Is Ridesourcing More Efficient than Taxis?

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Abstract

Ridesourcing services such as Uber, Lyft, and DiDi are purported to be more efficient than traditional taxis because they can match passengers with drivers more effectively. Previous studies have compared the efficiency of ridesourcing and taxis in several cities. However, gaps still exist regarding the measurement and comparison between the two modes, and the reasons for the higher efficiency of ridesourcing have not been empirically examined. This paper aims to measure, compare, and explain the efficiency and variation of DiDi and taxis. The case study is conducted in Chengdu, China. We use Vehicle occupancy rate (VOR) as the efficiency measure--the percentage of time that a vehicle is occupied by a fare-paying passenger. We measure the VORs of DiDi and taxis and their spatial and temporal variations using the trip origin-destination data from DiDi and the trajectory data for taxis. The VOR patterns between DiDi and taxis are compared and contrasted, and the underlying factors that affect the difference are examined: more efficient driver-rider matching algorithm, larger scale of ridesouricng services, and the number of taxi trips per capita. Results show that the overall VOR of DiDi is six percentage points higher than taxis on the weekday and 12 percentage points higher on the weekend. However, the VOR of taxis is slightly higher than DiDi during the weekday morning peak in downtown areas. Regression models reveal that the more efficient matching and the greater scale of DiDi drivers enlarge the VOR gap between DiDi and taxis, while the number of taxi trips per capita reduce the gap. The findings have implications for both business operation and transportation policies in terms of service design, service coordination, and location-specific regulations.

Keywords: Vehicle Occupancy Rate; Service Efficiency; Ridesourcing; DiDi; Taxi

1. Introduction

Ridesourcing is supposed to be a more efficient transportation mode compared to taxi because it could connect drivers and customers instantaneously. However, it still remains unknown whether ridesourcing is more efficient under all circumstances, and to what extent such 'algorithm-based hailing' of ridesourcing is more efficient than the traditional 'sight-based street hailing' of taxi. This paper measures vehicle occupancy rate (VOR) to evaluate the efficiency of ridesourcing and taxi.

VOR could be calculated by either the percentage of the overall time that a vehicle is occupied by passengers (time-based VOR) or the percentage of the overall distance that a vehicle is occupied (distance-based VOR). Previous studies have calculated the VORs of ridesourcing and taxi in several cities to compare their efficiencies (Cramer and Krueger, 2016; Jiang et al., 2018). However, gaps still exist regarding the measurement of the VOR, the comparison of VOR between the two transportation modes, and the reasons for the VOR difference. For measurement, due to the data limitation, it remains challenging to estimate the vehicle vacant time/distance if the GPS trajectory is not available; for comparison, existing literature has revealed that ridesourcing is more efficient than taxi regarding the VOR (Cramer and Krueger, 2016; Castiglione et al., 2016; Jiang et al., 2018), but it remains unknown of the spatiotemporal heterogeneity; for explanation, previous studies have discussed the reasons that cause the difference in VOR (Cramer and Krueger, 2016), but there is a lack of empirical support for these explanations. To address these gaps, this paper develops a method to estimate the VOR from trip origin-destination (OD) data, and measures and compares the VORs of ridesourcing and taxi. We also examine three hypothetical reasons that impact the difference in VORs between ridesourcing and taxi: matching efficiency of ridesourcing, scale effect, and the number of taxi trips. The case study in Chengdu, China is conducted. The results lead to discussions on implications for both ridesourcing business operation and transportation policy interventions.

This paper is structured as follows. The next section reviews literature on the measurement, comparison, and explanation of ridesourcing and taxi VOR, and highlights the hypothesis being tested by this paper. Then, the data and methodology are introduced. Following that, results are reported and discussed. Finally, the conclusions, policy implications, limitations, and potential future research directions are summarized.

2. Literature Review

2.1 Measurement of VOR

The ideal dataset to measure VOR is a GPS trajectory which provides full information on when the vehicle is vacant or occupied by passengers. Unfortunately, due to the privacy concern, most of the data accessible only provide the trip OD with time stamps, making it difficult to accurately measure the VOR. For taxi, as most drivers work continuously, we can estimate vacancy as time/distance between drop-off and next pick-up. However, for DiDi (an Uber like service), as most drivers do not work continuously, the estimation of vacant time/distance is challenging.

Previous studies have used different methods to estimate and measure VOR. Cramer and Krueger (2016) reported both the time-based and distance-based VOR of UberX (computed by Uber company) in Boston, Los Angeles, New York, San Francisco, and Seattle. The collaboration with the ridesourcing companies is a prerequisite to obtain such data. Henao and

Marshall (2018) conducted a quasi-natural experiment in Denver, Colorado, demonstrating that the distance-based VOR of ride-hailing is at most 65.4% and the time-based VOR could be lower. This measurement of VOR is accurate but time- and labor-consuming, and only obtains a small sample. Dong et at. (2018) used the distance between the trip OD to the OD of the associated work and home cluster center to estimate the detour distances of commuting DiDi Hitch drivers in Beijing, which can only be applied to trips that have regular patterns (e.g. commuting drivers). Jiang et al. (2018) estimating the idling time of Uber and Lyft by collecting data from their apps, based on the fact that vehicles no longer display on the apps once they are occupied. This method only works if the ridesourcing apps display all the vacant vehicles, which is usually not the case for the other ridesourcing apps. Zhan et al. (2016) analyzed the taxi trip data in NYC to plot the distribution of taxi idle time probability and optimize the efficiency of taxi via a graph-based approach.

Due to the different cruising patterns of taxi and ridesourcing, the VORs of the two modes may vary temporally and spatially. Taxi drivers search for the passengers by cruising around the city. Based on personal experience, they decide where to go for passenger-searching (Kim et al., 2005). As a result, more experienced drivers often have higher VOR (Sirisoma et al., 2010; Veloso et el., 2011; Zhang et al., 2014), since they are more sensitive to demand variations in the city (Liu et al., 2010). In addition, it is reasonable to hypothesize that the VOR of taxi is higher in the city center, as the higher population density in the center makes it easier for drivers to find passengers via street-hailing. Unlike taxi, most ridesourcing drivers are part-time drivers and do not work continuously throughout the day. Instead of street-hailing, the matching algorithm of the ridesourcing platform pairs passengers and drivers instantaneously based on real-time information. Such matching algorithm has been demonstrated to be more efficient than street-hailing (Feng et al., 2017). However, in certain cases, the algorithm-based hailing of ridesourcing could be less efficient than the street hailing if an idle driver is matched with a distant passenger and has to drive a long time to pick up the passenger (Castillo et al., 2017), which is referred to as Wild Goose Chase effect and occurs when the fleet size of ridesourcing exceeds a certain amount (Xu et al., 2019). Also, the experience of drivers is less influential on the VOR of ridesourcing.

A few studies have demonstrated the spatiotemporal variation of VOR. For example, Rayle et al. (2016) revealed that if considering working trips alone, the VORs of ridesourcing and of taxi are nearly identical; Zuniga-Garcia et al. (2018) examined the spatial pattern of ridesourcing idle time of a local TNC in Austin, Texas, and found that the idle time for weekday evening rides and airport-originated rides tended to be longer; Zhang et al. (2017) found that taxi VOR is significantly impacted by trip length, airport trip, income, employment rate at the zip code level of the trip OD, and the relationship between taxi and other transportation modes, and the impacts represent significant spatial and temporal heterogeneity.

In this paper, we develop a method based on distribution fitting, to estimate the vehicle vacant time and VOR from the OD data. This method could be applied to different cities and ridesourcing services. Using the measurement approach, we calculate the VOR of ridesourcing and taxi in our study area, and examine the spatial and temporal variation of the VORs.

2.2 Comparison of VOR between DiDi and taxi

Cramer and Krueger (2016) compared the VOR of Uber and taxi in Boston, Los Angeles, New York, San Francisco, and Seattle, and found that except for New York, the VOR of Uber in the other four cities are 30% higher than taxi in time, and 50% higher measured in mileage. The SFCTA report (Castiglione et al., 2016) calculated the distance-based VOR in intra San Francisco areas based on the data collected from Uber and Lyft APIs, and revealed a 54.5% VOR for taxi and 80.3% VOR for TNCs. Jiang et al. (2018) reached similar results on time-based VOR in San Francisco: Lyft drivers spend 19% of their time idling, while taxis spend 48%. Besides the comparison between ridesourcing and taxi, some studies focused on how ridesourcing function improves taxi service. Nie (2017) found that ridesourcing helped improve the VOR of taxis in Shenzhen especially during the off-peak period. These studies revealed that the overall VOR of ridesourcing is higher than taxi.

Whether the higher VOR of ridesourcing could be translated into congestion reduction is another story (Jin et al., 2018). Although some studies conclude that ridesourcing decreases congestion (Li et al., 2016) or does not have significant impacts on congestion (Bialik et al., 2015; Nie, 2017), some reached the opposite conclusion. For example, Anderson (2014) found that ridesourcing has worsened congestion in the city center of San Francisco, as people living outside drove to the city to provide ridesourcing services, while taxi drivers could not do the same thing due to regulations. Erhart et al. (2019) revealed that ridesourcing is the biggest contributor to growing traffic congestion in San Francisco, and claimed that even the higher vehicle occupancy rate because of the ridesplitting is not sufficient to offset its impacts on increasing congestion. The study conducted by Qian et al (2020) reached the similar conclusions for ridesourcing in NYC. Schaller (2017) also claimed that the mileage reductions from ridesplitting may be offset by the 'dead-head' miles between dropping-off one passenger and picking-up the next passenger, and drivers' personal use of driver-owned vehicles.

