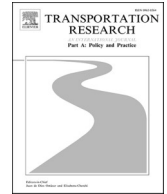




ELSEVIER

Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Impact of pricing policy change on on-street parking demand and user satisfaction: A case study in Nanning, China

Baichuan Mo^{a,b}, Hui Kong^{c,d}, Hao Wang^e, Xiaokun (Cara) Wang^f, Ruimin Li^{a,g,*}^a Institute of Transportation Engineering, Department of Civil Engineering, Tsinghua University, Beijing 100084, China^b Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, MA 02139, USA^c Department of Urban Studies and Planning, Massachusetts Institute of Technology, Cambridge, MA 02139, USA^d Humphrey School of Public Affairs, University of Minnesota, Minneapolis, MN 55455, USA^e Traffic Police Department of Public Security Bureau of Nanning, Guangxi 530022, China^f Department of Civil and Environmental Engineering, School of Engineering, Rensselaer Polytechnic Institute, Troy, NY 12180-3590, USA^g Hang Lung Center for Real Estate, Tsinghua University, Beijing 100084, China

ARTICLE INFO

Keywords:

On-street parking
Pricing policy adjustment
Parking demand
User satisfaction

ABSTRACT

Understanding the pricing policy effect is important for on-street parking management. This study investigates the impact of the on-street parking price adjustment with a case study in Nanning. Parking meter data and survey data are used to analyze the impact of the policy intervention on parking demand and user satisfaction, respectively. Regression discontinuity design (RDD), structural equation model (SEM), and binary logistic regression (BLR) models are implemented. Results show that the increase in parking pricing significantly decreases the parking volume (by around 20%) and parking duration (by around 10%). Drivers' parking costs also increased. The influence varies across different sub-areas, days of the week, and trip purposes. After the policy adjustment, people feel that the parking price is higher, the distance of parking lots to the final destination is closer, and the parking lots are more vacant. On-street parking users after the policy intervention have higher incomes. As they are less sensitive to the price but more on quality, the overall parking satisfaction is increased.

1. Introduction

Parking is an important component of urban transportation systems. With the continual increase of car ownership and the limited supply of infrastructure and land resources, parking problems are becoming a severe challenge for transport authorities (Xiao et al., 2018). For example, by the end of 2017, the amount of vehicles in Beijing has reached 5.64 million, while the number of parking spaces is only 3.82 million, which leads to the prominent imbalance between parking supplies and demands (Beijing Municipal Commission of Transport, 2017). Due to the limited land resource in metropolitan areas, on-street parking facilities have become an important component of urban parking systems (Amar and Chow, 2017). In Beijing, nearly 14% of vehicles park on the street overnight (Beijing Municipal Commission of Transport, 2017).

The high demand for on-street parking raises a great challenge for transport management, which also gains increasing attention from the literature. Over the past few decades, a great amount of studies has been done to improve on-street parking management,

* Corresponding author.

E-mail address: lrmin@tsinghua.edu.cn (R. Li).

<https://doi.org/10.1016/j.tra.2021.04.013>

Received 14 November 2020; Received in revised form 12 April 2021; Accepted 14 April 2021

0965-8564/© 2021 Elsevier Ltd. All rights reserved.

either from the survey-based perspective (Cats et al., 2016; Hensher and King, 2001; Kelly and Clinch, 2009) or the modeling-based perspective (Calthrop et al., 2000; Fosgerau and De Palma, 2013; Thompson and Richardson, 1998; Zheng and Geroliminis, 2016). Most of these studies regarding on-street parking are related to price, which implies that the parking pricing policy is a powerful tool for parking management. Given that, many researchers also investigated the impact of pricing policies. One major stream of previous research focuses on the policy effect on passengers' travel behaviors. Literature has investigated the influence of parking price policy on individuals' mode choice (Wilson, 1992), parking places choice (Hensher and King, 2001), and driving behaviors (Kelly and Clinch, 2006). Another stream of research focuses on an aggregate level impact: how parking price affects passengers' parking and travel demand temporally and spatially. Findings are various: Cain et al. (2001) and Syed et al. (2009) found that increasing the parking price in peak hours failed to introduce a significant peak spreading effect, while Milosavljević and Simićević (2014) found that the rise in parking prices led to a decrease in parking volume, garage occupancy, and average parking duration.

Recently, from the psychological perspective, users' satisfaction with parking service also gained the attention of academia. For example, Gumasing and Aienza (2018) and Suksanguan (2018) studied users' satisfaction in the parking places near the shopping malls and airports, respectively. Sidorchuk et al. (2020) used a clustering method to analyze people's satisfaction in parking spaces organization.

Despite many existing studies discussing the impacts of parking pricing policies, there are still research gaps. First, in terms of parking demand, most of the previous studies only considered the short-term (e.g., one week or one month) effects after changes in parking prices. However, given the gradual adaptation properties of human behaviors, it is worth investigating the long-term effects (e.g., several months). Second, most previous studies about parking policies are based on stated or revealed preference surveys, whereas only a handful are based on actual observed data. With the adoption of parking management and information systems, real-world parking records data becomes available. Combining both surveys and actual parking records can help to better understand the impact of parking pricing policies on both individual behavior and the aggregated spatial-temporal demand patterns. Third, in terms of parking satisfaction, most of the previous research focused on users' attitudes on the service itself, instead of connecting it to a specific pricing policy. And the comparison of users' satisfaction before and after pricing policy adjustment is rarely studied.

