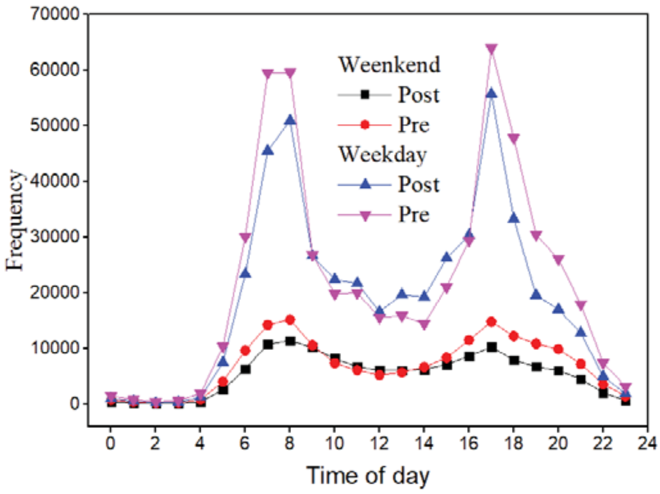
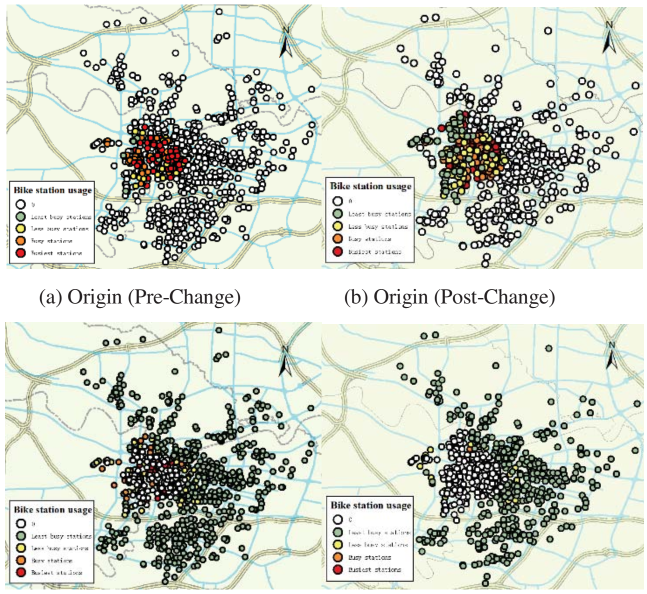


Fig. 4. Frequency distribution by time of day

bicycle trips before and after the change in the week and weekend. Simultaneously, it also gives details of the fluctuation trend of the number of trips in the time of the day during the two analysis periods. Morning and evening peaks appear to be on weekdays and a relative flat fluctuation on the weekend is evident. The obvious tide of public bicycle trips during the weekdays indicated that users tend to public bicycle commute trips on weekdays. Additionally, by comparing the trends in pre- and post-change of the corresponding period, it's notable that the reduction in the number of bike trips was mainly evident in the peak period, and frequency of trips during the off-peak period had no much difference. This certainly indicated that some of the users who used public bicycles during peak hours turned to use free-floating shared bikes after free-floating shared bicycles were launched.

The frequency of usage of the bike station was counted to reflect how busy the stations were. And as the table indicates, over half of all trips originate from the busiest stations. Percentage of trips from the busiest stations was71.8% in June 2016, corresponding to 59.5% in June 2017, which indicated that free-floating shared bikes helped in relieving the riding pressure of the busiest public bike stations. Fig. 5 reflects the spatial distribution of trip origins and destinations with different usage frequency and it's obvious that the busiest trip origins are mainly concentrated in the eastern part of the analysis area. Compared to the pre-change dataset, the number of busiest stations decreased gradually to illustrate how often people used the public bikes, a frequency of usage variable was produced. As it is seen, over 36% of users ride public bikes on a daily basis, and over 75% of people use public bicycles once or twice a week. Due to the availability of limited data, the variable of distance travelled describes the linear distance between bike stations rather than distance estimated by tracking cyclists in the network. Although it may not be accurate, it is a good way to characterize the distribution of travel distance.