It remains unknown in the existing literature whether the VOR of ridesoucing is higher all the time and across all places. Rayle et al. (2016) found that the average number of passengers per trip (not including the driver) is 2.1 for ridesourcing and 1.1 for taxi, but the VOR of the two modes are almost the same as for the journeys-to-work trips. This indicates that under some circumstances the VOR of taxi may be the same as, or even higher than, that of ridesourcing. Therefore, this paper compares the VOR of DiDi and taxi at different time periods and in different areas, to explore the temporal and spatial variation of the differences in the efficiency of the two modes.

2.3 Explanation for the VOR difference

What causes the disparity of the VORs of ridesroucing and taxi? We propose and examine the hypothesis based on the work of Cramer and Krueger (2016). Their paper discussed four reasons that lead to the higher VOR of ridesourcing: (1) more efficient driver-rider matching algorithm than sight-based street hailing by taxi; (2) the flexible labor supply and surge pricing of ridesourcing more closely match supply with demand; (3) ridesourcing has more drivers on the road than the taxi. Therefore, the efficiencies from scale effect add to the chance that ridesourcing drivers being closer to a potential customer than a taxi driver; (4) inefficient taxi regulations can prevent taxi drivers from picking up a customer in areas outside the one that granted their licenses. However, the effects of these four reasons on the VOR difference has not been empirically examined.

3. Data and Methodology

3.1 Study area

Chengdu, China is selected as the study area of this paper. Chengdu consists of 11 districts, 5 county-level cities, and 4 counties. The 11 districts constitute what is referred to as 'Central Urban Areas', including 5 in the city center (Jinjiang, Qingyang, Jinniu, Wuhou, Chenghua) and 6 in the suburban areas (Pidu, Xindu, Qingbaijiang, Longquanyi, Shuangliu, Wenzhou). The rest 5 county-level cities (Pengzhou, Dujiangyan, Chengzhou, Qionglai, Jianyang) and 4 counties (Jintang, Dayi, Pujiang, Xinjin) constitute 'Suburban New Cities'. Chengdu has the highest ridesourcing adoption rate (around 60%) in southwestern China. DiDi entered Chengdu in 2012, but the proportion of DiDi market share was small in the first two years after its entry. It was not until DiDi Express service became available in August, 2014 and the user pool of DiDi began to grow. Most of the DiDi and taxi trips occur in the 11 districts in the Central Urban Areas, so this study focuses on these districts instead of the whole city region (Figure 1).

Figure 1. Chengdu city and the study area

3.2 Data

The taxi trajectories and DiDi trips are used for analysis. Considering the time periods covered by the two datasets, Cramer and Krueger (2016) discussed two arguments: on one hand, it is desirable to compare ridesourcing and taxi at the same time period; on the other hand, it makes more sense to analyze the taxis services before the ridesourcing entered the market, which allows to evaluate the VOR of taxi without being disrupted by its competitor. The presence of ridesourcing could have caused changes in both the supply and demand of taxi service, and taxi drivers may choose to use ridesourcing apps to search for customers. These two choices serve different research purposes: comparing usage during the same time helps evaluate the actual performance of taxis after ridesourcing enters and disrupts the market and taxi has adjusted to the changes, while comparing at different time periods gives the implications on how the transformation of predominant mode from one to the other changes the overall VOR. This work focuses on the latter case and compares the VOR of taxi in August 2014 (before DiDi's expansion) with the VOR of DiDi in November 2016 (after DiDi has entered the market and expanded its service).

Taxi trajectory data record the vehicle id, location, timestamp, and occupied status (1 = have passenger(s); 0 = no passenger) every 30 seconds. DiDi trip data contain information of the driver id, trip id, and the time and location of pick-up and drop-off for a sample of trips. The data only include DiDi Express service (similar to UberX). The datasets cover all the trips in the study area.

For each mode, we select one Tuesday (August 5, 2014 for taxi and November 8, 2016 for DiDi) and one Saturday (August 9, 2014 for taxi and November 12, 2016 for DiDi) for analysis. All the dates used for the study are not holidays. However, as we do not have access to the taxi and DiDi data of the same month, different months of data are used for DiDi and taxi, so the seasonal variation of supply and demand is not controlled in this study. Since the taxi trajectory data only record the vehicle status during 6:00 to 24:00, we remove the trips starting from 0:00 to 6:00 in the DiDi trip data to ensure consistency in comparison. Table 1 represents the number of taxi and DiDi trips and drivers on the days for analysis. Overall, the number of taxi trips is about three time of DiDi, while the number of DiDi drivers is about three times of the taxi drivers, as many DiDi driver work part time and only serve several trips per day.

Table 1. Number of the taxi and DiDi trips and drivers on the analysis days

	Weekday		Weekend	
	Taxi (Aug 5, 2014)	DiDi (Nov 8, 2016)	Taxi (Aug 9, 2014)	DiDi (Nov 12, 2016)
Trip number	491,956	176,800	477,087	186,451
Driver number	13,459	35,382	12,890	38,447

In addition, road network and housing price data are also used in this study. The road network was obtained from the OpenStreetMap[1], and the housing price data in July 2018 of 9,266 communities were obtained from Lianjia[2], a major real estate trading platform in many Chinese cities.

3.3 Methodology

3.3.1 Measurement

Both distance-based VOR and time-based VOR could be used to measure the efficiency. They carry different meanings when interpreting the service efficiencies of a transportation mode. However, due to the data constraint, a comparison of distance-based VOR is not feasible in this study, because DiDi trajectories were not available. Therefore, this paper adopts time-based VOR so that the efficiency of both modes could be measured and compared.

To measure the time-based VOR, we need to estimate vacant time (t_i^v) when no passenger is in the vehicle, and the occupied/ride time (t_i^r) when there is at least one passenger in the vehicle of each trip i. The vacant time in our measurement includes two situations: the time when the driver is searching for the next passenger, and the time when the driver is on his way to pick up the next passenger. If the vehicle is vacant but the driver has stopped working, we exclude this time

[1] https://www.openstreetmap.org
[2] https://cd.lianjia.com/

period from the vacant time as the vehicle does not cause extra dead-miles. The time intervals for passengers to get on and off the vehicle are not considered in this paper.

For taxi, the trajectory data record whether the vehicle has passengers (status = 1) or is vacant (status = 0) at each timestamp. Therefore, we can easily obtain the t_i^r and t_i^v for each trip and calculate the VOR. The timestamps when a vehicle is vacant and its location has not changed are removed from the dataset, to exclude the gap time that the driver stops working. For DiDi, only trip OD data are available, meaning we know the time and location when the driver picks up and drops off a passenger. We can obtain occupied time (t_i^r) by calculating the time duration between pick-up and drop-off, but the vacant time (t_i^v) is unknown. The gap time ($t_i^g = t_i^O - t_{i-1}^D$) between two trips (the picking-up time (t_i^O) of trip *i* and the dropping-off time (t_{i-1}^D) of trip *i-1*) can be computed, but since many DiDi drivers do not work continuously throughout the day, we have no idea whether the driver is searching for the next passenger and driving to pick up the next passenger during the gap time, or stops working and takes a shift. If the driver is searching for the next passenger or driving to pick up a passenger, the time period should be considered as the vacant time (t_i^v); but if the driver stops working, the gap time should be excluded from the vacant time. Besides, for the first trip of a day, and for the situation drivers taking shifts, the vacant time is tricky to compute. Therefore, we propose the following approaches to estimate the vacant time from trip OD.

The first step is to differentiate the situations between searching for or picking up the next passenger and taking a shift. Distribution fitting is applied to differentiate these two types of gaps. As there are two different situations, we assume that time gaps between trips are a mixture of two probability distributions: the distribution of vacant time (the driver is searching for the next passenger or on his way to pick up the next passenger) and the distribution of gaps between working shifts (the driver stops working for some time and resumes later). After fitting the two distributions, a threshold (t_{thed}) could be chosen to differentiate the vacant time and the gaps between working shifts.

The second step is to estimate the vacant time. With t_{thed} determined from the first step, if the gap time is shorter than t_{thed}, this time duration is considered t_i^v; For the first trip of each work shift (including the first trip of a day and the trips whose gap time is longer than t_{thed}), since there is no leading trip before such trips, it is difficult to directly estimate the search time. Therefore, the average vacant time t^{avg} is used to proximate t_i^v of the first trip at the beginning of each work shift, denoted as:

$$t^{avg} = \frac{\sum(t_i^O - t_{i-1}^D)}{m},\ t_i^O - t_{i-1}^D \leq\ t_{thed}\ and\ i \neq 1, (1)$$

$$t_i^v = \begin{cases} t_i^O - t_{i-1}^D, & t_i^O - t_{i-1}^D \leq\ t_{thed}\ and\ i \neq 1 \\ t^{avg}, & t_i^O - t_{i-1}^D >\ t_{thed}\ or\ i = 1 \end{cases}, (2)$$

where t_i^O is the pick-up timestamp of trip *i*, t_{i-1}^D is the drop-off timestamp of trip *i-1*, and *m* is the total number of trips whose gap time is shorter than the threshold.

The method proposed here enables us to estimate the vacant time for the VOR calculation with only OD information. However, we do recognize some potential biases[3] compared to calculating the VOR from trajectory data. Since only OD data are available, these biases are acceptable and unavoidable. Besides, we cannot differentiate the time when the driver is searching for the next passenger and the time when the driver is driving to pick up the next passenger.

