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Transportation Research Procedia 00 (2018) 000–000

Transportation Research Procedia

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World Conference on Transport Research - WCTR 2019 Mumbai 26-31 May 2019

Exploring the Change on Taxi Service Availability Under the Operation Mechanism of E-hailing Apps

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Abstract

E-hailing Apps of taxi service have captured a lot of drivers and passengers in Chinese cities. Due to its operation mechanism of trip origin and destination (OD) information pre-notified through Apps, the benefit disparity of different trips would entice drivers to tendentiously treat service demand. It is criticized that the situation would injure the taxi service availability in urban. This paper focus on the spatial-temporal changes and relative differences of taxi service availability during three different periods of e-hailing Apps developing, namely non-Apps stage, Apps-competition & transitions stage and all-Apps stage, with the help of calculated OD trip data of taxi on May 2012, May 2015 and December 2016. The analysis revealed that the operation mechanism of trip OD information pre-notified of e-hailing Apps and the resulting drivers' behaviors (e.g. picking orders) have significantly influenced service availability. On the one hand, the short-distance trip seems to be the biggest "victims" after the emerging of e-hailing Apps, especially in the high density urban areas. On the other hand, the coverage and intensity of these ride services are improved in the suburb areas or relative low density areas. All these changes are more remarkable when the market of App-based ride services remains steady. The findings can provide objective evidence for comprehensively understanding the market influence of e-hailing Apps in the cities, and also offer supports to better market regulations making for the authorities.

Keywords: E-hailing Apps; Service Availability; Operation Mechanism; Taxi OD Trip Data

1. Introduction

Smartphone-based e-hailing Apps in China have experienced a rapid and large-scale development since the first one emerged in 2012. During the spectacular rise of ridesourcing in the second half of 2015, there were more than 40 related Apps at the same time. In February 2015, Didi Chuxing, which was invested by two of Chinese internet giant

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Tencent and Alibaba, officially merged with Kuaidi Dache, and soon after acquired Uber China in August 2016. So far, there was only one leading mobile urban transport service platform in China. Without any doubt, e-hailing Apps and the diverse App-based ride services have played a significant role on Chinese taxi service market. As mentioned in the latest research report, Yan (2016) supposed there were over 400 million registered users of Didi distributing throughout 400 Chinese cities, and about 17.0 million orders were finished per day.

There are two representational taxi services available in China, namely conventional street-cruising taxi service and App-based ride services (e.g., ridesourcing or e-hailing). Before the e-hailing Apps emerged, all taxi service are based on street cruising, drivers pick up passengers randomly without any trip information previously known, and the taxi fare is regulated by government. Soon afterwards, the taxis' operation mechanism have greatly changed with the helping of e-hailing Apps. Passengers can alternatively send trip demand through Apps, while drivers of taxis or private cars response the orders by Apps. Obviously, there are two crucial differences among App-based ride services and conventional taxi service. Firstly, drivers have already been notified passengers' trip OD information before responding the orders, and then decide whether or not to offer service. Secondly, the price level of App-based ride services is set by the ride-hailing companies.

Despite the App-based ride services are widely embraced as a new transport option that offer services of higher level of real-time matching efficiency and ease-of-use, it suffers great question and discussion worldwide. The report released from Schaller Consulting (2017) in February 2017 demonstrated that, Transportation Network Companies (TNCs) have been the leading source of growth in auto travel in the city, which is not benefit for transit-oriented development in denser urban areas. At the beginning, e-hailing service in China cleared their essential goals for solving traffic congestion and "taxi-difficulty" problem. However, ECONOMIC INFORMATION DAILY (2017) reported that more and more residents complained about having more difficulties in taking taxi services, especially during the peak hour and overnight.

Obviously, the changes of taxi services' operation mechanism have raised widespread concerns about effects on the satisfaction level of taxi service. The criticisms hold that, taxi drivers are intend to response orders selectively after getting passenger's trip OD information, which can be summarized as "service discrimination" problem. Some trips that cannot bring high income or profit to them are more likely to be ignored, which eventually leads to the decreasing service availability. As was expected, e-hailing Apps are not approve of it. Unfortunately, the complete and valid evidence can hardly be accessed by the government or the public due to the secrecy of the real supply-demand information and the pushing algorithm of orders. Therefore, it might be interesting and necessary to ask "How factors affect taxi 'service availability' during the different stages of e-hailing Apps development?" and "How these factors can be observed and measured objectively?"

To attempt to answer the above questions, this paper proposes the concept of service availability to describe the realistic satisfaction level of service demand, and then explores the spatial-temporal changes of traditional taxi service and App-based ride services during the different stages of e-hailing Apps developing. For this purpose, this study rely on raw order dataset tracking more than 7500 taxis respectively on May 2012, May 2015 and December 2016, and calculate the OD trip data for further analysis. The findings can provide objective evidences for comprehensively evaluating the potential influence on service market of e-hailing Apps in the cities, and also offer supports to better market regulations making for the authorities.

The remaining parts of the paper are organized as follows. Section 2 summarizes the literatures related to App-based ride services. Section 3 gives the detailed explanation of dataset. Section 4 defines the service availability and introduces the evaluation method consisting of spatial and temporal dimensions, and then provides the results in section 5. Section 6 concludes the findings of the study.

2. Literature review

With the help of an extensive number of GPS dataset, various recent literatures focused on analyzing different aspects of taxi ridership and gaining insight into urban dynamics in the cities.

Due to the freely available access to online dataset provided by Taxi and Limousine Commission of New York City, some studies paid attention to the spatial-temporal patterns of taxi or Uber ridership in NYC. Santi et al. (2014) performed a simulation study based on a dataset of 150 million taxi trips, and found a large portion of trips were routinely shareable. It has been shown that the cumulative vehicles miles travelled could be reduced by 40% or more with a modest increase in passenger discomfort. Hochmair (2016) analyzed the spatial-temporal patterns of taxi trips via 29 million taxi trip records in 2013, and used multivariate regression further to explore the relationship between taxi trips and other explanatory variables in an urban environment. Another study by Yang et al. (2014) estimated a binary logit model to analyze the mode choice between transit and taxi modes, and Parfenov et al. (2014) compare trip characteristics between summer and non-summer months, and to develop a data visualization tool that allows users to visually query taxi trips by considering spatial, temporal, and other constraints by Rerreira et al. (2013).