(a) Origin (Pre-Change) (b) Origin (Post-Change)

(c) Destination (Pre-Change) (d) Destination (Post-Change)

Fig. 5. Spatial distribution of trip origin and destination in Pre- and Post-Change periods

The next set of variables explains the characteristics of the trip mainly from the perspective of the public bicycle stations. The variable of station capacity describes the number of parking slots in a public bicycle station, and it was used to study the effect of station size on the demand for bike stations. As expected, in June 2016, a large number of trips took place in stations with large capacity but compared to June 2017, trip generation was more concentrated on small stations. The results explain that public bicycle stations with larger capacity were generally located in most prosperous areas of the CBD and so they were frequently used; after the emergence of a large number of free-floating shared bikes in those prosperous regions, the usage frequency of bikes in large public bike stations was reduced to some extent and number of bike stations within 300m buffers indicated that larger bicycle station density led to high trip frequency.

To improve public transport service, public bikes are considered as a feeder mode of it to solve the problem of the last mile distance. To identify how the public transport affected the demand for public bike trips, we developed two variables describing the number of public bus stops within 300m buffer of a bike station in trip origin and destination. The results of the two variables displayed same characteristics, and it was noted that the greater the density of bus stops within 300m buffer of a public bicycle station, the higher the number of trips at that station. In conclusion, it was therefore noted that some public bicycles trips aimed to transfer bus and form a section of the travel chain can be drawn. The variable of weather condition was estimated according to the daily rainfall which was taken from the weather network [16] and results indicated that more biking trips took place in days without rain.

B. Differences test of travel time

In order to quantitatively measure the differences in travel time of public bicycle trips with respect to two datasets and day of the week, we implemented the testing for statistically significant differences between means of travel time. As a result of the central limit theory, it is assumed that the distribution of sample means is

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approximately normally distributed when sample sizes are sufficiently large, and according to the general rule of thumbs, the sample sizes are large if both $n_1 \geqslant 25$ and $n_2 \geqslant 25$ [17]. Obviously, the two datasets are large enough and approximate normality can be guaranteed. Under this assumption, the u test was adopted and the test statistic is z. The day of the week's travel time z value of public bicycle trips is calculated as:

$$z\,(w_{PBT}) = \frac{\overline{we}_{PBT} - \overline{wd}_{PBT}}{\sqrt{\frac{Std\overline{we}_{PBT}}{n_{\overline{we}_{PBT}}}} + \sqrt{\frac{Std\overline{wd}_{PBT}}{n_{\overline{wd}_{PBT}}}}} \tag{1}$$

where $z\,(w_{PBT})$ is the day of the week's travel time z-score of public bicycle trips; $\overline{we}_{PBT}$ is the average travel time for public bicycle trips of specific dataset made on weekends; and $\overline{wd}_{PBT}$ is the average travel time for public bicycle trips of specific dataset made on weekdays; *Std* is the standard deviation; n is the frequency. The two datasets z value of public bicycle trips is calculated as:

$$z\,(d_{PBT}) = \frac{\overline{d2}_{PBT} - \overline{d1}_{PBT}}{\sqrt{\frac{Std\overline{d2}_{PBT}}{n_{\overline{d2}_{PBT}}}} + \sqrt{\frac{Std\overline{d1}_{PBT}}{n_{\overline{d1}_{PBT}}}}} \tag{2}$$

where $z\,(d_{PBT})$ is the dataset's travel time z value of public bicycle trips; $\overline{d1}_{PBT}$ is the average travel time for public bicycle trips in first dataset; and $\overline{d2}_{PBT}$ is the average travel time for public bicycle trips in second dataset.

A 5% significance level was used, and the difference is announced as not significant if the z value is smaller than 1.96 [16].

Table Ⅱ. represents the travel time z value of the pre-change public bicycle trips and the post-change trips. Table Ⅱ. shows public bike trips before and after the usage of free-floating shared bikes which significantly shows the difference in travel time (z = 281.85 > 1.96) and users tend to spend longer time than previously in public bike trips. It is obvious that the total number of public bike trips reduced after the emergence of free-floating shared bikes and the reduction mainly concentrated on commute trips, which has been illustrated in the previous section. The statistic test results indicate that the decrease in the number of bike trips in the peak period led to the increase in average travel time because of the bike trips in peak period focus on short time trips.

Table Ⅲ. reports the travel time z value of bike-sharing aggregated by days of the week and indicated that the travel time of both pre-change and post-change on weekends was significantly longer than that of the weekdays (z = 53.78 > 1.96, z = 22.74 > 1.96). This was because public bike commuting trips which tend to short travel time generated mostly on workdays and hence this finding has been clearly stated in the previous section. At the same time, the z value of the travel time before and after the change is much larger on weekdays compared to weekends. The reason described in the previous section can be used to explain this outcome. That is, the frequency of public bicycle trips in the peak period of workdays and weekends decreased, but it was noted that it decreased more on weekdays than weekends after the change. All these results imply that free-floating shared bikes and public bicycles had a certain competitive relationship in peak periods.