With the vacant time (t_i^v) and the occupied/ride time (t_i^r) obtained, the VOR could be measured at different scales. At the disaggregated scale, for each trip i, the VOR is measured as:

$$VOR_i = \frac{t_i^r}{t_i^r + t_i^v} \, . \, (3)$$

At the aggregated scale, assuming there are N trips in total, the overall VOR is calculated as:

$$VOR = \sum_{i=1}^{N} VOR_i = \frac{\sum_{i=1}^{N} t_i^r}{\sum_{i=1}^{N} t_i^r + \sum_{i=1}^{N} t_i^v} \, . \, (4)$$

Formula (4) could be applied to measure the VOR for each driver, for different time periods, and over spatial units.

3.3.2 Comparison

Exploratory spatiotemporal analysis is conducted to compare the temporal and spatial variation of the VOR of taxi and DiDi.

Temporally, we divide the whole day into five time periods: early morning (6am – 8am), morning peak (8am – 10am), daytime (10am – 5pm), evening peak (5pm – 7pm), and late night (7pm – 12am). For each time period, we calculate the total vacant time and total occupied time[4], based on which the VOR could be calculated by formula (4).

Spatially, the trips are aggregated to township (*jiedao*) level according to their pick-up locations[5] and the VOR of each township is calculated using formula (4). To avoid the impacts of outliers, townships that have less than 5 trips per day are removed.

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[3] There are two potential biases: (1) bias from the distribution fitting: considering the null hypothesis H_0 as 'the gap is the vacant time', the distribution fitting suffers from both type-1 and type-2 errors. When type-1 error occurs, a driver is searching for passengers but is identified as stopping working, which leads to an underestimated t_i^v and overestimated VOR; on the contrary, when type-2 error occurs, a driver has stopped working but is considered as still searching for passengers, so the t_i^v is overestimated and the VOR is underestimated; (2) bias from the estimation of t_i^v for the first trip at the beginning of each work shift: if the actual t_i^v is greater than t^{avg}, the VOR will be overestimated, and vice versa.

[4] If a trip lasts over two time periods, it is separated accordingly. For example, if a vehicle is occupied during 7:50am to 8:20pm, then 10 minutes are added to the total occupied time of 'early morning' and 20 minutes added to that of 'morning peak'.

[5] We aggregate the trips based on pick-up locations instead of drop-off locations, since it is a better representation of where the trip occurs. However, the aggregation ignores the situation if a trip occurs across different spatial units. For example, if a vehicle travels from spatial unit k_1 to spatial unit k_2 searching for passengers, and finally picks up the passenger in k_2, then the VOR of k_2 will be underestimated, as some segments of the searching in k_1 is counted into the overall vacant time of k_2; on the other hand, if a vehicle carries a passenger from spatial unit k_2 to k_3, some

3.3.3 Explanation

Section 2.3 reviewed four reasons that lead to the higher VOR of ridersourcing: more efficient driver-rider matching algorithm, the flexible labor supply and surge pricing, the efficiencies from scale effect, and inefficient taxi regulations. Among these four reasons, the first and second reasons, though having different mechanisms, both indicate that the more efficient matching of ridesourcing improves its VOR, and thus enlarges the difference of VOR between ridesourcing and taxi. The fourth reason "inefficient taxi regulations" is not applicable in China, but it does imply that taxi market may have impacts on the VOR of both modes. Therefore, we propose and test the following three hypothesis: (1) matching efficiency of ridesourcing improves its VOR and enlarges the difference in two modes; (2) scale effect: the greater scale of ridesourcing service than taxi improves the VOR of ridesourcing while decreases the VOR of taxi, and thus enlarges the VOR difference between the two modes; (3) as a major competitor of ridesourcing, the number of taxi trips improves the VOR of taxi while decreases the VOR of ridesourcing, thus decreases the VOR difference between the two modes.

To examine the factors that impact the difference in VOR between the two modes, we apply Ordinary Least Squares (OLS) regression and spatial autoregression (SAR) at the township (*jiedao*) level. OLS model is the base model, the SAR model is used to accommodate spatial variation. For each township *j*, the difference in VOR between DiDi and taxi ($VOR_j^{didi} - VOR_j^{taxi}$) is calculated and used as the dependent variable in the regressions.

Based on the hypotheses proposed in section 2.4, better supply-demand matching of DiDi, the greater service scale of DiDi than taxi, and the number of taxi trips are the three reasons for the difference of VOR between the two modes. Therefore, we construct three indices to measure the three reasons.

The matching efficiency index (MEI) of township *j* is constructed to measure the supply-demand matching of DiDi and taxi, denoted as:

$$MEI_j^{DiDi} = [\sum_{t=1}^{n} \frac{\left(S_{jt}^{didi} - D_{jt}^{didi}\right)^2}{D_{jt}^{didi^2}}]^{-1}, (5)$$

$$MEI_j^{taxi} = [\sum_{t=1}^{n} \frac{\left(S_{jt}^{taxi} - D_{jt}^{taxi}\right)^2}{D_{jt}^{taxi^2}}]^{-1}, (6)$$

where MEI_j^{DiDi} and MEI_j^{taxi} measures the supply-demand matching efficiency of DiDi and taxi in township *j*; *t* denotes a time periods; *n* is the total number of time periods; s_{jt} measures the supply (the total number of vehicles in township *j* during the time period *t*, including the vacant and occupied vehicles); d_{jt} measures the demand (the total number of pick-ups in township *j* during the time period *t*). Square is used to ensure non-negative values. We take the inverse to the formula so that the greater MEI_j^{DiDi} or MEI_j^{taxi} indicates that township *j* has a more efficient

segments of the ride in k_3 will be counted into the overall riding/occupied time of k_2, which overestimates the total ride time in k_2 and overestimates the VOR.

supply-demand matching: if the supply-demand matching is efficient, $S_{jt} - D_{jt} \to 0$, $\sum_{t=1}^{n} \frac{(S_{jt}-D_{jt})^2}{D_{jt}^2} \to 0$, and $MEI_j^{DiDi}, MEI_j^{taxi} \to \infty$; otherwise, if the supply-demand matching is inefficient, $S_{jt} - D_{jt} \to \infty$, $\sum_{t=1}^{n} \frac{(S_{jt}-D_{jt})^2}{D_{jt}^2} \to \infty$, and $MEI_j^{DiDi}, MEI_j^{taxi} \to 0$.

MEI_j measures the difference of DiDi and taxi in supply-demand matching efficiency:

$$MEI_j = MEI_j^{DiDi} - MEI_j^{taxi}. (7)$$

The scale effect index (SEI) is denoted as:

$$SEI_j = \frac{\sum_{t=1}^{n} S_{jt}^{didi}}{\sum_{t=1}^{n} S_{jt}^{taxi}}, (8)$$

where SEI_j indicates the scale effect, measured by the ratio of scale between DiDi and taxi in township *j*; *t* denotes a time period; *n* is the total number of time period; S_{jt}^{didi} and S_{jt}^{taxi} denote the number of DiDi and taxi drivers in township *j* during the time period *t*, including both the drivers that are searching for the passengers and the drivers who are carrying trips. The greater SEI_j indicates greater scale of DiDi than taxi in township *j*.

We also measure the number of taxi trips per capita, denoted as:

$$TAXI_j = \frac{\sum_{t=1}^{n} D_{jt}^{taxi}}{p_j}, (9)$$

where $TAXI_j$ measures the number of taxi trips per capita in township *j*; *t* denotes a time period; *n* is the total number of time period; D_{jt}^{taxi} is the number of taxi pick-ups in township *j* during the time period *t*; p_i denotes the total population in township *j*. The greater $TAXI_j$ means there are more taxi trips per capita in township *j*, thus indicates a more mature taxi market.

Besides, four control variables are included in the regression: trip time ratio, population density, road density, and income. Trip time ratio is the ratio of the average riding time of DiDi and taxi in township *j*. The road density of each township is calculated by the overall length of roads in the township (km) divided by the township area (km^2). We don't have access to high-resolution income data, so average housing price in the township is used to measure income.

The OLS model is constructed as follows:

$$\mathrm{Y} = \beta_0 + \beta_1 X + \delta + \varepsilon, (10)$$ [6]

[6] According to the hypotheses, the coefficient of s expected to be positive, as the more efficient supply-demand matching of DiDi is supposed to improve the VOR of DiDi and thus enlarges the VOR difference; β_2 is expected to be positive, as the greater scale of DiDi compared to taxi is supposed to increase the VOR of DiDi and decrease the

where Y is the difference of VOR between DiDi and taxi, measured by ($VOR_j^{didi} - VOR_j^{taxi}$); X are the independent variables, including 1) the difference of supply-demand efficiency between DiDi and taxi (MEI_j), measured by equation (7); 2) the scale effect index (SEI_j); 3) the number of taxi trips per capita ($TAXI_j$); δ are the control variables, and ε denotes the error term.

We further adopt spatial autoregressive models (spatial error model or spatial lag model) to accommodate spatial variation of the efficiency measures of both DiDi and taxi. If there are omitted spatially correlated covariates influencing the relationship over space, a spatial error model should be used to capture the correlation of the error terms across different spatial units:

$$\mathrm{Y} = \beta_0 + \beta_1 X + \delta + \lambda \mathrm{W}\varepsilon + \mu, \quad (11)$$

where λ represents the spatial error coefficient and μ is the unobserved error term. W is the spatial weights matrix, defined by Queen contiguity neighborhoods.