There are also some research concerning about relationship among traditional taxis and App-based ride services. One recent study conducted by Nie (2017) attempted to examine the impact of ridesourcing on the taxi industry and to explore where, when and how taxis can compete more effectively based on GPS data during three years. Cramer and Cramer and Krueger (2015) compared the capacity utilization rate of both UberX and taxis in several cities, concluding that the previous one is about 30%-50% higher than taxi drivers in both time and distance. Correa et al. (2017) investigated the impact of the app-based for-hire vehicles on taxi industry through an empirical analysis from 2014 to 2015, and they found the high spatial correlation between taxi and Uber pick-ups, especially in the central areas. Another studies emphasized on App-based ride services, urban transport and taxi market. Harding et al. (2016) concluded that taxi apps had the potential positive influence on urban transportation, especially in private motor vehicle use. Rayle et al. (2016) conducted an intercept survey study in San Francisco and showed that at least half of the ridesourcing trips replace modes other than taxis. It indicated that the markets of two services share similarities but also significant differences, and ridesourcing consistently outperforms taxis in terms of waiting time. Contreras and Paz (2017) demonstrated that ride-hailing companies have a negative and significant effect on taxicab ridership, and another remarkable finding is that transit ridership actually complements taxi ridership, instead of competing directly with the taxi industry.

In summary, these research working on traditional taxis and emerging ride-hailing ride services were largely based on taxi GPS dataset, concerning about the impacts on urban dynamics and taxi market in the cities. However, the long-sequence, continuous dataset in the cities were limited used in one empirical research, and thus measuring and analyzing the changes of taxi service during the long-period development of e-hailing Apps remained relatively scarce. In addition, these studies reached conclusions mainly relied on overall evaluation methods or indexes, such as traffic operation index, economic indicators, so that the intuitive and objective judgment of taxi service demand were not well understood.

More importantly, compared to the dispatching regulations of Uber, the App-based ride services in China relies on drivers' choice of whether or not to response demands with the previously known trip OD information, which is completely different. And it might also lead to the distinct impacts on taxi service market. This paper can better fill in the gaps in evaluating the effects on service market of App-based ride services under the operation mechanism of trip OD pre-notified, by the comparisons and analysis based on the order dataset of street-cruising taxis and App-based taxis.

3. Data explanation

3.1. Basic background

In Shanghai, like other megacities in the world, taxi is the key component of urban integrated transportation system. According to the Shanghai Comprehensive Transportation Annual Report (2017), there were 48926 taxis in the city by the end of 2015, which means about 20 vehicles per 10 thousand persons. Around 479 million passengers were carried by taxis during 2015, and the average occupied travel distance of taxis reached 10.76 billion kilometers per day.

Based on the 5th Shanghai Comprehensive Transport Survey (2015), Figure 1 gives a brief introduction of the study area in Shanghai, and the distribution of population and land use are gradually reducing from the center zones to the suburbs (see Fig.1(a)). For detailed analysis, the study area are divided into three types based on population density, namely Zone_1, Zone_2 and Zone_3, as following Fig.1(b). Moreover, the 24 hour are also broken into three separate durations, including peak hour(7:30-9:30 am), mid-of-day(11:00-13:00) and overnight (23:00-5:00).

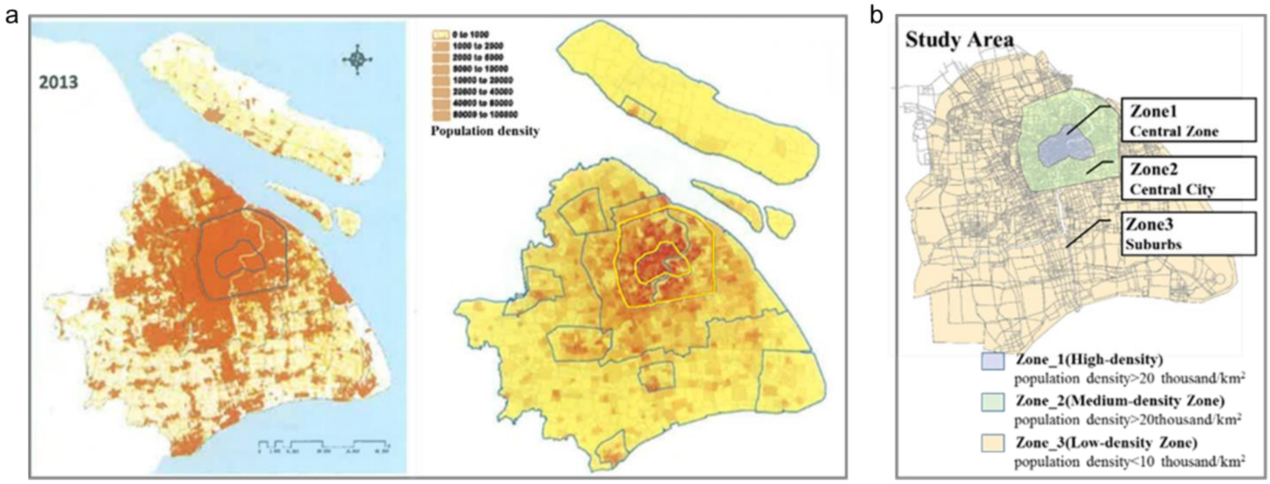

Fig. 1. (a) Land construction and population in Shanghai; (b) study area.

3.2. Dataset description and overall statistics

The raw order dataset used in the study covers three periods in 2012, 2015 and 2016 respectively, when the service market of App-based ride services was at the totally different stages, so that the dataset is of good representativeness. As listed in Table 1, almost all taxi orders on May 2012 were finished by street-cruising taxis, and then the e-hailing Apps experienced a booming development with fierce competition at around the middle of 2015 so that appreciable percentage of taxi orders were generated by Apps, and finally the dataset on December 2016 is all from the Apps.

The taxi order data in each periods tracked more than 7500 taxis (above 15% of registered taxis in Shanghai), and the average daily quantity is over 3000 thousand records. The time interval of GPS signals in different years is roughly every 6s for each order. The dataset includes the trip information like orders' ID, each record points' timestamp and corresponding location (i.e., longitude and latitude), spot speed and operation status (i.e., empty or occupied), as well as the drivers' ID.