To address these gaps, this study investigates the impact of pricing policy change on on-street parking demand and user satisfaction. We aim to answer the following questions: 1) How does the change of parking pricing policy affect the parking demand temporally and spatially, and what are the impacts on the short term (several weeks) and the long term (several months)? 2) How does the change of parking pricing policy affect the drivers' parking satisfaction? We selected Nanning City in China as the study area, where car ownership is increasing dramatically and people highly rely on on-street parking facilities. The first question is analyzed based on one-year parking meter data collected before and after the policy intervention. Parking demand is investigated in three respects: parking volume, parking duration, and parking costs. The second question is analyzed by survey data using a structural equation model (SEM) and a binary logistic regression (BLR) model. Two surveys about drivers' parking satisfaction before and after the policy adjustment are conducted. The major contributions of this paper are summarized as follows:

- Combine both parking meter data and survey data to analyze the impact of pricing policy change on parking demand and user satisfaction, providing a more comprehensive analysis for the policy influence.
- Conduct a comprehensive spatial and temporal analysis for the parking demand before and after the policy adjustment. The short-term and long-term policy impacts are revealed using a regression discontinuity design (RDD).
- Propose a trip purpose inference method for meter data to uncover different policy impacts on shopping trips and other trips.
- Collect user satisfaction surveys before and after the policy adjustment and implement a binary-form SEM and a BLR model to analyze the impact of the policy intervention on user satisfaction.

The remainder of the paper is organized as follows. Section 2 reviews related literature. Section 3 presents the background of Nanning's on-street parking facility and details of the policy adjustment. Section 4 describes the data and analytical methods used in this research. Section 5 and 6 represent the effect of policy on parking demand and parking satisfaction, respectively. Section 7 discusses the influence of the parking policy adjustment and the future policy implications and Section 8 concludes the paper.

2. Literature review

2.1. Impact of parking pricing policies

Parking pricing policies are considered a powerful tool for solving parking problems and other issues of the transportation system in general. Existing literature has explored the impacts of parking pricing policies on different perspectives, one of which is passengers' travel behaviors.

Wilson (1992) used multinomial logit models to assess the effect of parking prices on commuters' mode choices. Via the case study of commuters in Los Angeles, the results showed the number of commuters driving to work could be decreased by 25%–34% if they had to pay for parking. Hensher and King (2001) used a stated preference survey to investigate the impacts of parking pricing and supply by time of day on whether to drive and park in the central business district (CBD). The results showed that the imposition of curtailment at specific locations under existing tariffs could lead to a relocation of parking places. Albert and Mahalel (2006) conducted a comparison of drivers' attitudes towards congestion and parking toll and explored their effect on travel behavior. The results indicated that drivers are sensitive to congestion tolls and are willing to change their travel habits to avoid these tolls. Kelly and Clinch (2006) surveyed 1,007 users of on-street parking in Dublin, Ireland, and found a gap in price sensitivity between trips made for

business purposes relative to non-business purposes. [Becker and Carmi \(2019\)](#), through survey data, showed that adding a parking fee not only increased the tendency to leave the car at home, but also influenced people's attitudes toward other factors such as environment and comfort level. In summary, parking price policy can influence travel behaviors in various aspects, such as mode choices, parking location choices, and driving route choices.

Many studies also looked at the impacts of parking price policy on parking demand. For example, [Kelly and Clinch \(2009\)](#) estimated the on-street parking price elasticity of demand in an area of Dublin, Ireland, based on the revealed-preference parking trend data before and after a price change of on-street parking. [Ottosson et al. \(2013\)](#) investigated the impact of the parking rate change on on-street parking demand using the automatic transaction data from parking payment stations in Seattle. Results showed that the price elasticity of the parking occupancy was inelastic and varied with the time of day and neighborhood characteristics. [Milosavljević and Simićević \(2014\)](#) investigated and quantified the impact of on-street parking prices on parking demand and garage operation based on the revealed preference data in central Belgrade, Serbia. They found that the rise in parking prices led to a decrease in parking volume, garage occupancy, and average parking duration. [Pu et al. \(2017\)](#) investigated the spatial heterogeneity in the sensitivity of parking occupancy to price change using data obtained in downtown San Francisco between 2011 and 2014. Results showed that there is a significant negative correlation between parking demand and parking price, and the sensitivity of on-street parking demand to price change has an obvious trend of spatial variation. From the above literature review, we can summarize the research gaps as follows: 1) lack of analysis on long-term policy impacts and 2) lack of analysis using both survey and meter data.

Recently, [Wang et al. \(2020\)](#) used parking meter data to analyze the impact of parking policy change on parking turnover and duration considering long-term policy impacts. However, they only used data from 4 selected weeks and 12 selected roads with straightforward visualization analysis. The long-term trend of policy adoption is not revealed. Our paper fills the research gap by using a larger parking meter data set (4 months before and 8 months after the policy change with 47 roads) and an RDD model with more comprehensive spatial and temporal analysis to evaluate the impact of policy change on parking volume, duration, and cost at the city, subarea, and trip levels. Besides, we also propose a trip purpose inference model to uncover different policy impacts on shopping trips and other trips.

2.2. User satisfaction

Users' satisfaction is an important indicator to evaluate services and policies. In the field of transportation, previous research has studied the users' satisfaction with airlines ([Ali et al., 2015](#); [Clemes et al., 2008](#); [Tsafarakis et al., 2018](#)), railways ([Eboli and Mazzulla, 2015](#); [Givoni and Rietveld, 2007](#); [Shen et al., 2016](#)), and buses ([Adebambo and Adebayo, 2009](#)).