If spatial lag exists, suggesting that the dependent variable is also affected by the neighboring independent variables, a spatial lag model should be used to incorporate the additional effect of neighboring attribute values:

$$\mathrm{Y} = \beta_0 + \beta_1 X + \delta + \rho W Y + \mu, \quad (12)$$

where ρ represents the spatial lag coefficient and μ is the unobserved error term. W is the spatial weights matrix, defined by Queen contiguity neighborhoods.

4. Results

4.1 Measurement of the VOR

4.1.1 DiDi vacant time estimation

We firstly estimate the vacant time of DiDi from the trip OD data. By inspecting the distribution of the gap duration of all DiDi trips, six combinations of distributions are fitted. The combination (lognormal distribution and gaussian distribution) with the smallest Chi-square Goodness-of-Fit is selected (Table 2), indicating that the vacant time follows a lognormal distribution while the gaps between working shifts follow a gaussian distribution.

Table 2. Distribution fitting results

	Vacant time	Gaps between working shifts	Chi-square GOF
Gaussian + Uniform	Gaussian	Uniform	1.575
Gaussian + Exponential	Gaussian	Exponential	0.410
Gaussian + Gaussian	Gaussian	Gaussian	0.239
Lognormal + Uniform	Lognormal	Uniform	0.062
Lognormal + Exponential	Lognormal	Exponential	0.061
Lognormal + Gaussian	Lognormal	Gaussian	0.056

VOR of taxi; β_3 is expected to be negative, as the number of taxi trips per capita increase the VOR of taxi and thus decrease the difference of VOR between DiDi and taxi.

Figure 2a plots the fitting of the lognormal and gaussian model. The yellow line in the figure represents the fitting of the vacant time, which includes the time when the driver is searching for the next passenger and when the driver is on the way to pick up the next passenger. The green line represents the fitting of the gap time between working shifts when the driver stops working. We can choose a threshold to reject the null hypothesis H_0 that the gap is vacant time. If the gap time is greater than the threshold, the percentage of area under the lognormal distribution (the yellow line) is considered as the probability of the type-1 error since H_0 is true but rejected; and if the gap time is smaller than the threshold, the percentage of areas under the gaussian distribution (the green line) is considered as the probability of the type-2 error since H_0 is false but accepted (Figure 2b).

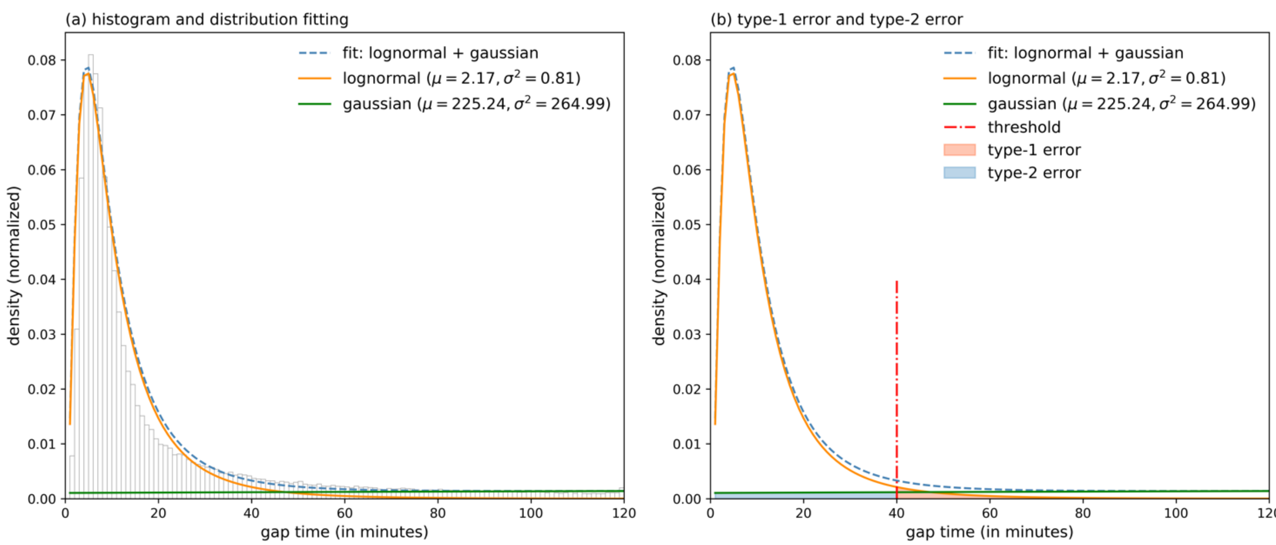

Figure 2. The fitting of lognormal distribution and gaussian distribution

Sensitivity analysis is conducted to examine how the VOR of DiDi varies if different vacant time threshold is used (Figure 3). The VOR of DiDi for different threshold (Figure 3a) reveals that with the increase of vacant time threshold, the VOR of DiDi decreases. To examine the variation more carefully, we calculate the change of VOR with regard to the change of threshold for every 1 minute (Figure 3b). For example, the change of VOR for threshold 10-minute is calculated by VOR($t_{thed} = 10$) - VOR($t_{thed} = 9$). We find that the variation of VOR is larger but reduces sharply when the threshold is smaller than 10 minutes, but remains around 0.2% when the threshold is greater than 30 minutes.

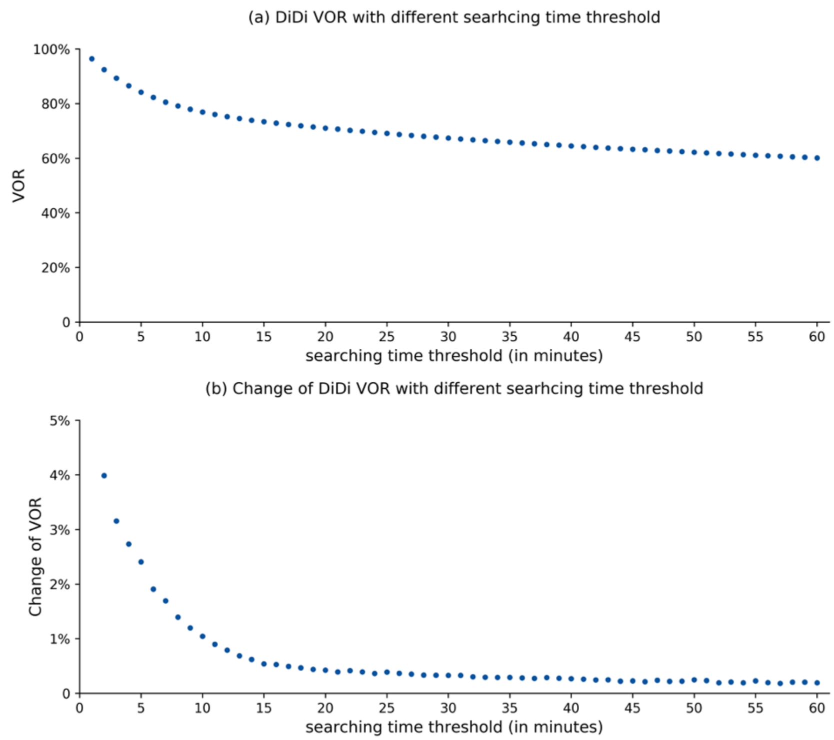

Figure 3. Sensitivity analysis of the threshold

Considering the fitted distributions of the vacant time and the gaps between working shifts, and the sensitivity analysis, we select 40 minutes as the threshold of vacant time and gaps between working shifts. The probability of type-1 error is 0.057, and that of type-2 error is 0.045, so the total error is around 0.1.

4.1.2 Measurement of the VOR

Formula (3) is used to calculate the VOR at trip level for DiDi and taxi. The two modes have different distributions (Figure 4). For taxi, the polarization of VOR is observed: about 25% of the trips have very high VOR (>=90%), and there are around 10% of trips whose VOR is very low (<=30%). For DiDi, the distribution of VOR follows a normal distribution, and around half of trips have the VOR between 60% to 80%. The VOR distributions of taxi and DiDi give us two implications. Firstly, the sight-based street hailing of taxi may lead to the fluctuation in taxi VOR, and the VOR could be very high under some conditions (e.g. high density) but drops sharply for some other circumstances. Secondly, since the VOR of some taxi trips are very high, it is possible that taxi is more efficient than DiDi under certain conditions.