The study is then conducted based on the calculated OD trip data after three-step of data processing, namely coordinate systems transformation, OD trip calculation and OD re-cleaning. To ensure the comparability within the dataset among three years, the overall process is under strictly consistent data preprocessing and cleaning rules.

Table 1. Average statistics of OD trip data.

Dataset	Number of taxis in dataset(vehicles)	Total number of taxis in Shanghai(vehicles)	Number of OD trips(records/day)	Operation mode of taxi company*
2012/5/12-2012/5/17	13170	50683	356059	double-shift
2015/5/12-2015/5/18	9620	48926	151533	single-shift
2016/12/22-2016/12/24	9224	48050	14094	single-shift

* Ye et al. (2018) illustrated that many taxi companies in Shanghai have adjusted their operation mode from double-shift to single-shift since 2014. The total number of drivers of single-shift mode is half as many as that of double-shift mode, and each driver has shorter working hours per day while has more working days per month under the single-shift mode.

4. Methodology

4.1. Service availability

It should be noted that, firstly, the behaviors of service providers (drivers and Apps platform) are directly influenced under the operation mechanism of the App-based ride services. With the previously known order origin and departure time, drivers offering e-hailing services were highly not likely to take the relatively "uneconomical orders" (e.g., short-distance orders, overnight orders or orders in suburbs) in reality, which often called "order-picking" or "service discrimination" issue. Accordingly, the service availability changes can be classified into different time periods, spatial areas and trip distance (actually reflect the riding price).

Secondly, observing and measuring of service availability are almost impossible due to no access to the real satisfaction level of all potential taxi service demand. Although such information, like when and where that passengers first ordered and actually obtained services, can be download from the Apps, these information remains highly privacy.

Therefore, this study was conducted to compare and analyze service availability based on the calculated OD trip data of realistic finishing orders, namely, regarding these order information as the final product of service availability.

4.2. Evaluation equations

The OD trip data is calcula ted depends on two main indexes, namely trip distance and trip duration of each orders (Pathlen*nx*, Pathtime*nx*). *n*, *x* distinguish the taxi order and the year respectively, *nxF* and *nxT* represent the first and the terminal ordinal record of the *n*th order reordered by timestamp in the year *x*.

$$Pathlen_{nx} = \{\sum_{i=Order_{nxF}}^{Order_{nxT-1}} [(OX_{nxi} - OX_{nxi+1})^2 + (OY_{nxi} - OY_{nxi+1})^2]\} \times \frac{1}{1000} \quad (1)$$

$$Pathtime_{nx} = Timestamp_{nxT} - Timestamp_{nxF} \quad (2)$$

where $x = 2012, 2015, 2016$

The detailed analysis consists of three parts, (1) time-distance service availability, (2) coverage service availability and (3) typical period-area service availability. An important premise is that taxi orders in 2012 (all generated from traditional cruising taxis) are regarded as the benchmark sample (set to 1), as well as the base case of service availability.

The hourly driving trip distance (*HDTD*) and the hourly driving trip time (*HDTT*) can be obtained by aggregating $Pathlen_{nx}$ and $Pathtime_{nx}$ of orders into each hour of the day. And then the relative changes of service availability in 2015, 2016 compared to non-App stage can also be measured, consisting of the relative difference ratio of distance (*RDRD*), the relative difference ratio of time (*RDRT*).

$$RDRD_{nx} = \left({HDTD_{nx}}/{HDTD_{2012}}\right) \quad (3)$$

$$RDRT_{nx} = \left({HDTT_{nx}}/{HDTT_{2012}}\right) \quad (4)$$

In spatial analysis, these indexes reflects the distribution changes of realistic finishing demand among different periods of years, namely vehicle utilization rate of distance, time ($VURD, VURT$) and accordingly relative difference, pick up rate (the percentage of the order quantity in the all orders, the numerator is obtained by searching around with 1000m from a certain point). $ONx_{d_{i1}}$, $ONx_{t_{i2}}$ represent the order number during the distance d_i and t_i, and AON_x represents the total number of orders.

$$VURD_x = \left({ONx_{d_{i1}}}/{AON_x}\right) \quad (5)$$

$$VURT_x = \left({ONx_{t_{i2}}} / {AON_x} \right) \tag{6}$$

where

$i1 = 1,2,3,4,5,6,\quad d_{i1} \in \{(0,3], (3,6], (6,9], (9,12], (12,15], (15,+2,\}$

$i2 = 1,2,3,4,5,6,7\quad t_{i2} \in \{(0,10], (10,20], (20,30], (30,40], (40,50], (50,60], (60,+6\}$

$$RDR - VURD_x = \left({VURD_x} / {VURD_{2012}} \right) \tag{7}$$

$$RDR - VURT_x = \left({VURT_x} / {VURT_{2012}} \right) \tag{8}$$

Additionally, the OD trip data is selected by the location of the origin point, destination point and both end points, according to typical zones in the city. $\mathrm{OR}_{xj}, \mathrm{DR}_{xj}, \mathrm{ODR}_{xj}$ is calculated in the following equations, where OON_{xj}, DON_{xj} and $ODON_{xj}$ represents the order number with the qualified origin, destination and OD trip.

$$\mathrm{OR}_{xj} = \left({OON_{xj}} / {AON_x} \right) \tag{9}$$

$$\mathrm{DR}_{xj} = \left({DON_{xj}} / {AON_x} \right) \tag{10}$$

$$\mathrm{ODR}_{xj} = \left({ODON_{xj}} / {\sum_{j=Zone\_1}^{Zone\_3} ODON_{xj}} \right) \tag{11}$$

where $j \in \{Zone\_1, Zone\_2, Zone\_3\}$

5. Results

5.1. Time-distance service availability

Figure 2 shows the changes of hourly driving distance and duration of taxi orders during the period of three stages on weekdays and weekends respectively. There is an obviously similar trend of average hourly distance distributing on both weekdays and weekends among 2012, 2015 and 2016(see Fig.2(a), Fig.2(b)). The driving distance increases rapidly from 3:00 to 6:00 am and then reaches longest distance (at around 9.1km, 11.4km and 12.3km in three years respectively) on 5:00-6:00 am, while during other period of days remain fluctuant in a certain range. The average hourly distance on weekdays and weekends in the same year is roughly equal.