Studies on parking satisfaction mostly focused on the service itself or considered parking as a factor for the whole trip satisfaction. [Xue et al. \(2019\)](#) showed that the drivers' satisfaction with the trip from the suburbs depends on the parking place status. The satisfaction level decreases with a decrease in the remaining parking spaces number. [Suksanguan \(2018\)](#) studied users' satisfaction in the parking places in the Don Mueang Airport and found that people with different incomes and ages would show different levels of satisfaction. Similarly, [Gumasing and Atienza \(2018\)](#) studied driver's satisfaction with parking services in shopping centers in Metro

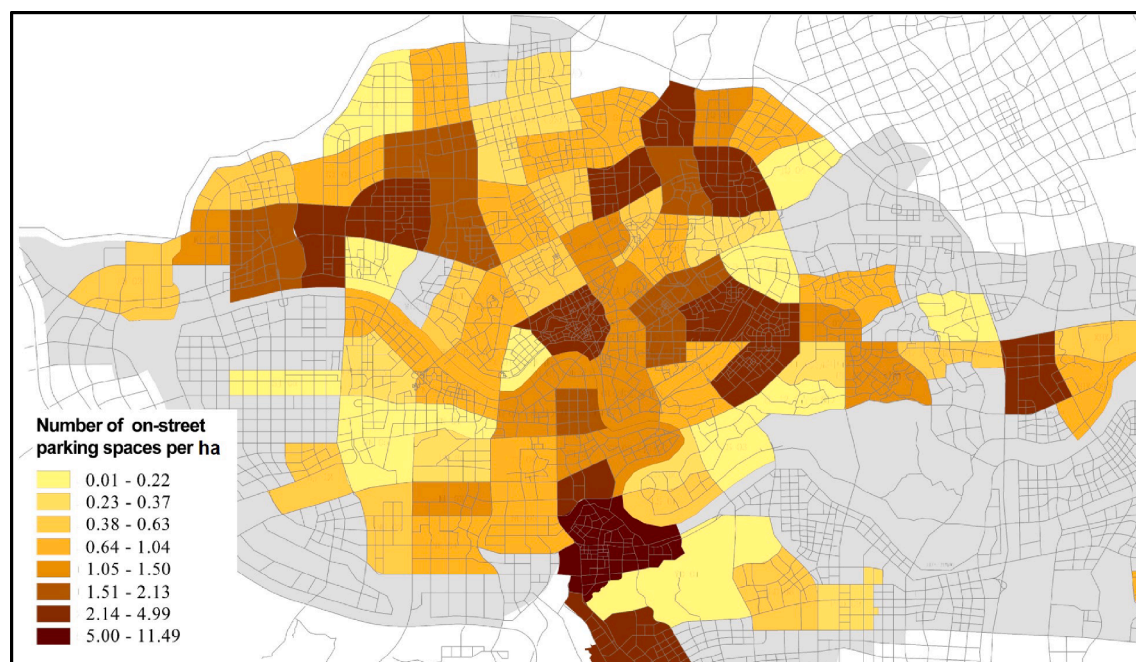


Fig. 1. Spatial distribution of on-street parking places in Nanning.

Manila and found that the time spent on a parking space search and spare parking place indication significantly influences the satisfaction level. Budiani et al. (2018) investigated user satisfaction with the parking facility in the Faculty of Geography based on descriptive statistics on a survey and showed that the average user satisfaction level was good. Sidorchuk et al. (2020) used a clustering method to analyze people's satisfaction in parking space organization. Five clusters of administrative districts of the City were developed in accordance with customer satisfaction.

As evident from the literature review presented above, the impact of a specific policy change on users' satisfaction with parking is seldom investigated. Users may have different attitudes toward a parking policy. Understanding users' corresponding satisfaction can guide policy design and adjustment. This paper fills the research gap by evaluating passengers' satisfaction with parking via three mediated variables (distance, price, and vacancy) using surveys collected before and after the policy change.

3. Background

3.1. On-street parking in Nanning

Nanning is the capital city of Guangxi Zhuang Autonomous Region in the south of China. Over the past decades, the car ownership of the city increased at an average annual rate of around 100,000, leading to a growing conflict between parking demands and supplies. The on-street parking charging system was first implemented on several roads in Nanning in 2001, and then gradually expanded to the entire downtown area. According to Wang et al. (2020) by August 2015, there were a total of 34,836 on-street parking spaces in Nanning, and this number keeps increasing. The spatial distribution of on-street parking spaces in Nanning is shown in Fig. 1. Note that the gray part in the figure shows the urban area of Nanning where no on-street parking facilities are available there.

3.2. Adjustment of on-street parking price

In December 2014, the Nanning government decided to adjust the on-street parking price to accommodate the increasing parking demand. The adjustment is composed of two parts: price increasing and charging area re-division. In terms of parking price, the comparison before and after the policy adjustment is shown in Table 1. From 8:00 to 22:00, parking areas A and B are charged based on parking durations with a step-wise pricing scheme, which means any parking duration that does not cover a whole interval is charged the whole-interval fee. For example, if a driver parked for 35 min in Area A before the policy adjustment, he/she would be charged 6 RMB even though he/she only exceeded 5 min to the second charging interval. Area C has a fixed parking fee no matter how long the vehicle parks. Parking is free in all areas before 8:00 and after 22:00. After the parking pricing policy adjustment, the unit parking prices for areas A and B are nearly doubled and have a more fine-grained pricing interval (from 30 min to 15 min), and there is no fixed maximum fee.