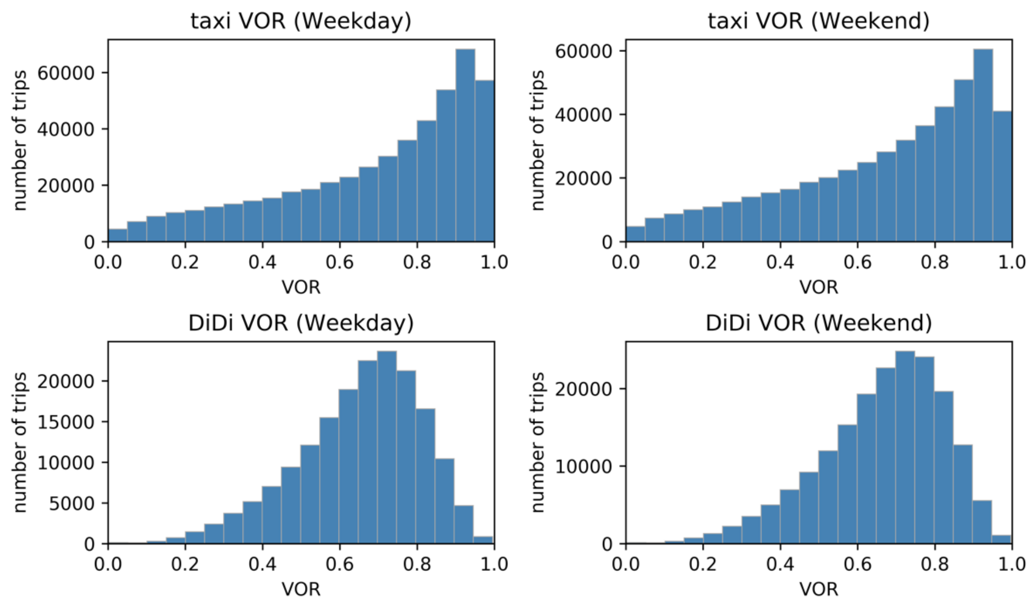

Figure 4. Histogram of taxi and DiDi VOR

Formula (4) is used to calculate the overall VOR. The VOR of taxi is 60.2% on the weekday and 56.8% on the weekend, and the VOR of DiDi is 66.7% on the weekday and 68.6% on the weekend. The overall VOR of DiDi is higher than that of taxi for about 6 percentage points on the weekday and 12 percentage points on the weekend, indicating that ridesourcing does achieves higher VOR and the effect is greater on the weekend. This result is in consistency with the existing literature that ridesourcing is in general more efficient than taxi (Castiglione et al., 2016; Cramer and Krueger, 2016; Jiang et al., 2018).

4.1.3 Variation of the VOR

We further examine the variation of the DiDi and taxi VORs among drivers, over time, and across space.

Taxi and DiDi drivers behave differently (**Figure 5a**). Most taxi drivers work continuously throughout the day, and most taxicabs take as many as 40 trips per day. Only around 5% of taxi drivers conduct less than 10 trips per day. While for DiDi drivers, most of them only take one to two trips per day, and around 85% of drivers conduct less than 10 trips per day.

We use formula (4) to calculate the VOR for each driver and plot the average VOR for drivers who take different number of trips (**Figure 5b**)[7]. The results reveal two interesting facts. First, taxi drivers conducting more trips have higher VOR. This finding is in accordance with previous studies that reveal a positive correlation between the efficiency in searching for passengers with the numbers of trips conducted by taxi drivers (Liu et al., 2010), as more experienced drivers are often more efficient in finding the next passenger and they conduct significantly larger number of trips (Zhang et al., 2014; Haggag et al., 2017). While for DiDi, the VOR is almost identical

[7] Since very few taxi drivers conduct less than 20 or more than 60 trips per day, and very few DiDi drivers conduct more than 20 trips per day, we only plot the taxi drivers who conduct 20 to 60 trips and DiDi drivers who conduct less than 20 trips.

among drivers, since the matching is dictated by the system algorithm, the experience of drivers has less or even no effect than in taxi service. Second, the VOR of taxi drivers are higher on the weekday than on the weekday. Since commuting trips have higher regularity, taxi drivers can leverage their experience to serve areas with high demand and thus to reduce the vacant time. However, the VOR of DiDi drivers on the weekday and on the weekend does not differ too much, because the matching algorithm enables a relatively stable VOR.

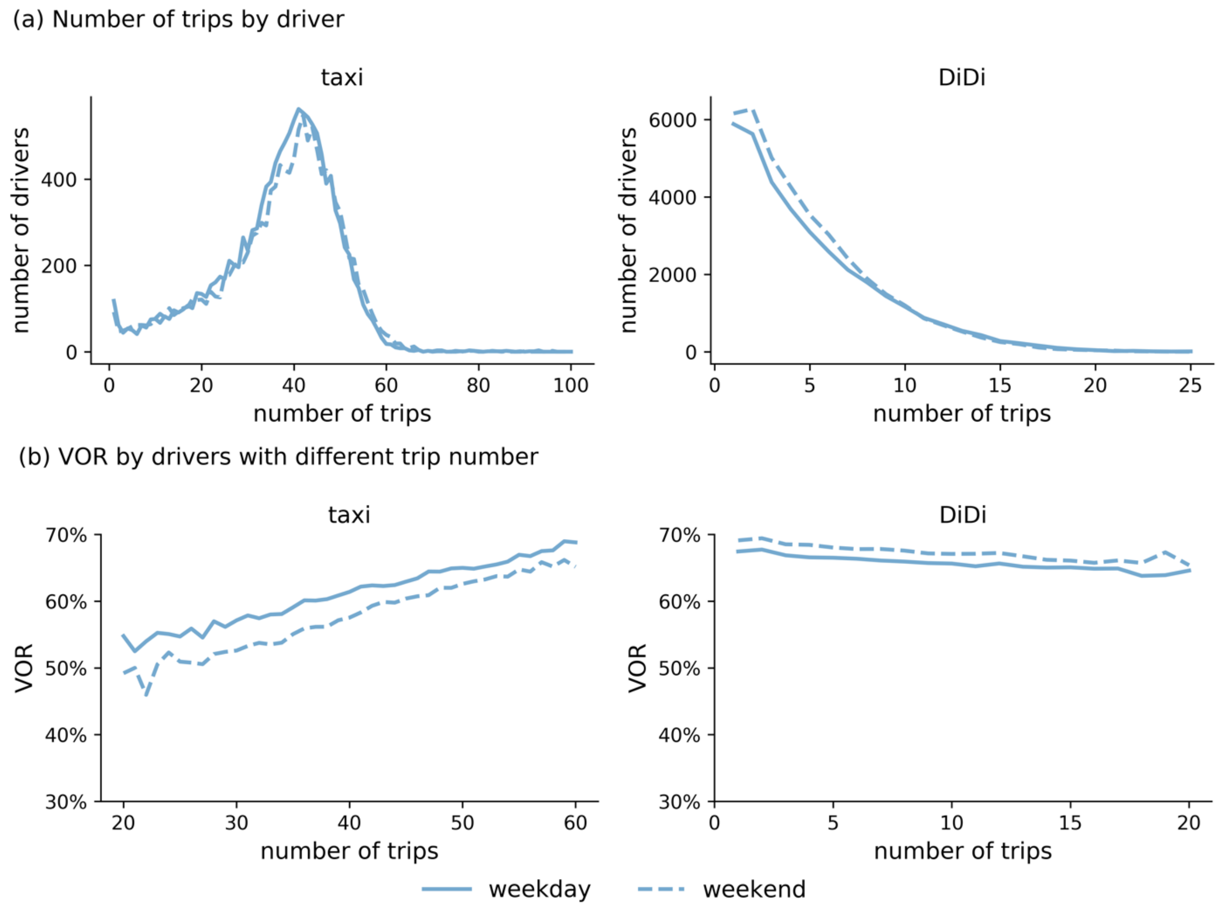

Figure 5 Variation of VOR among drivers: (a) number of drivers conducting different number of trips per day; (b) VOR by drivers with different trip number[8]

Figure 6 presents the temporal variation of the VORs. The VOR of DiDi does not have much variation, as the matching algorithm enables a relatively stable VOR. The VOR of taxi is very low in the early morning, but increases significantly after 8AM. However, the lower VOR in the early morning does not necessarily mean that it is inefficient for taxi drivers to work during this time period. Firstly, taxi drivers have to pay a predetermined rental fee to the taxi companies (about 340 RMB per day). This high rental fee stimulates taxi drivers to work for a long time to subset the cost. Even during the hours that the VOR is low, some drivers still choose to work as

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[8] Since very few taxi drivers conduct less than 20 or more than 60 trips per day, and very few DiDi drivers conduct more than 20 trips per day, we only plot the taxi drivers who conduct 20 to 60 trips and DiDi drivers who conduct less than 20 trips.

long as there is some possibility of picking up passengers. Secondly, the VOR does not necessarily translate into drivers' net income, which is a combination of the fixed cost (i.e. vehicle rental fee, ridesourcing platform fee), variable cost (i.e. oil price, vehicle depreciation), trip unit price, working hours, and other additional charges (e.g. toll fee). Therefore, it is too early to conclude the lower net income of drivers (and thus lower motivations for drivers to work) during the early morning hours.

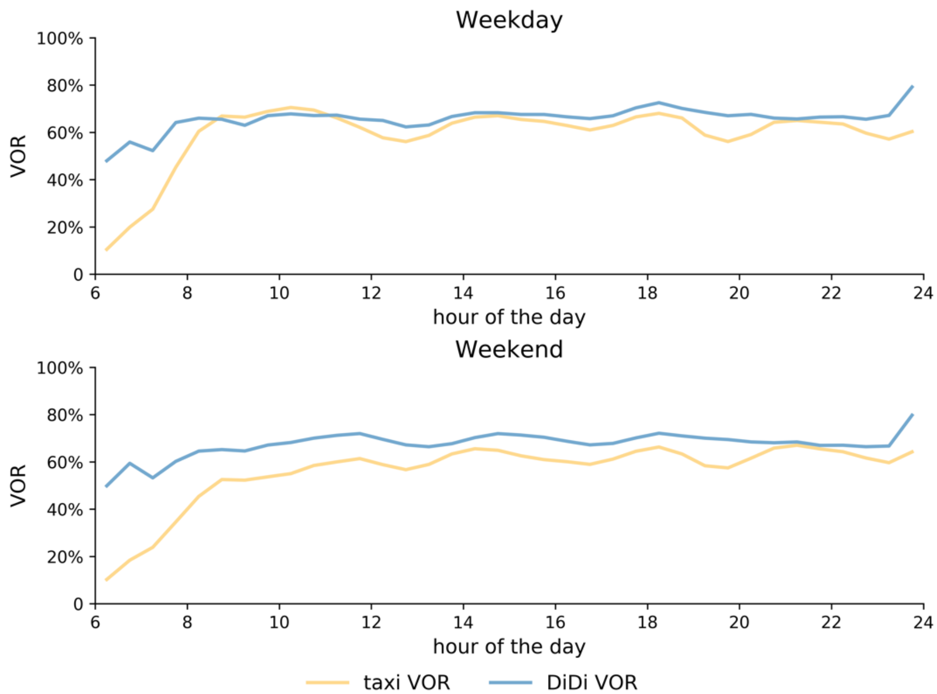

Figure 6. Variation of VOR throughout the day

Spatially, the VOR of taxi is higher in the city center (>=70%) and lower in the periphery (Figure 7a, 7b). This pattern could be explained by the behaviors of taxi drivers, as it has been confirmed by previous studies that taxi drivers with high VOR tend to serve within the central areas (Jiang et al., 2017). On the contrary, the VOR of DiDi is lower in the central areas (<=65%) but higher in the peripheral areas (Figure 7c, 7d). This indicates that the potential market of DiDi is larger than taxi, since it can rely on the matching algorithm to achieve high VOR in low-density peripheral areas.