Figure 2(d) presents quite different time-varying trends of driving duration among the day mostly due to the real-time discrete, random urban traffic flows. In particular, the curve on weekdays in Fig. 2(c) among three years shows double highest value (over 23min in later 2015 and 2016, and 18 min in 2012) from 7:00-9:00 am and from 16:00-18:00 which are in accordance with the daily two peak hour. And the overall incensement of average trip time is also seen below (from 13.9min in 2012 to 18.3min in 2016). Figure 3 calculates the average hourly speed accordingly, and there are no significant changes on it from 2012 to 2015, showing the general similarities of traffic operation (the fastest speed reaches 47.5km/h during 4:00-6:00 am, and average 25km/h in the daytime) in the cities on weekdays and weekends respectively.

The remarkable but not counterintuitive changes showed in the Figure 2 are the gradually growth of hourly distance and hourly duration with the booming development of Apps since 2012. For example, the average driving distance increases from 6.7 km in 2012 to over 9.6 km in 2016, and all orders are much further than 3km (basic distance of taxi fare, also called short-distance trip) during the whole day. A reasonable inference can be drawn is that short-distance(or short-duration) demands are much possibly restricted or “discriminated” by drivers’ picking orders at the Apps-competition & transitions stage and later all-Apps stage, while the long-distance demands are more and more likely to be satisfied.

The relative differences of hourly distance and hourly duration are demonstrated in Figure 4. All numbers of RDRD and RDRT are larger than 1, which prove that the popularity of e-hailing Apps indeed promote the travel demands of taxi service both on distance and duration. And another finding is that the average growth of driving distance and driving time on weekdays are both much higher than that on weekends, and it seems that residents are more rely on taxis on weekdays than on weekends.

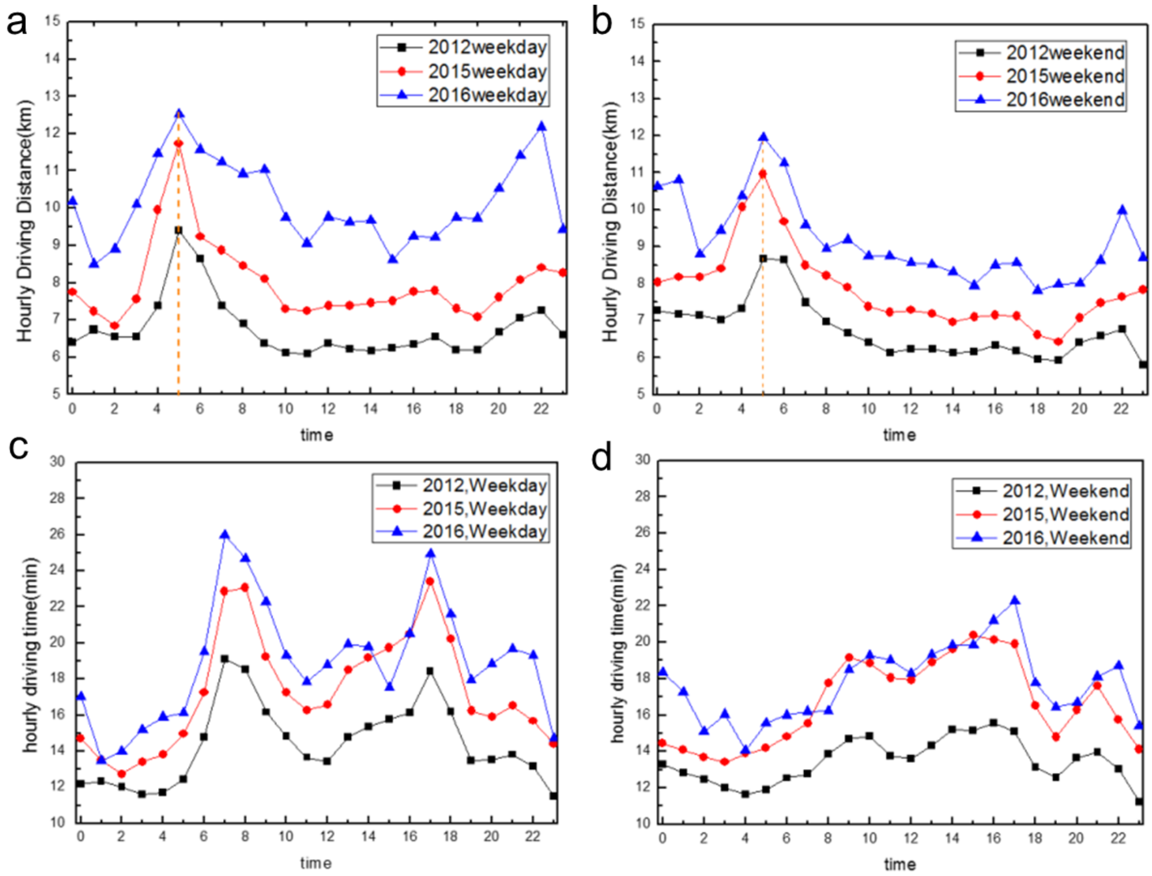

Fig. 2. (a) average driving distance on weekdays; (b) average driving distance on weekends; (c) average driving time on weekdays; (d) average driving time on weekends