In addition to the increase in parking prices, the divisions of parking charging areas are also changed. As shown in Fig. 2a, before the policy adjustment, only a small number of areas are included in the duration-based charging system (i.e., areas A and B), which are mainly the central shopping and recreational regions in Nanning. However, after the new policy implementation (Fig. 2b), the duration-based charging system covers nearly all downtown areas, and the delineation of areas A and B is also changed. The new type A area becomes the center of the city with a mixture of commercial and residential areas, which almost covers the previous areas A and B before the policy adjustment. The new type B area becomes the newly developed sub-central region surrounding the new area A. Both A and B areas are expanded after the policy adjustment. The rest of the areas in the city are divided as area C.

4. Data and methodology

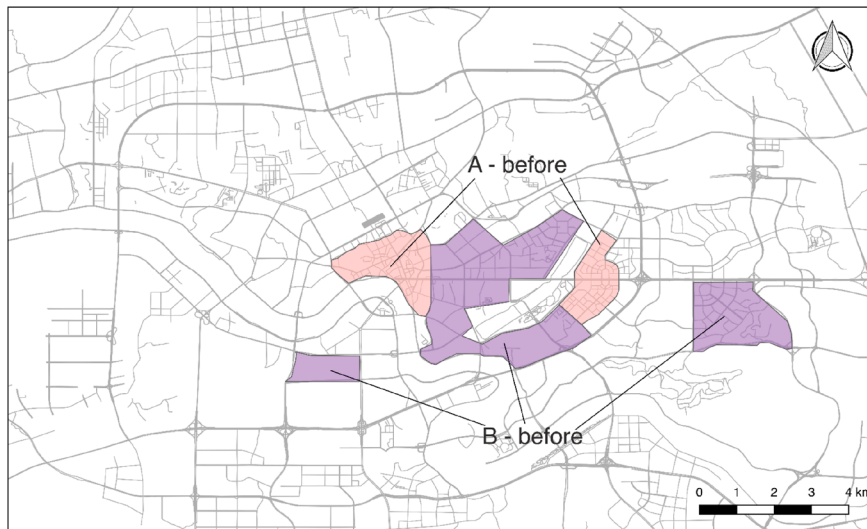
4.1. Parking meter data

The on-street parking management system (i.e., parking meter) can provide start and end times for each parking during the billable time (8:00 to 22:00). The parking records from September 2014 to August 2015 (1 year) are collected (around 0.5 million records in total), which covers 3 months before and 8 months after the policy adjustment. Table 2 represents the number of records in each charging area. It is worth noting that the distribution of the records is a reflection of both the parking demand and the supply of parking meters. Some areas with a low number of records may be due to the low density of parking meters. The distribution of the number of parking records at the street level is shown in Fig. 3. Since the parking meter data covers 8 months after the policy adjustment, it allows

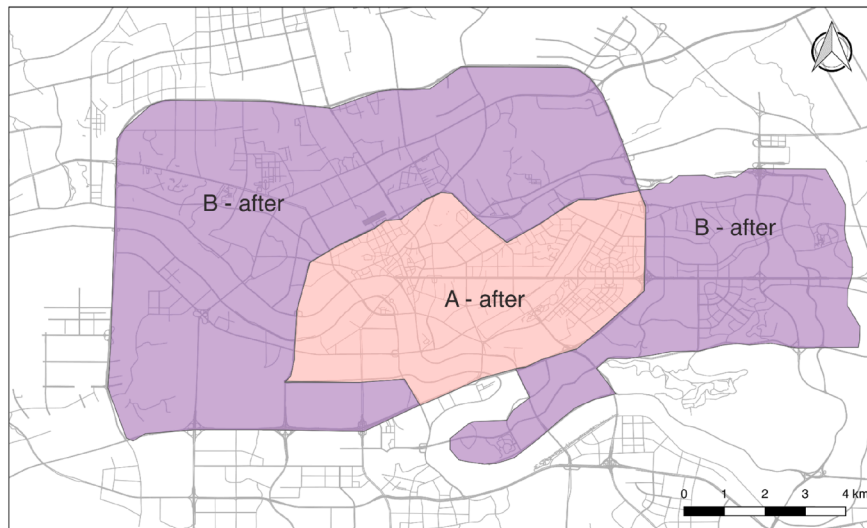
Table 1
On-street parking prices before and after policy adjustment.

| Area type | Before adjustment | | | After adjustment | | |
|-----------|-------------------|----------------|-------------|------------------|----------------|-------------|
| | Price (¥) | Billable hours | Maximum fee | Price (¥) | Billable hours | Maximum fee |
| A | 3/(veh·30 min) | 8:00–22:00 | 60 | 2.5/(veh·15 min) | 8:00–22:00 | + ∞ |
| B | 2.5/(veh·30 min) | 8:30–22:00 | 40 | 2/(veh·15 min) | 8:00–22:00 | + ∞ |
| C | 5/veh | 8:00–22:00 | N.A. | 5/veh | 8:00–22:00 | N.A. |

N.A.: not applicable.



(a) Parking charging area division before policy adjustment



(b) Parking charging area division after policy adjustment

Fig. 2. Divisions of parking charging area before and after policy adjustment.