TABLE II. Z VALUE OF TRAVEL TIEM IN TWO PERIODS

Bikesharing trips	Pre-Change			Post-Change			z
	N	Mean	SD	N	Mean	SD	
Total analysis	694328	13.84	10.95	591330	15.69	16.15	281.85

TABLE III. Z VALUE OF TRAVEL TIEM BY DAY OF WEEK

Bikesharing trips	Weekday			Weekend			z
	N	Mean	SD	N	Mean	SD	
Pre-Change	525742	13.72	10.89	168586	14.22	11.08	53.78
Post-Change	460067	15.63	15.96	131263	15.92	16.79	22.74
z	256.60			122.17			

C. *Multinomial logistic regression model*

In order to identify the factors affecting the travel time and find the differences of factors in different periods to have an in-depth understanding of the reasons for travel time reduction, the multinomial logistic regression model was adopted since the dependent variable had more than two discrete values, and independent variables was inclusive of categorical variables and real-valued variables. This regression model has therefore been applied to solve similar problems [14][15][17].

Multinomial logistic regression analysis uses multiple binary logit regression analysis models to describe the magnitude of the effect of each category compared to a reference category. In this study, the multinomial logistic regression model was conducted using IBM SPSS Statistics 22 to analyze the characteristics within the dataset. Here, the dependent variable of travel time was segmented into four categories according to predefined thresholds, and all other variables are independent variables (see in Table I). Individual n of travel time falls into alternative i from the choice set $C_n = \{1,2,3,4\}$ with four alternatives and associates a utility U_{in} with each alternative $i \in C_n$. Random utility $U_{in}=V_{in} + \varepsilon_{in}$, where ε_{in} is the random error term. Maximize utility $P(i/C_n)=P(U_{in} \geqslant U_{jn}, \forall j \in C_n)$.

The model form is as shown in the following:

$$P(i|C_n) = \frac{e^{\mu V_{in}}}{\sum_{j \in C_n} e^{\mu V_j}} \tag{3}$$

This can be transformed into the following formula:

$$logit(P) = log\frac{p}{1-p} = \alpha + \beta X + \delta Y + \varepsilon \tag{4}$$

where α is the intercept, βX represents the trip characteristics (day of the week, time of day, frequency of usage, distance travelled, weather conditions), δY describes the characteristics of bike station (usage of the bike station, station capacity, number of bike stations within 300m buffer, number of bus station within 300m buffer in origin, number of bus station within 300m buffer in destination), ε is the random error term and p is the probability that the travel time falls into one of the four categories.

The regression model established in this research examines factors that impact travel time, and several considerate insights of usage of the public bikes are presented. Table 6 presents all the parameters and their test results in two analysis period, and the reference category is the travel time over 19 minutes to clarify the relative influence of various factors and also lists the coefficient estimates for each variable. If the coefficient estimates are

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significantly positive, it means that the observers who took this factor level had a higher probability than the reference category when the other factors were constant. For example, in the category where the travel time is less than 6 minutes, the estimated coefficient of the weekday was found to be 0.181, indicating that the probability that the traveler chooses to travel during the weekday is greater than the probability of traveling on the weekend. The Nagelkerke R^2 of regression models in pre-change and post-change periods were 0.551 and 0.569, respectively, which displayed clearly it was a good model fit. The results of likelihood ratio chi-square test for each independent variable in the final model are also presented in Table Ⅳ. The null hypothesis is that the coefficient does not change after the factor is removed from the model. Since the significance is less than 0.05, the null hypothesis is rejected, and the influence of each independent variable on the coefficient is considered to be significant.

Basically, the signs of most variable coefficients are in the expected direction. Comprehensively, the variables of weekday and AM peak have a positive effect on public bicycle trips with shorter travel time, indicating that the public bicycle system in Ningbo CBD area shows an obvious commuting pattern on weekdays and commuters prefer short trips. Compared to weekends, the findings indicate that public bicycle trips with shorter travel time are most likely to take place on weekdays. The positive signs show that travelers were likely to have the shortest journey during AM peak in both periods. Trips from the busiest stations in pre-change analysis period were found to be the shortest trips, while in post-change analysis period travelers from the busiest stations tend to trips with longer duration. The negative coefficients of station usage in the category of less