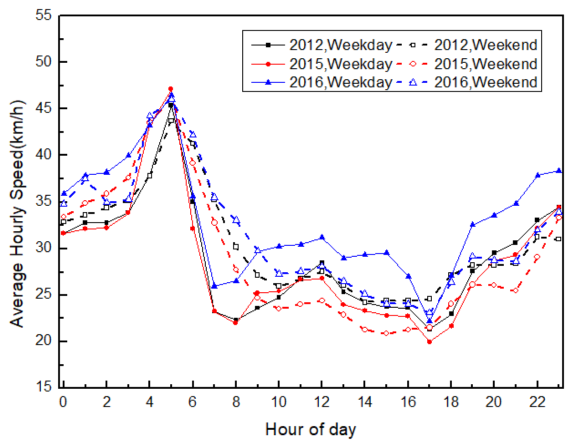

Fig. 3. average hourly speed in 2012, 2015 and 2016

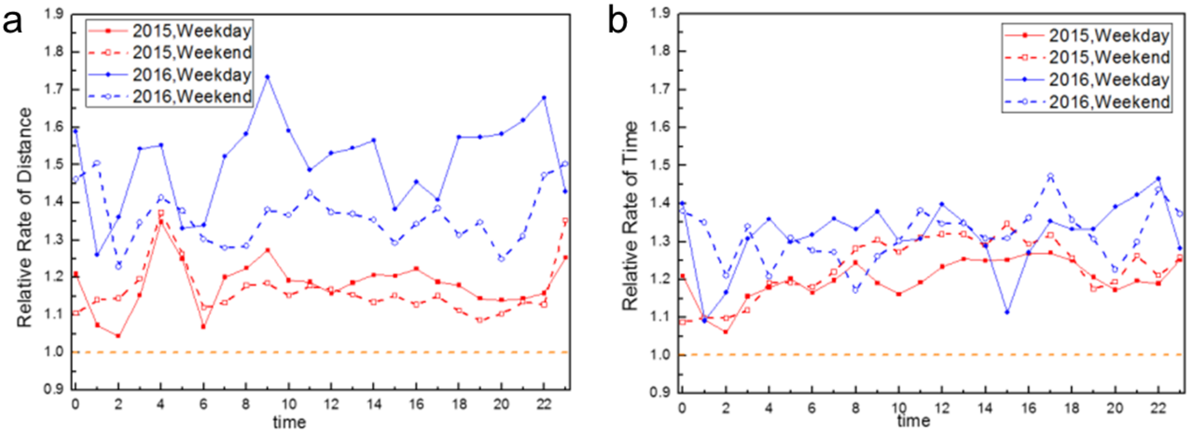

Fig. 4. (a) relative differences of hourly distance; (b) relative differences of hourly time

5.2. Coverage service availability

Figure 5 shows the statistical vehicle utilization rate of driving distance and time. It can be observed in the Fig.5(a) and Fig.5(c) that, the overall distribution of VURD is in a rough parabola upward, while the trend of VURT is generally monotone decreasing during each year. The similar trend of driving trip distance can be concluded, namely, relative shorter-distance trips(less than 6km) and longer-distance trips (more than 12km) account for 70% of total taxi orders. Meanwhile, the short-time trips (not longer than 30 min) are majorities occupied about 80%.

Significant differences can be also found across the changes and relative difference in Figure 5. For example, the two end of the parabola seem to move left from 2012 to 2016, about 5%-15% of short trips shift to further trips, the trips more than 15km experience large decrease (see Fig. 5(a)). Besides, the percentage of trips over 15km is more than 20% in 2016, which means that taxi service is an important alternative choice for long-distance trips during the e-hailing stage. This is not the case in Fig. 5(c), trips less than 40 minutes are of obvious changes in the later 2015 and 2016. A part of short-duration trips are gradually replaced by relative longer-duration trips (20-40km).

Figure 5(b) and Figure 5(d) show the relative difference based on the benchmark of 2012. Much apparently, at the stage of all-Apps, the trips of relatively further-distance and longer-duration are much more possible to be satisfied by ride-hailing services.

The origin point, destination point and OD point are further aggregated into three types of spatial zones of the city for detailed comparison (see OR, DR and ODR respectively) in Figure 6. There are some common similarities among these figures, the curve is changed from roughly monotone decreasing to monotone increasing. In the Fig.6(a) and Fig.6(b), the portion of taxi service starting or ending from the central city experience remarkable drop-off in the later 2015 and 2016, and while the portion of OR or DR in the outer areas of the city climbed to over 40% in 2016. By contrast, the changes occurred in 2016 is obvious and the trend of 2015 is remains basically same compared to the previous 2012. Figure 6(c) represents the distribution pattern of taxi service with both ends in the zones, which also reveals the monotone increasing trend but with larger slope.

Across the development stages of e-hailing Apps, both city center and suburbs suffered significant influence. For one thing, passengers are more and more convenient to receive taxi service in the surrounding area of the city, no matter from where or to where. That is to say, the Apps largely improve the service availability in denser urban areas. Another unusual phenomenon is that the App-based ride services seem to be no longer popular in the central area as the non-Apps stage.

Another essential effecting factor, namely the wide using of sharing-bikes in denser urban areas of the Chinese megacities, should be also considered. By the end of 2016, Mobike and ofo (the two largest bike-sharing companies in China launched since the middle of 2016, have already put over 800 thousand and 500 thousand bikes in the market at the end of 2016) have offered service to more than 2 million users, and achieved 4.5% ridership within 5 kilometer from auto trips. It is reasonable to believe that sharing-bike is the strong competitors with ride-hailing services, especially in the trips of less than 5 kilometers.