Table 2
Regional distribution of parking records in the parking meter data.

| Area type | Number of parking records (Sep 2014 to Aug 2015) | | | Total |
|-----------|--|---------|---------|---------|
| | A-after | B-after | C-after | |
| A-before | 295,896 | N.A. | N.A. | 295,896 |
| B-before | 169,239 | 8,384 | N.A. | 177,623 |
| C-before | 0 | 0 | 10,701 | 10,701 |
| Total | 465,135 | 8,384 | 10,701 | 484,220 |

N.A.: not applicable because such changes (e.g., from A to C) do not exist.

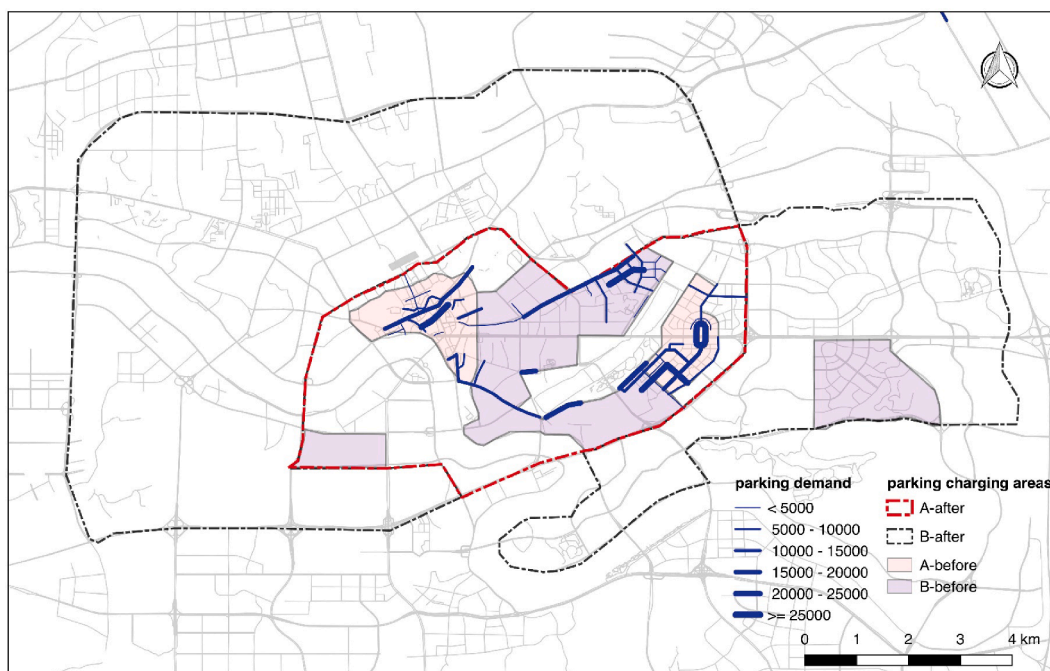


Fig. 3. Spatial distribution of the total number of parking records.

analyzing the long-term impact of policy on parking demand temporally and spatially.

4.2. Survey data

4.2.1. Survey design and data collection

Two on-site surveys were conducted in September 2014 (3 months before the policy adjustment) and April 2015 (4 months after the policy adjustment), respectively. The data were collected for a whole week from Monday to Sunday 8:00 to 22:00 (billable time). Drivers who just parked on the side of a street were asked to finish the questionnaire.

After filtering out the incomplete and invalid responses, we got 704 valid samples for 2014 and 1130 valid samples for 2015. The spatial distribution of respondents is shown in Table 3. Different proportion of samples were collected in 2014 and 2015 for each parking area, as a response to the change of parking area division: a larger proportion of samples were collected for area A in 2015 as there is an expansion of area A after the policy adjustment, while a smaller proportion of samples were collected for area C in 2015 due to the shrinkage of this type of area after the policy adjustment.

In this survey, users' parking satisfaction is captured by an overall question ("Are you satisfied with your parking place? Yes/No") and three sub-dimensions of service evaluation: distance ("How is the distance from your parking place to your destination? Close/Moderate/Far"), price ("How is the price of this parking? Low/Moderate/High"), and vacancy ("How is the degree of crowding of this parking place? Vacant/Moderate/Crowding"). Users' demographics information (e.g., gender, age, income, etc.) is also collected. We admit that it is more reasonable to design the answer of the overall satisfaction question as graded response categories (e.g., 5-Likert scales), instead of a "yes/no" response (Whitty et al., 1996). However, there are no resources and opportunities for authors to change the questionnaire and conduct the survey again. On the other hand, the "yes/no" satisfaction questions were also used in previous studies on customer satisfaction as they are easy for respondents to answer (Samorodnitzky-Naveh et al., 2007; Tin-Oo et al., 2011; Turner and Paech, 1991).

Table 3
Spatial distribution of respondents.

| Area type | 2014 Number of respondents | 2015 Number of respondents |
|-----------|-------------------------------|-------------------------------|
| A | 144 | 663 |
| B | 312 | 311 |
| C | 248 | 156 |
| Total | 704 | 1130 |

4.2.2. Descriptive analysis

Survey respondents are adult drivers using on-street parking services before and after the parking price service adjustment. Owing to the price increase, samples in 2014 may have different demographics from samples in 2015. To compare the sample demographics between the two survey years, we plot the sample income and age distribution of 2014 and 2015, respectively (see Fig. 4). As shown in Fig. 4a, an obvious discrepancy can be found between respondents in 2014 and 2015. Overall, respondents in 2015 have a higher monthly income than those in 2014. There are fewer low-income (< ¥2,500) samples and more mid-income (¥2,500 - ¥7,500) samples in 2015. While for the high-income samples (> ¥10,000), the density of the two groups is similar. Note that this increment is much higher than the average income increase from 2014 to 2015 in Nanning. This implies the price increasing suppressed the demand of low-income people. In terms of the age distribution (see Fig. 4b), the patterns of two years are similar. Most of the drivers are middle-aged.