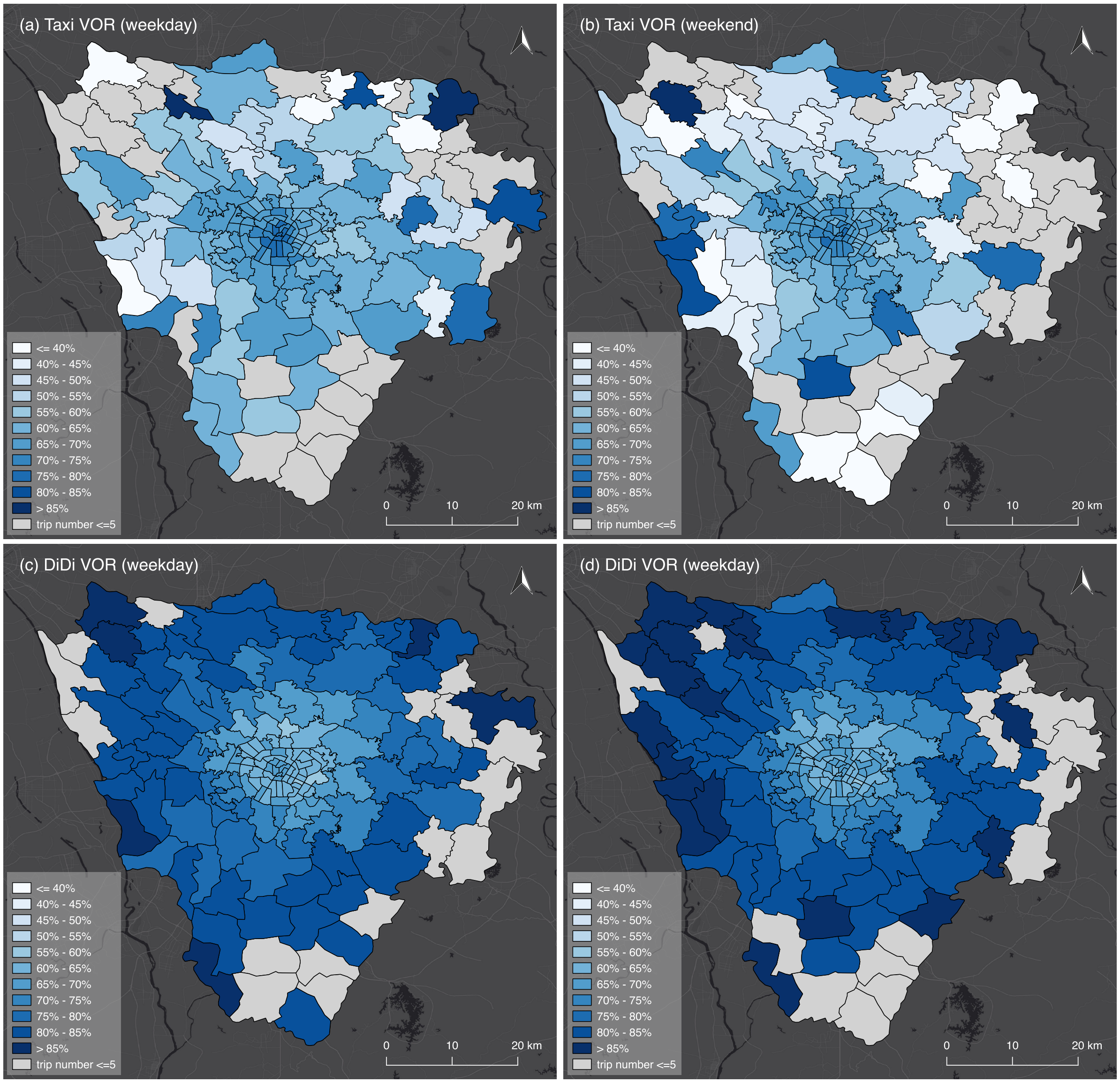

Figure 7. Variation of VOR across space: (a) VOR of taxi on the weekday; (b) VOR of taxi on the weekend; (c) VOR of DiDi on the weekday; (d) VOR of DiDi on the weekend.

4.2 Comparison of the VOR between DiDi and taxi

Trip number and duration vary significantly throughout the day for both DiDi and taxi (Figure 8). Taxi trips concentrate in the evening, while DiDi trips are more spread, and the distribution differs on the weekday and the weekend: on the weekday, there are more trips during the morning peaks mid-day hours, while on the weekend, the percentage of mid-day trips and evening trips is higher. Regarding the trip time, most DiDi trips take longer time than taxi trips – around 70% of DiDi trips take more than 15 minutes, while the proportion is less than 40% for taxi trips. Therefore, the operational patterns of taxi and DiDi are distinctive and are possible to cause the difference in the VOR of the two modes.

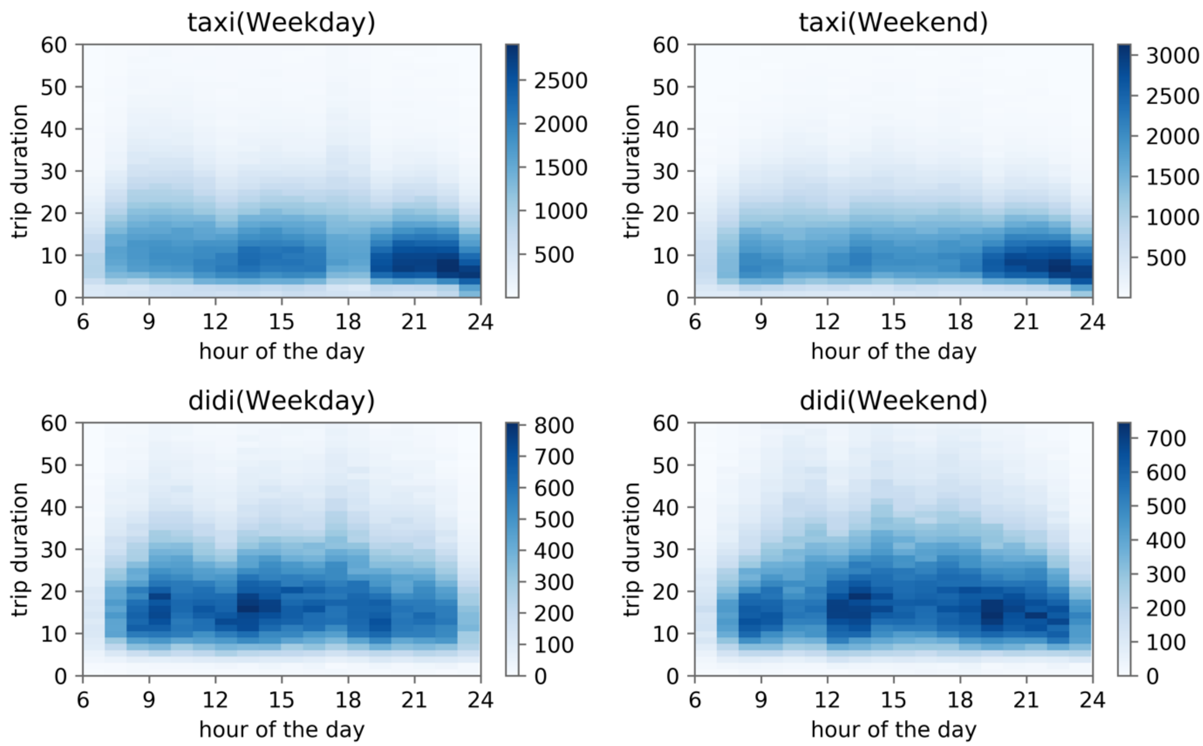

Figure 8. 2D histogram of trip number: X-axis is hour of day, and Y-axis is trip duration

The VOR of DiDi is higher than taxi most of time (Figure 9), except for the morning peak on the weekday, which could be explained by the high regularity of mobility patterns in this time period. In the early morning, the VOR of taxi is low since the demand is low, but the VOR of DiDi, although also lower than the other time periods, does not decrease too much. This implies the advantage of algorithm-based hailing during the time periods when the demand is low.