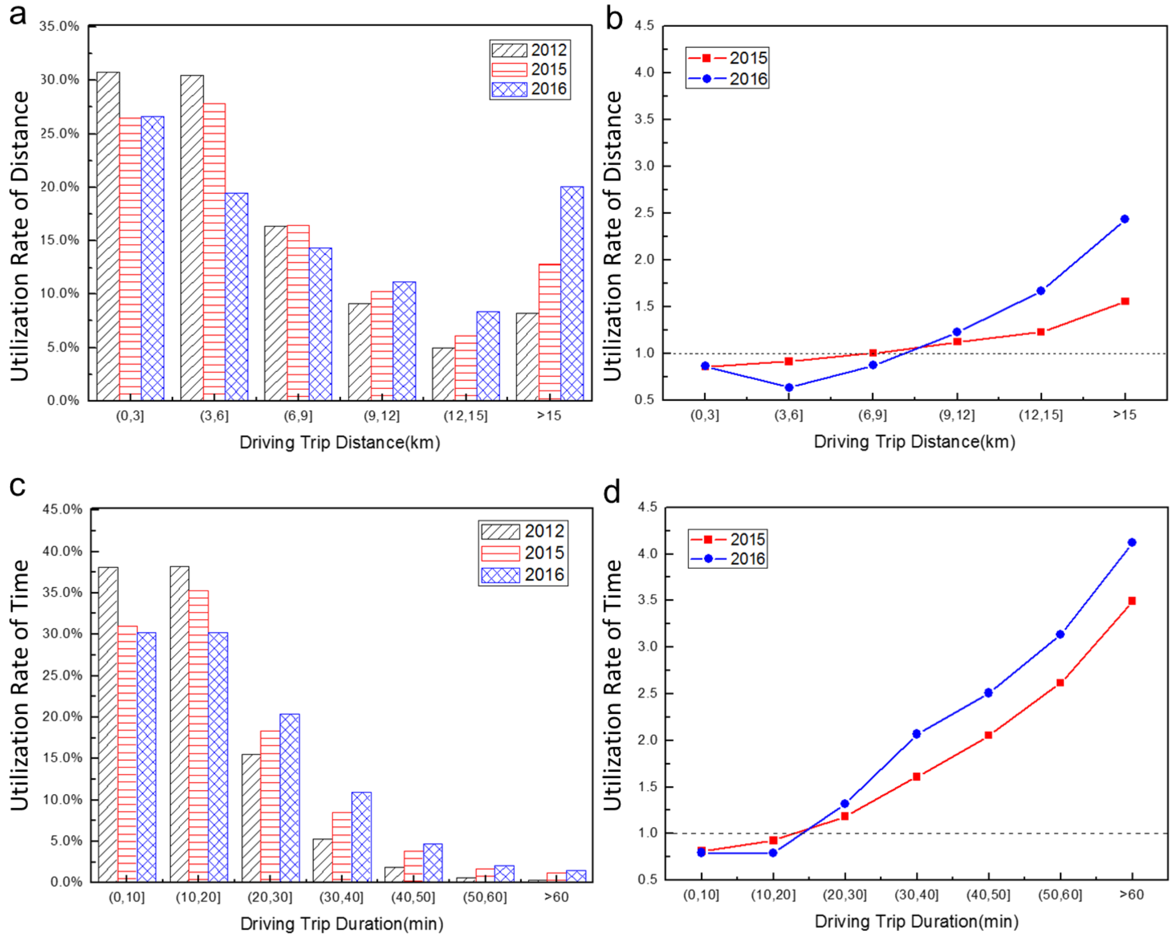

Fig. 5. vehicle utilization rate of distance and vehicle utilization rate of time

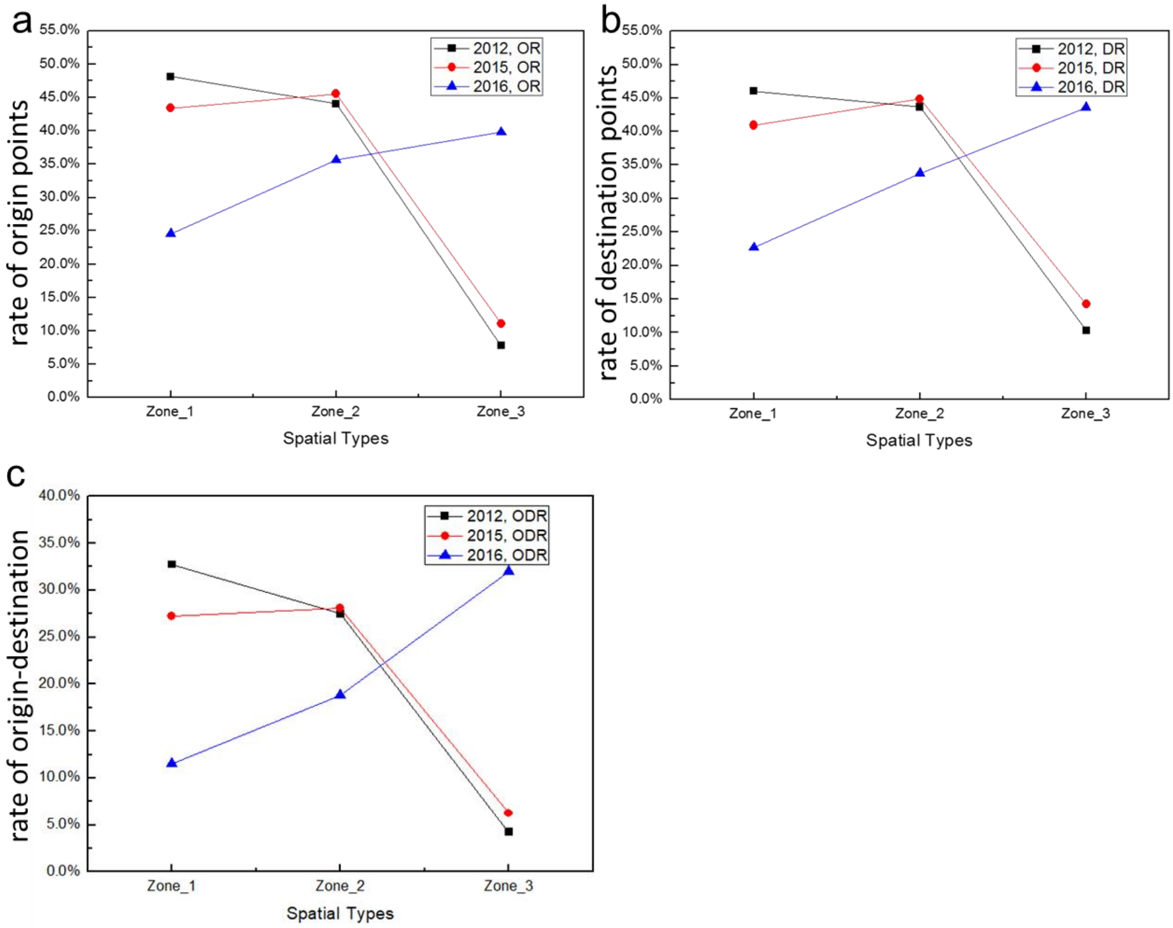

Fig. 6. (a) distribution of origin points rate; (b) distribution of destination points rate; (c) distribution of orign-destination rate

5.3. Typical period-space service availability

In spatial analysis, Figure 7 provides a visual presentation of spatial distribution and changes of service availability during different time periods. It is clearly showed that, compared to the highly centralized pick-up points in 2012, the scope of drivers' picking up passengers have gradually spreading from the city center to the suburbs, and the pick-up density is also getting much lower, especially in 2016.