In addition to age and income, the comparison of other demographics is summarized in Table 4. We found there is no obvious gender difference between 2014 and 2015. Most of the drivers are still male. The private parking space ownership has changed after the policy adjustment. In samples of 2015, a majority of drivers own their private parking place, which is converse to 2014 where a majority of the samples are not. This is in line with our expectations because drivers with private parking places are generally more reliant on cars and they are less elastic to the parking price increase. In terms of payment sources, most of the people paid by themselves. And the percentage for two years of samples is similar. We also observe that the proportion of working trips increases from 36.5% to 45.7% after the policy intervention. This is as expected because working trips are less flexible and they are affected by the parking price compared to other trips. Drivers are also asked about whether they own the parked car or not. In 2014, 71.6% of respondents said that they owned the parked car but this proportion decreased to 58.8% in 2015. This may be due to the fact that the proportion of working trips increases and drivers with the purpose of working are more likely to use cars owned by their companies rather than themselves.

Fig. 5 shows the distribution of responses to the satisfaction question. For survey periods before and after the policy adjustment, more than half of drivers are satisfied with their parking place. Interestingly, comparing results in 2014 and 2015, samples in 2015 show a higher satisfaction rate, although the parking prices are increased. This may be explained by two reasons. First, as shown in Fig. 6b and c, the perceived distance to the final destination is reduced and the vacancy of parking space is increased, which suggests a better parking experience. Second, sample drivers in 2015 have a higher income than those in 2014, and thus may be less sensitive to the price and more sensitive to the service quality (i.e., distance and vacancy).

Fig. 6 shows the distribution of three sub-dimensions of service evaluation: price, distance to the final destination, and vacancy of the parking place. Overall, the distribution patterns for the two years are similar. Most of the drivers thought that prices and vacancies are moderate, and the parking place is close to the final destination. Comparing samples before and after the policy adjustment, we observe the perceived parking price and vacancy are increased, and the perceived distance is decreased. This implies that the new pricing policy reduced the parking demand. Since few people choose on-street parking, there are more free parking spaces (higher vacancy), and more opportunities to park near the destination (lower distance).

4.3. Regression discontinuity design

The regression discontinuity design (RDD) is a quasi-experimental pretest-posttest design that elicits the causal effects of interventions by assigning a cutoff or threshold (Angrist and Pischke, 2008). By comparing observations lying closely on either side of the threshold, the treatment effect of the intervention and whether the causal effect is statistically significant or not can be estimated (Liu et al., 2018).

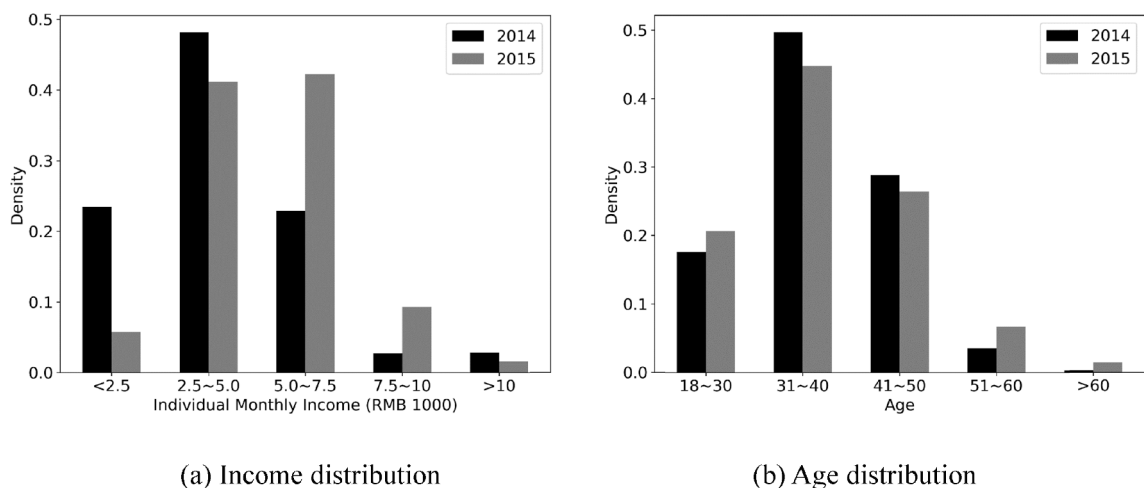


Fig. 4. Income and age distribution comparison between samples in 2014 and 2015.

Table 4
Characteristics of survey respondents.

| Characteristic | 2014 ($N_{2014} = 704$) Percentage (%) | 2015 ($N_{2015} = 1130$) Percentage (%) |
|--|---|--|
| <u>Gender</u> | | |
| Male | 65.6 | 62.8 |
| Female | 34.4 | 37.2 |
| <u>Private parking space ownership</u> | | |
| Owning | 48.2 | 62.5 |
| Not owning | 51.8 | 37.5 |
| <u>Payment source</u> | | |
| Paying by yourself | 76.3 | 77.6 |
| Paying by others | 23.7 | 22.4 |
| <u>Trip purpose</u> | | |
| Working | 36.5 | 45.7 |
| Others | 63.5 | 54.3 |
| <u>Driving your own car</u> | | |
| Yes | 71.6 | 58.8 |
| No | 28.4 | 41.2 |