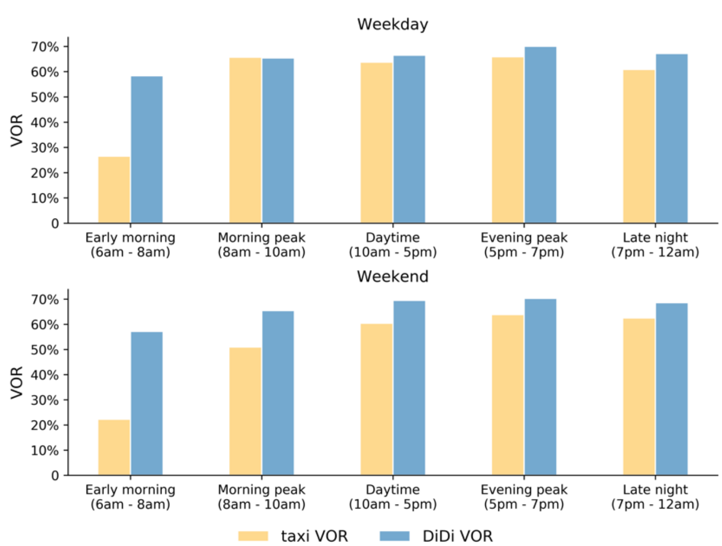

Figure 9. VOR in different time periods

The spatial pattern of taxi and DiDi VOR implies that the VOR of taxi is higher than DiDi in the city center. To further explore the spatial variation of the difference between the two modes, we plot the VOR difference between DiDi and taxi on the weekday and on the weekend (Figure 10). The townships in blue color means the VOR of DiDi is higher than taxi, while the townships in red color means the taxi VOR is higher. Results reveal that DiDi is more efficient than taxi in peripheral areas, but in the central areas, the VOR of taxi is 14% higher than DiDi. The population density may play a role in this pattern. In Chengdu, the population density is high in city center. Therefore, it is easier for taxi drivers to find the passengers via street hailing, so the advantage of ride-hailing matching algorithm is less significant, not to mention that in some situations the DiDi drivers have to follow the orders from the app to detour in order to pick up passengers. On the contrary, in the periphery where the population density is low, taxi drivers have to search for a longer time to find the next passenger, while DiDi drivers just need to follow the guidance of the platform to reach the next passenger. The different trip length in the central and peripheral areas may be another reason for the VOR difference. Longer trips have longer vehicle occupied time, but the trip length does not have significant impacts on the vacant time. As a result, the VOR of longer trips is potentially higher. Via exploratory data analysis, we find that most long DiDi trips take place in the peripheral areas, which may also contribute to the higher DiDi VOR in these areas.

However, density is a crucial determinant of the VOR of taxi, as the street-hailing feature of taxi services relies heavily on the density of people on the street. Therefore, it is highly likely that the phenomena of taxi being more efficient only occur in high-density areas. This has also been demonstrated by Cramer and Kreger (2016), as in New York City where the population density is high, the VOR of Uber and taxi is almost the same; while in the rest four cities, where the population density is not as high as NYC, the VOR of Uber is much higher than taxi. Thus, the findings in a densely-populated Chinese city as Chengdu might not be applicable to other cities with lower population density.

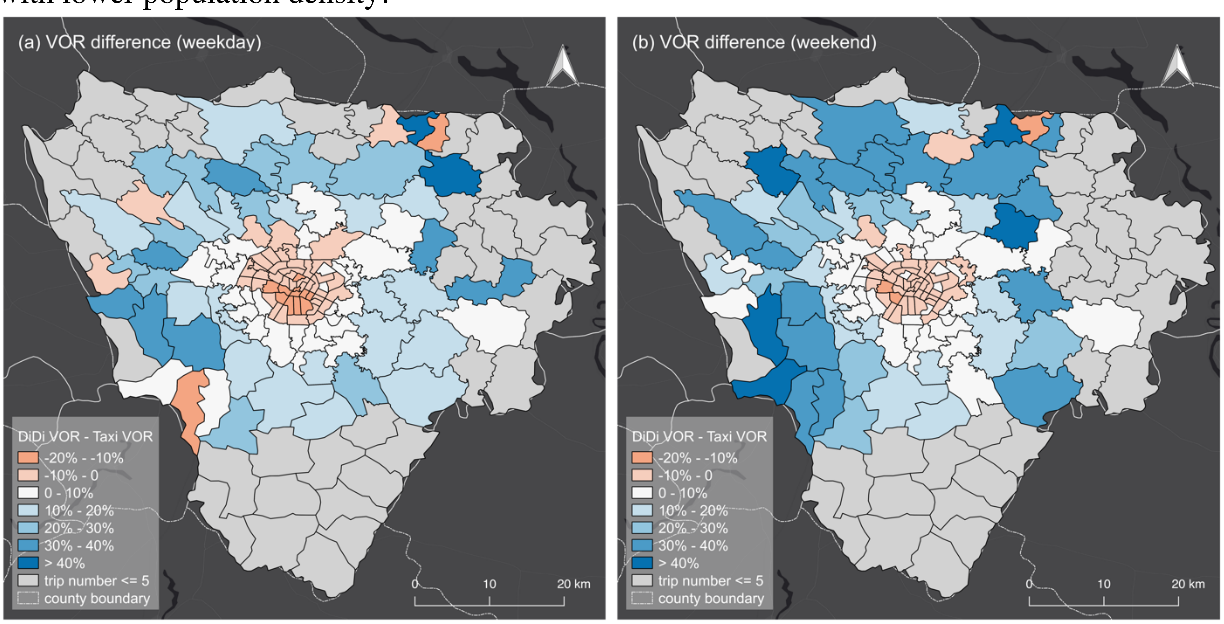

Figure 10 VOR difference between DiDi and taxi on (a) the weekday and (b) the weekend

4.3 Explanation for the VOR difference

Equations (10-12) are used to examine the impacts of supply-demand matching efficiency, scale effect, and the number of taxi trips per capita on the difference of efficiency between DiDi and taxi. As the temporal patterns of the VORs do not have much variation, we only examine the variations of difference between the two modes over space. The study area contains 161 townships. In the regression, we removed the townships with less than or equal to 5 trips. The descriptive statistics of all variables are represented in Table 3.

Table 3. Descriptive statistics

	Mean	**Std.dev**	**Min**	**Max**
A. Weekday (N=109)				
$VOR^{didi} - VOR^{taxi}$	0.04	0.12	-0.14	0.36
MEI	2.56	3.50	-2.22	14.00
SEI	0.66	0.90	0.07	5.19
TAXI	0.08	0.09	0.00	0.42
t^{ratio} (=t^{didi}/t^{taxi})	1.48	0.50	0.24	4.25
pop	1.32	1.20	0.05	4.66
road	0.84	0.41	0.09	1.96
houseprice	2.95	0.58	0.00	3.09
B. Weekend (N=103)				
$VOR^{didi} - VOR^{taxi}$	0.07	0.13	-0.12	0.43
MEI	2.45	3.69	-0.95	22.10
SEI	0.75	1.05	0.08	5.79
TAXI	0.08	0.09	0.00	0.49
t^{ratio} (=t^{didi}/t^{taxi})	1.67	0.58	0.67	3.59
pop	1.39	1.20	0.06	4.66
road	0.87	0.39	0.20	1.96
houseprice	3.07	0.01	3.05	3.08

After calculating the correlation matrix for the independent and control variables (Table 4), we found that road density has high and significant correlation (correlation coefficient >= 0.7) with some of the other variables. Therefore, this variable is removed from the regression to avoid multicollinearity.

Table 4. Correlation matrix

A. Weekday							
	MEI	SEI	TAXI	t^{ratio}	pop	road	houseprice
MEI	1						
SEI	0.40	1					
TAXI	-0.58	-0.32	1				
t^{ratio}	0.40	0.26	-0.19	1			
pop	-0.61	-0.30	0.50	-0.29	1		
road	-0.60	-0.36	0.80	-0.19	0.71	1	
houseprice	-0.28	NA	NA	NA	0.20	0.26	1
B. Weekend							
	MEI	SEI	TAXI	t^{ratio}	pop	road	houseprice
MEI	1						
SEI	0.47	1					
TAXI	-0.50	-0.34	1				
t^{ratio}	0.41	NA	NA	1			
pop	-0.55	-0.35	0.48	-0.29	1		
road	-0.55	-0.43	0.77	NA	0.69	1	
houseprice	0.23	0.67	NA	-0.21	NA	-0.22	1

Note: NA = insignificant at the 0.05 level.

Since the spatial variation exists in the efficiency measures of the VOR difference, we conduct the diagnostics for spatial dependence to determine the necessity of applying spatial regression to examine the impacting factors (Table 5). The diagnostics reflect that, on the weekday, the Moran's I index is small and insignificant, indicating that the results of OLS regression could be used to explain the reasons of the VOR difference. While on the weekend, the Moran's I index is significant, indicating the necessity of applying SAR model on the weekend to take into account the spatial heterogeneity. The (Robust) Lagrange Multiplier (LM) tests show that both the Lagrange multiplier (lag) and robust Lagrange multiplier (lag) are more significant, thus the spatial lag model fits better in our case.

Table 5. Diagnostics for spatial dependence

	A. Weekday		***B. Weekend***	
	b	***p***	***b***	***p***
Moran's I	0.035	0.246	0.207	0.000***
Lagrange multiplier (lag)	7.563	0.006**	43.218	0.000***
Robust Lagrange multiplier (lag)	12.511	0.000***	36.962	0.000***
Lagrange multiplier (error)	0.337	0.561	11.959	0.001**
Robust Lagrange multiplier (error)	5.285	0.022*	5.203	0.023*
SARMA	12.848	0.002**	48.921	0.000***

Statistical significance is indicated as p-value: · < 0.1, * < 0.05, ** < 0.01, *** < 0.001.