The demand of taxi service in 2012 is strongly spatial correlated with the population, and thus it mainly distributed surrounding around the Central Business District (CBD) and the crucial transportation infrastructures in the city (e.g., ring road, vertical or horizontal elevated road). After the e-hailing Apps widely used, on the hand, ride-hailing taxi services can better satisfy the larger-scope travel demand in some suburb areas than before; on the other hand, the potential influence on taxi drivers' behavior(e.g., order-picking) subsequently are more likely resulting in the obvious decrease of pick-up rate in the city center. In particular, the intensity of pick-up rate drops significantly during the period of mid-of-day - a possible explanation is the more severe "order-picking" issue during the off-peak period. Under the operation mechanism of trip OD pre-notified, taxi drivers are more concerned about the benefits from each finished orders due to the longer time interval between every two orders, so that they would rather "miss" some short-distance orders in order to response the relatively "economical orders".

As previously analyzed in the Figure 6, the large-scale of sharing-bikes in city center have indeed influenced the travel behavior of passengers. And hence, the role of sharing-bikes in the city deserves special attention and penetrating explore.

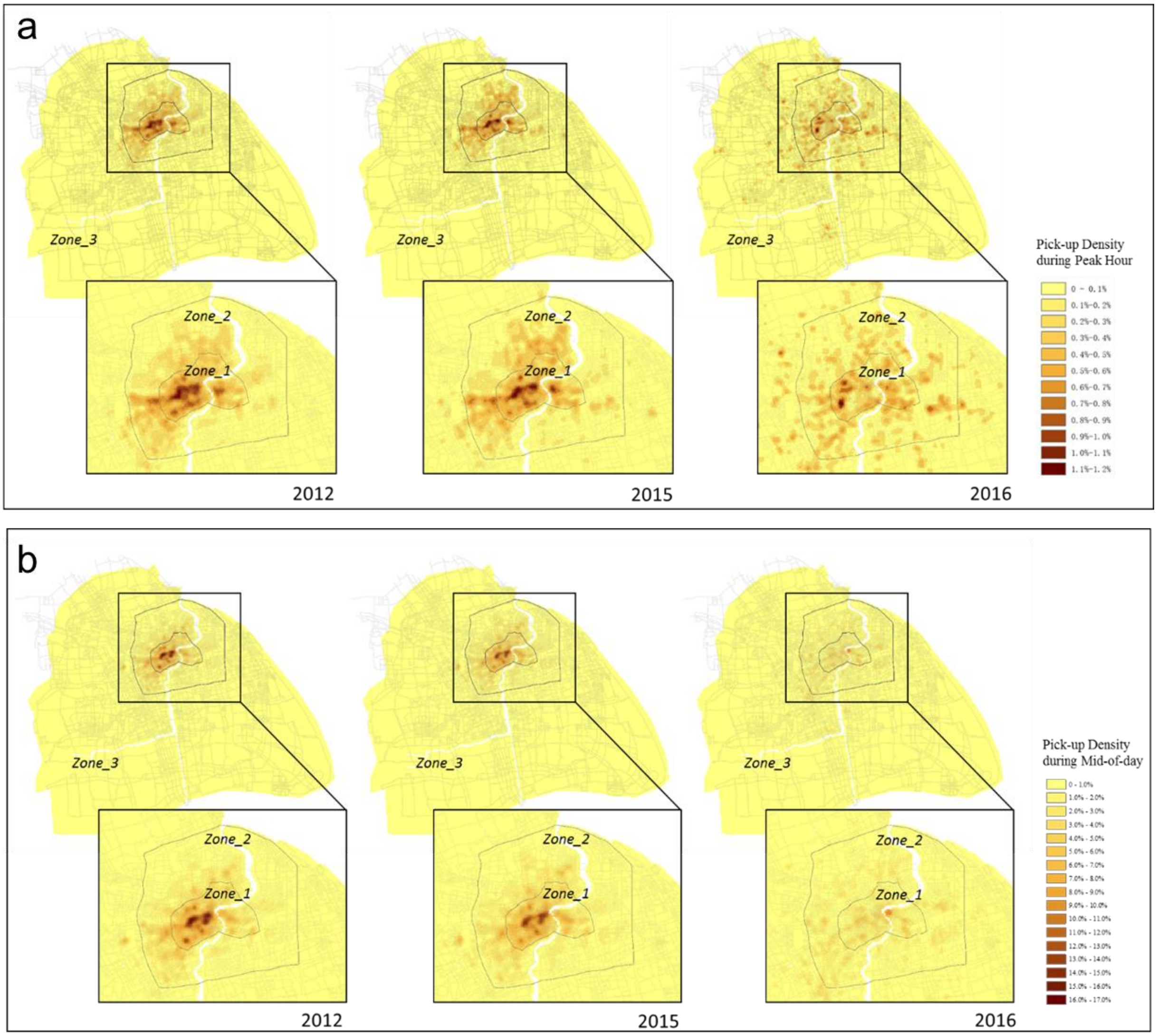

Fig. 7. (a) pick-up rate visualization during peak hour; (b) pick-up rate visualization during mid-of-day

The four typical spatial-temporal scenarios are set in Figure 8, namely peak hour in city center, overnight in suburbs, mid-of-day in city center and mid-of-day in suburbs.

Combined with driving distance in city center and suburbs, the percentage of short-distance trips(less than 3km) in city center represents obvious decrease during both the peak hour and mid-of-day (see Fig.8(a), Fig.8(c)), which demonstrated the severe “order-picking” issue found in the above Figure 8. And meanwhile, no significant changes in suburbs no matter in the overnight or mid-of-day can be observed in Fig.8(b) and Fig.8(d), and the emerging App-based ride services seems nothing to add to enlarge the ridership of surrounding areas.

In city center, the influencing range of driving distance during the peak hour is wider than that in mid-of-day, and the percentage of less than 6km’s orders decreased from 80% in 2012 to around 50% in 2016(see Fig.8(a), Fig.8(c)). It can be supposed that there are much more order demands than driving taxis during the peak hour in denser urban areas, so that taxi drivers tend to choose relatively longer-distance trips. Figure 8(c) and Figure 8(d) show the evident difference and changes during the same period. The orders in city center are mainly distributed in the distance of less than 9km in three years, while in the suburbs, the demands of more than 15km remain 10% of total orders.

The findings can be conducted from the perspective of the typical periods and zones. Firstly, service availability in the suburbs or some low population density area remains stable, mainly because taxi drivers' behavior of picking orders is not obvious due to the limited demands of taxi service in suburbs. And on the contrary, under the ample passenger orders in the denser urban area, service availability is obviously dropped of the short-distance orders (especially less than 3km).