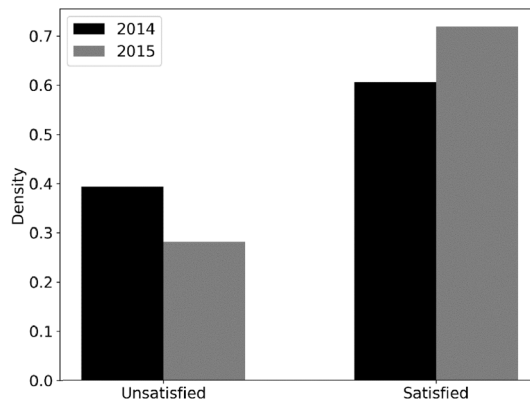
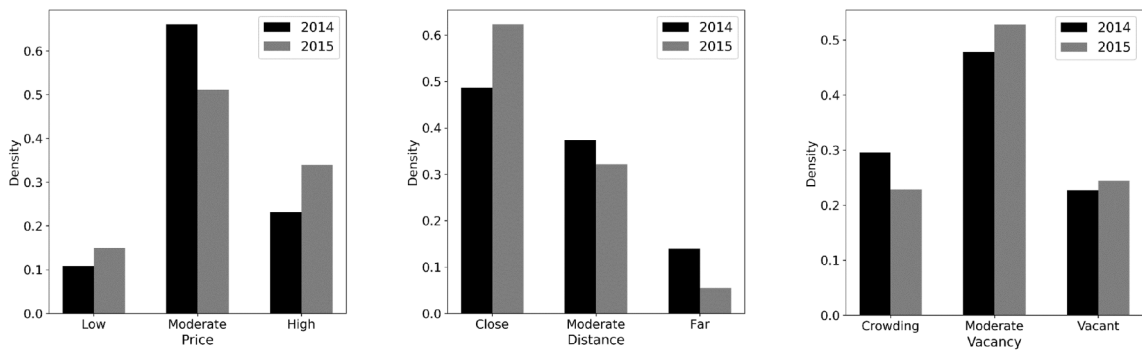


Fig. 5. Satisfaction distribution of survey respondents.



(a) Perceived price distribution (b) Perceived distance distribution (c) Perceived vacancy distribution

Fig. 6. Distribution of three sub-dimensions of service evaluation.

In this study, the RDD is used to estimate the policy adjustment effect on parking volume and duration. Specifically, let Z be the dependent variable (i.e. parking volume or duration), T be the time index, and \bar{T} be the time when the intervention is implemented. The RDD is formulated as

$$Z = \beta_0 + \beta_1 \cdot (T - \bar{T}) + \beta_2 \cdot D + \beta_3 \cdot (T - \bar{T}) \cdot D + \varepsilon, \tag{1}$$

where $D = 1$ when $T \geq \bar{T}$ and otherwise $D = 0$. ε is the error term. $\beta_0, \beta_1, \beta_2$ and β_3 are parameters to be estimated. Specially, β_0 is the intercept, β_1 is the slope of the fitted line before the treatment. β_2 is the instantaneous treatment effect (ITE). β_3 is the treatment effect on the slope (TES). ITE (TES) reflects the short (long) term effect of the treatment. To test whether the treatment effect is statistically significant or not, the null hypothesis is $\beta_2 = 0$ and $\beta_3 = 0$, that is, the intervention generated no effect.

According to the numerical tests, we observe that in most of the experiments, β_1 is not significantly different from zero because no remarkable factors affected either parking duration or volume in the short term before the policy (Sep 2014 – Dec 2014). Therefore, we fix $\beta_1 = 0$ in the RDD to reduce the impact of random fluctuation before the policy intervention.

4.4. Shopping trip inference for meter data

The policy intervention may have a different impact on trips with different purposes. For example, working trips may be less influenced due to the requirement of employers. Entertainment trips such as shopping are more flexible in terms of their occurrence and duration. However, the raw meter data does not include the trip purpose information. Hence, in this section, we propose an approach to infer potential shopping trips in the meter data based on geographical information. The reasons for inferring shopping trips rather than other trip purposes are as follows. First, due to the data limitation, we can only access the entertaining point of interest (POI) information in Nanning, which makes the inference of other trip purposes (e.g., working) difficult. Second, shopping malls are one of the representative entertaining POIs that can be directly related to shopping trips, providing a direct inference method. In this study, we identify two kinds of trips for comparison: 1) high-probability shopping (HPS) trips and 2) low-probability shopping (LPS) trips, where the former is highly likely to be shopping trips, while the latter is highly likely to be non-shopping trips. The inference procedure is as follows:

- **Step 1:** For each parking record in the meter data, create a 500 m buffer surrounding its location and count the number of shopping-related POIs within the buffer.
- **Step 2:** Calculate the 25th and 75th percentiles for the number of shopping-related POIs of all trips.
- **Step 3:** The trips with the number of shopping-related POIs greater than or equal to the 75th percentile are inferred as HPS trips. While the trips with number shopping-related POIs less than or equal to the 25th percentile are inferred as LPS trips

The underlying assumption is that with more shopping-related POIs around the parking location, the trip is more likely to be a shopping trip. Note that the 500-meter radius is used because it is a typical walking distance threshold (Carpio-Pinedo, 2014; Mashhoodi and Berghauser Pont, 2011). Compared to another typical threshold of a 400-meter radius, the 500-meter radius also captures the effect that people are willing to walk longer for shopping trips than working trips (Yang and Diez-Roux, 2012).