Therefore, we run the OLS and SAR for both the weekday and weekend (Table 6), but only interpret the OLS results on the weekday and the SAR results on the weekend. According to the OLS regression on the weekday, MEI is positively correlated with the VOR difference, indicating that the greater difference of the matching efficiency between DiDi and taxi significantly enlarges the VOR difference between two modes. The scale effect does not have significant correlation with the VOR. Number of taxi trips has significantly negative correlations with the VOR difference, indicating that DiDi does not have much advantage over taxi in areas with many taxi trips. Among the control variables, the ratio of trip time between DiDi and taxi is positively correlated with the VOR difference. Population density is negatively correlated with the VOR difference, indicating that DiDi has less advantages over taxi regarding VOR in the high population density areas.

Regarding the weekend, the pseudo R^2 and the spatial pseudo R^2 are both higher in the SAR than in the OLS regression, indicating that SAR provides a better fit than the OLS model. Both MEI and SEI are positively correlated with the VOR difference, indicating that the greater difference of the matching efficiency and the greater scale effect both positively associated with larger VOR difference. TAXI is negatively correlated with the VOR difference, but only significant at the 0.1 level. The ratio of the trip time between DiDi and taxi is significantly correlated with the VOR difference at the 0.001 level, and houseprice is correlated with the VOR difference at the 0.1 level. The coefficient of population density is significant in the OLS regression, but becomes insignificant in SAR, indicating that the effects of population is mainly a spatial effect. The spatial lag coefficient is positive and significant, indicating the agglomeration effect of the VOR difference.

The results indicate that the greater difference of the matching efficiency (MEI), the greater scale of DiDi compared to taxi (SEI), and the number of taxi trips (TAXI) all significantly correlate with the difference of VOR between DiDi and taxi. The MEI has the most significant coefficient (significant at 0.001 level on the weekday and at 0.01 level on the weekend). These results are in accordance with the hypothesis put forward by Cramer and Krueger (2016). First, thanks to its mobile internet technology, more flexible labor supply model, and surge pricing, DiDi achieves a more efficient matching between drivers and passengers. As a result, it is easier for DiDi drivers to find the next passenger, thus the searching time of DiDi drivers is shorten and the VOR of DiDi is greater than taxi. Second, the greater scale of DiDi drivers in the market improves the possibility that a DiDi driver is closer to a potential passenger than a taxi driver, which reduces the time for DiDi drivers to reach to the next passenger and improves the VOR difference between the two modes. Lastly, the greater number of taxi trips makes taxi a stronger competitor of DiDi, thus reducing the VOR of DiDi and making the VOR difference between the two modes smaller.

Table 6. Regression results

	A. Weekday		**B. Weekend**	
	Model 1: OLS	**Model 2: SAR**	**Model 1: OLS**	**Model 2: SAR**
(Intercept)	-0.025 (0.036)	-0.060 (0.037)	9.153* (4.556)	-0.093* (0.032)

MEI	0.014*** (0.003)	0.013*** (0.002)	0.015*** (0.003)	0.006** (0.001)
SEI	0.010 (0.007)	0.008 (0.007)	0.033** (0.010)	0.014* (0.018)
TAXI	-0.378*** (0.084)	-0.241** (0.087)	-0.361*** (0.092)	-0.132 · (0.078)
t^{ratio}	0.029* (0.013)	0.020 (0.012)	0.025 · (0.014)	0.024*** (0.000)
pop	-0.023*** (0.006)	-0.011 (0.007)	-0.025** (0.007)	-0.004 (0.474)
houseprice	0.012 (0.011)	0.017 · (0.011)	-2.974* (1.485)	0.022 · (0.052)
spatial lag coefficient		0.316** (0.106)		0.690*** (0.000)
Summary of Statistics				
number of observations	109	109	103	103
(pseudo) R2	0.760	0.781	0.762	0.866
adjusted (pseudo) R2	0.746	-	0.747	-
spatial (pseudo) R2	-	0.781	-	0.833

Note: (*) = standard error; statistical significance is indicated as p-value: · < 0.1, * < 0.05, ** < 0.01, *** < 0.001.

5. Conclusions

This work measures the VORs of DiDi and taxi, contrasts the spatial and temporal patterns of VORs between DiDi and Taxi, and examine underlining reasons that determine such difference. Overall, DiDi achieves higher VOR as its VOR is 6 percentage points higher than taxi on the weekday and 12 percentage points higher on the weekend. For taxi drivers, VOR rises as the trip number increases and is higher on the weekday than on the weekend, indicating that the drivers' experience and the regularity of mobility play an important role in taxi VOR. Temporally, the VOR of taxi is only slightly higher than DiDi during the morning peak on the weekday. Spatially, the VOR of taxi is higher in the city center but lower in the periphery, while the VOR of DiDi is higher in the periphery but lower in the center. The VOR of taxi is slightly higher than DiDi in the central areas but is lower in the rest of the areas. Further exploration of the reasons that cause the difference in VORs between DiDi and taxi indicates that the higher supply-demand match of DiDi and greater scale of DiDi drivers enlarges the difference between DiDi and taxi, while the number of taxi trips per capita reduces the difference.

The results have implications for both business operation and public policy. Regarding business operation, similar to the study of Cramer and Krueger (2016), our results confirm that ridesourcing does not significantly improve the efficiency in high population density areas. Two efforts can be made based on our results. The first is to cooperate the taxi and ridesourcing systems. Since taxi is more efficient in high-density areas while ridesourcing is more efficient in low-density areas, a system that integrates or coordinates between both services can take advantage of both algorithm-based hailing and street-hailing. Further system and operational design are required to achieve this. The second is to improve the matching and searching mechanism of ridesourcing in high-density areas. Admittedly, there is a VOR ceiling even with a perfect matching algorithm, but there are some rooms for the improvement. For example, pick-up locations within an acceptable walking distance for passengers can be designed to avoid congested routes or reduce detour. Allowing a more flexible matching by enlarging the time/distance buffer for driver-passenger pairing can also improves driver-passenger matching rate and reduces the vacant time of vehicles.

The implications for policy intervention lie in the potential of designing the location-specific regulations to encourage or discourage certain types of mobility services in a specific area to improve the overall system efficiency. The regulations can be in the forms of quota control, subsidies or fees, and physical boundary setting. Take the TNC fee as an example, instead of the flat charges that some governments have imposed on the TNC trips (e.g. Chicago charges \$0.67 for each ridesourcing trip), the charges can be dynamic over space and time (e.g. charge a higher 'TNC fees' in high-density areas). However, such regulations may distort the market and change the supply of both services, which may in return impacts the spatial variation of the VOR. Therefore, their effects must be examined carefully before being put into practice.
This paper contributes to the existing literature from several perspectives. First, we propose the approaches to estimate the vacant time for each trip from the OD information when the trajectory data are unavailable. Since many datasets that are open to the public have only released the OD information, our approaches could be widely applied. Second, this study is among the first to empirically examine the variation of the VOR, and reveals spatial patterns of the VORs and the difference, which leads to discussions on the implications for business operation and location-specific regulations. Also, this paper examines three hypothetical reasons for the VOR difference. Although the underlying mechanisms could be complicated and other microeconomic models besides regression should be applied to obtain a comprehensive picture, this study provides a better understanding of VOR variations and lays the foundations for the future research.

Admittedly, this study encounters several limitations. Firstly, without the access to DiDi trajectory data, we have to estimate the vacant time for each DiDi trip via distribution fitting. Therefore, the calculation of DiDi VOR is less accurate than that of taxi VOR. Besides, we are not able to calculate the distance-based VOR since DiDi trajectory data is not available. Distance-based VOR and time-based VOR carry very different meanings in terms of the efficiency of each mode. The two VORs are likely to be correlated. For taxi, we hypothesize a high correlation as taxi driver needs to cruise continuously to search for customers. The differences between the two VORs may influenced by the different driving speeds in cruising and serving passengers. For ridesourcing services (like DiDi), the difference of VORs are complicated by both driver's experience and matching efficiency of the platform. If we think cruising is less needed for DiDi driver, we may expect a higher distance-based VOR, but all these need to be tested by empirical studies. Secondly, since we do not have the data of DiDi and taxi in the same time period, we cannot compare the VOR of the two modes in the same market.

However, our selection of time period for each mode allows us to evaluate the VOR of taxi without being disrupted by ridesourcing. Besides, due to data limitation, we have to analyze the two modes in the different months of the year, so the seasonal variation of supply and demand is not controlled in this study. Third, without access to the price of each trip, we cannot tell how the price differences between the two modes affect the VOR difference. Lastly, this paper has not included the ridesharing services.

The results and limitations of this paper indicate the potentials for future research. This paper has observed the variation of the VORs, which indicates the importance of examining the underlying mechanisms under the VOR. Besides the regressions conducted in this paper, the impacts of supply, demand, and price on VOR should be examined carefully based on microeconomic theories, to derive their intertwined impacts on each other. Based on which, a dynamic fare structure of taxi and ridesourcing could be designed to achieve different policy targets, e.g. improving overall VOR, protecting traditional taxi market, improving the welfare of drivers. Another interesting research direction is to compare the VOR of taxi both before and after the ridesourcing becomes dominant, should the data be accessible, to help policy makers understand the disruption of ridesourcing on the taxi market.

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