Secondly, both distance distribution during the peak hour and mid-of-day in city center experience the significant changes. However, the short-distance demand is largely influenced during the peak hour, due to the severe "order-picking" issue under "demand exceeds supply" of taxi service and large-scale of sharing-bikes.

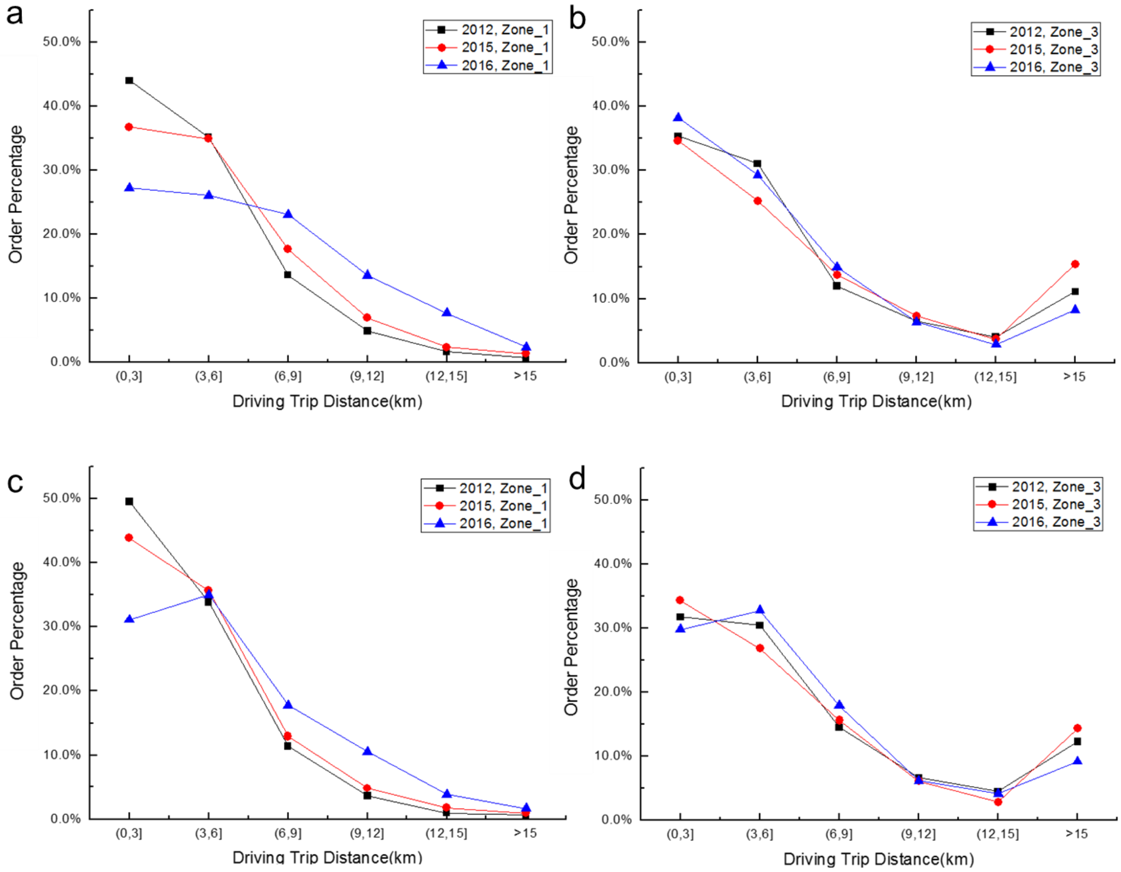

Fig. 8. (a) distance distribution in city center during peak hour; (b) distance distribution in surburbs during overnight period; (c) distance distribution in city center during mid-of-day; (b) distance distribution in surburbs during mid-of-day;

6. Conclusions

The App-based ride services is the main representative of the innovative urban transport service in recent years. During their rapid expansion in the service market, at the same time, e-hailing Apps have also aroused discussion and criticism on their potential negative impacts on urban transport and service availability. This study focus on exploring and analyzing the spatial-temporal influences on taxi service availability of App-based ride services under the operation mechanism of trip OD pre-notified, with the help of order dataset during three different periods of e-hailing

Apps developing (in 2012, 2015 and 2016). Findings from the study can objectively evaluate the potential influence of e-hailing Apps on taxi service market in the cities.

Generally speaking, the conclusion is that the operation mechanism of trip OD information pre-notified of e-hailing Apps and the resulting drivers' behaviors (e.g. picking orders) have significant impacts on service availability, especially when the market of App-based ride services remains steady. Some interesting and remarkable findings are listed as follows.

Firstly, further-distance and longer-duration demands are more likely to be satisfied than before, while the short-distance orders seem to be the biggest "victims" after the emerging and developing of e-hailing Apps, especially in the denser urban areas. This remarkable phenomenon is largely resulting from the changes of operation mechanism and corresponding tendentious behaviors of taxi drivers.

Secondly, there are different changes of service availability in the denser urban areas and suburbs. The service availability in suburbs or some low population density areas remains stable or even getting promoted, mainly because taxi drivers are unlikely to select orders under the limited service demands of taxis. On the contrary, with the excess orders in the denser urban areas, the largely decrease of short-distance orders (especially less than 3km) can be observed both during the peak hour and mid-of-day. Drivers' tendentiously treating service demand (e.g., order-picking), large-scale growth and usage of sharing-bikes in the city center, are considered as the possible influencing factors.

With the supporting dataset generated by App-based ride services, there is still lots of interesting topics worthy of sustained exploration. For example, how the different taxi fare and price mechanism affect taxi service availability. Further research will conduct the empirical research to investigate and analyze the potential impacts of e-hailing Apps emphasizing on the special weather or particular place. As we all know, the service of these typical locations and periods is the key consideration of the public to measure and evaluate the overall social service, and thus the research findings can also help the government to further discuss and develop the regulation measures in terms of dynamic spatial-temporal dimensions.

Acknowledge

This research was sponsored by Natural Science Foundation of China (No.71603186), the Natural Science Foundation of China (Project: No. 71734004) and the Open Foundation of Key Laboratory of Road and Traffic Engineering of the Ministry of Education at the Tongji University (Project No.TJDDZHCX003).

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