TABLE IV. PARAMETER ESTIMATES OF THE REGRESSION MODEL

Analysis periods		**Post-Change**			**Pre-Change**		
Variables		**Less than 6 mins**	**6-11 mins**	**11-19 mins**	**Less than 6 mins**	**6-11 mins**	**11-19 mins**
intercept		1.118**	0.397**	-0.686**	1.072**	0.344**	-0.581**
Day of the week	Weekday	0.181**	0.057**	0.010*	0.240**	0.1**	0.019**
	Weekend	0b	0b	0b	0b	0b	0b
Time of day	AM Peak	0.162**	0.49**	0.047**	0.202**	0.094**	0.028**
	Off Peak-Day	-0.146**	-0.127**	-0.045**	-0.096**	-0.135**	-0.127**
	Off Peak-Night	-0.050**	-0.017**	0.006*	-0.266**	-0.107**	-0.049**
	PM Peak	0b	0b	0b	0b	0b	0b
Usage of the bike station	Busiest stations	-0.013**	0.038*	0.111**	0.160**	0.137*	0.124**
	Busy stations	-0.019**	0.087**	0.113**	0.092**	0.128**	0.106**
	Least busy stations	-0.039*	0.059*	-0.027*	0.064**	0.052**	-0.138**
	Less busy stations	0b	0b	0b	0b	0b	0b
Frequency of usage	Every day	0.365**	0.339*	0.202*	0.506**	0.386*	0.114**
	At least twice a week	0.319**	0.159**	0.165**	0.438**	0.219**	0.091**
	At least once a week	0.235**	0.145**	0.107**	0.258**	0.111**	0.051**
	Less than once a week	0b	0b	0b	0b	0b	0b
Distance travelled	Less than 838m	0b	0b	0b	0b	0b	0b
	838-1286m	-1.218**	-1.268**	-0.740**	-1.273**	-1.212**	-0.686**
	1286-2000m	-5.108**	-4.359**	-0.930**	-4.608**	-3.295**	-0.831**
	Greater than 2000m	-12.9**	-3.821**	-1.319**	-5.838**	-2.747**	-1.224**
Station capacity	Less than 25	0b	0b	0b	0b	0b	0b
	25-40	0.22**	-0.024*	-0.06**	0.031**	0.051**	0.013**
	Greater than 40	0.31**	0.102**	-0.003*	0.087**	0.067**	0.041**
Number of bike Stations within 300m buffer	Less than 2	0b	0b	0b	0b	0b	0b
	2-4	0.105**	0.064**	0.017*	0.034*	0.009*	0.013**
	Greater than 4	0.124*	0.070**	0.058**	0.068**	0.093**	0.088**
Weather	Heavy rain	0.031*	0.029*	0.015*	0.139*	0.046*	0.026*
	Light rain	0.048**	0.055**	0.018*	0.043*	0.027*	0.013*
	No rain	0b	0b	0b	0b	0b	0b
Number of bus station within 300m buffer in origin	0	0.438**	0.163**	0.044**	0.377**	0.288**	0.166**
	1-2	0.241**	0.158**	0.121**	0.221**	0.165**	0.081**
	3-5	0.069**	0.036**	0.019*	-0.038**	0.034**	0.004*
	More than 5	0b	0b	0b	0b	0b	0b
Number of bus Station within 300m buffer in destination	0	0.206**	-0.061**	-0.301**	0.267**	-0.065*	-0.294**
	1-2	0.035**	-0.037**	-0.088**	0.089**	0.014*	-0.043**
	3-5	-0.092**	-0.104**	-0.125**	-0.074**	-0.08**	-0.096**
	More than 5	0b	0b	0b	0b	0b	0b
N		591289			694914		
-2Log-likelihood at convergence		229284.673			267531.612		
Nagelkerke R^2		0.569			0.551		
Chi-squared statistic		138589.199			167460.703		
Degrees of freedom		75			75		

* Significant at a 95% level
** Significant at a 99% level
b The parameter is set to zero

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than 6 minutes in the post-change period indicated that the shortest trips were likely to take place in less busy stations, which was contrary to the pre-change period. It's common sense that the busiest stations are mostly located at the bustling area where bike rental demand is large, and generally speaking, the number of free-floating shared bikes in this region is also large, so there is a certain competitive relationship between public bikes and free-floating shared bikes. Thus, the above finding can be explained that those who typically used public bicycles in busiest stations for short trips eventually changed and turned to free-floating shared bicycles, which leads to a lower frequency of the shortest bike trips. It's therefore evident that the average travel time of public bikes increased after free-floating shared bicycles were launched.

The subsequent set of results show that most frequent users of public bike system were more likely to have habitual short trips. As one might expect, the results of the distance travelled variable indicated that those traveling longer distances were likely to have longer travel time. Although this was obvious, travel distance is particularly significant to the regression model and this factor is therefore added to the final model. Afterwards, the variables describing the characteristics of public bike stations are analyzed. The station capacity variable demonstrated that public bike stations with larger capacity were likely to generate trips with the shortest travel time. As we all know, the public bike docking station is arranged according to traffic demand and the greater the population density, the larger the capacity of the docking station. It illustrates that docking stations with a larger trip demand tend to enhance more commuter trips. With the increase in a number of the bike stations within 300m buffer, shorter trips were noted to be generated more. The results of the weather variable demonstrated that longer cycling trips were likely to take place on days without rain. The results of the last two variables also exhibited that users were more likely to have medium distance trips by public bikes since the number of bus stops within 300m buffer in destination increased. This, therefore, suggested that these trips were as a result of modal shift and users tend to transfer from public bikes to buses instead of transferring from buses to public bicycles.

The results presented in table Ⅳ. provide a special insight into understanding the time use patterns of public bike system. It's found that trips generated during peak period on weekdays were short and habitual trips. By comparison, the average travel time of public bikes reduced after the emergence of free-floating shared bikes. Naturally, there are many factors that affect public bicycle usage, and weather is a significant one. Although the variable describing weather conditions was introduced into the regression model, further study needs to consider the finer-grained weather data because biking activity is flexibly adjusted according to the real-time weather conditions [13].

V. Conclusion and Future Work

In the above analysis, the time use patterns of the public bike system and how the emergence of free-floating shared bike affected the usage of public bicycles are explored. With the advent of the era of big data, large-scale data acquisition and processing became possible, and these data are used to measure and reflect the usage pattern of the system operation. The work conducted in this paper has focused on IC card data of public bicycle system in Ningbo, China and data analysis and statistical modeling methods have been used to describe what usage pattern of Ningbo's public bike system is and how time use pattern changed when free-floating shared bikes were launched. At the aggregated level, similar usage patterns emerged, with obvious morning and evening peaks on weekdays and there were usage frequency differences in peak period between the pre-change and post-change trips. To quantitatively measure the differences in the travel time of public bicycle trips concerning two datasets, the differences test of travel time was conducted. It was found that travel time in two analysis periods was significantly different and that customers tended to spend longer time on public bicycle trips than before the emergence of free-floating shared bikes. This was caused by the decrease in public bike usage frequency in the peak period, which implied that public bicycles and free-floating shared bikes had a competitive relationship on travel mode choice in the peak period. Afterwards, we adopted a logistic regression model to identify factors that affected travel time and found the differences of factors in different periods to have an in-depth understanding of the reasons for travel time reduction. It was found that trips generated in peak period on weekdays had the shortest journeys and model results clearly validated the above conclusions.

Analyzing time use patterns of public bicycles system under the influence of free-floating shared bikes quantitatively was one of the key strengths of research. The aim of the research was also to identify the gap in the relationship between public bicycles and free-floating shared bicycles. The conclusions of this study play a key role in coordinating public bicycles and free-floating shared bicycles for sustainable development, especially in case a large number of free-floating shared bikes emerged in the city. We explored the usage differences of public bicycles system before and after the emergence of free-floating shared bikes using two accurate datasets of public bicycle trips. To minimize the effects of seasons and weather conditions, we first chose two datasets of the same month in the year 2016 and 2017. Afterwards, the findings of this study were based on the analysis at an aggregated level since the previous study has indicated that cycling pattern was more unrelated to weather at the aggregated level [13]. This research found that there was a certain competitive relationship between free-floating shared bikes and public bicycles in the peak period, while Ma thinks both have a certain complementary relationship from the aspect of supply mode [19]. The complementarity and competition of free-floating shared bikes and public bicycles are not contradictory to a certain extent. The competition of the two can alleviate the pressure of rebalancing public bike rental stations to a certain extent in the peak period. Free-floating shared bikes at the same time can make up for defects such as the fixed location of public bicycle rental. Operators should, therefore, make full use of the competition and complementarity between free-floating shared bicycles and public bicycles to promote healthy development between the two.

However, this research still has several aspects that need further study. This is because first of all, it's helpful to explore differences in spatial use patterns which may give

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more visual information and secondly the difference of usage pattern in local station activity is worth exploring, which will give more details on the mechanism of influence.

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