4.5. Survey analysis

4.5.1. Structural equation model

To examine the impact of the on-street parking price change on user satisfaction, we assume that such impact is mediated by individual’s perceived quality of the parking: the change of parking price not only directly impacts individual satisfaction about the on-street parking, but also has indirect effects on the satisfaction by changing individual perception about on-street parking characteristics – including distance (the distance of the parking space to the final destination), price, and vacancy (how vacant is the on-street parking).

To do this, we run a structural equation model (SEM) that simultaneously estimates the direct and indirect impacts of the policy on user satisfaction. The indirect impacts are estimated via drivers’ perceived distance, price, and vacancy as mediated variables. The model controls all outcomes for individual demographics such as gender, age, income, private parking space ownership, parking payment source, etc. As the model does not include any latent variables, only the path analysis part of the SEM (mediation model) is constructed. Eq. (2–5) shows the construction of mediated variables and their error terms correlation structures.

$$M_d = a_d \cdot P + d_d \cdot X + e_d \tag{2}$$

$$M_p = a_p \cdot P + d_p \cdot X + e_p \tag{3}$$

$$M_v = a_v \cdot P + d_v \cdot X + e_v \tag{4}$$

$$e_d \sim \sim e_p, e_d \sim \sim e_v, e_p \sim \sim e_v, \tag{5}$$

where P is the exogenous variable representing the on-street parking price policy, and $P = 0$ for samples in 2014 and $P = 1$ for samples in 2015; M_d is the mediated variable ‘distance’, which measures the perceived distance from the parking space to the final destination; M_p is the mediated variable ‘price’ that measures the perceived price by the respondent; M_v is the mediated variable ‘vacancy’, which measures the perceived vacant space by the respondent; $a_d, a_p,$ and a_v indicate the effects of on-street parking price policy on the perceived distance, price, and vacancy, respectively. X are the control variables (e.g., gender, income, etc.) and $d_d, d_p,$ and d_v are corresponding parameters to estimate; e_d, e_p, e_v are the error terms and $e' \sim \sim e''$ represents e' and e'' are correlated.

Let Y be the user satisfaction of the on-street parking, where $Y = 0$ indicates that the user is unsatisfied with the parking and $Y = 1$

indicates that the user is satisfied; The typical SEM model requires the dependent variable to be continuous. However, the dependent variable Y in this study takes binary values. A conventional way to model binary (or ordinal) responses in SEM is assuming that there is an underlying unobserved continuous variable $Y^* \in (-\infty, +\infty)$ that drives the binary responses Y (Muthén, 1984; Yang-Wallentin et al., 2010). Then the measurement equation of Y^* can be assumed to follow the typical continuous form:

$$Y^* = b \cdot P + c_d \cdot M_d + c_p \cdot M_p + c_v \cdot M_v + d_y \cdot X + e_y \tag{6}$$

where e_y is a normally distributed error term with a mean of zero. b is the direct effect of on-street parking price policy on user satisfaction. c_d , c_p , and c_v are the effects of perceived distance, price, and vacancy on user satisfaction, respectively. Therefore, the indirect effect of on-street parking price policy on drivers’ satisfaction mediated via their perceived distance, price, and vacancy are $a_d \cdot c_d$, $a_p \cdot c_p$, and $a_v \cdot c_v$, respectively. The relationship between Y and Y^* can be expressed as

$$Y = 1 \Leftrightarrow Y^* > \tau, \quad \text{and} \quad Y = 0 \Leftrightarrow Y^* \leq \tau, \tag{7}$$

where τ is the threshold parameter to be estimated. The probability of observing $Y = 1$ can be expressed as:

$$\Pr(Y = 1) = \Pr(Y^* > \tau) = \int_{\tau - (b \cdot P + c_d \cdot M_d + c_p \cdot M_p + c_v \cdot M_v + d_y \cdot X)}^{+\infty} \phi_y(e) de \tag{8}$$

where $\phi_y(\cdot)$ is the probability density function of e_y . The model structure is summarized in Fig. 7.

The estimation of the binary form of the SEM has two steps. First, the threshold and polychoric correlations are estimated using a maximum likelihood estimation through bivariate contingency tables (Bollen, 1989; Jöreskog, 2005; Olsson, 1979). An estimated polychoric correlation captures the linear relationship between normal, latent response variables. Second, parameter estimates and the associated standard errors are obtained using the estimated asymptotic covariance matrix of the polychoric correlation and threshold estimates in a weight matrix to minimize the weighted least squares (WLS) fit function (Muthén, 1984). The model is estimated using the R package “lavaan” (Rosseel, 2012). It is worth noting that, instead of using the full weight matrix, “lavaan” only uses the diagonal elements for parameter estimation. This so-called diagonally weighted least squares (DWLS) method is mathematically simple and more flexible because it does not need the matrix to be positive-definite. Many previous studies have indicated the relative superiority of DWLS over WLS in the analysis of measurement models with binary or ordinal indicators (Flora and Curran, 2004; Kaplan, 2008; Muthén, 1993).

4.5.2. Logistic regression model

In addition to the SEM, we also apply a simpler and more direct binary logistic regression (BLR) model to estimate the effects of the policy intervention on drivers’ general satisfaction towards on-street parking. The construction of the BLR model is based on a parking utility assumption. Let U be a driver’s latent utility on his/her on-street parking service. We assume that a driver would be satisfied with the parking service if his/her U was bigger than an underlying threshold \bar{U} . This idea is in line with the typical utility maximization assumption in the discrete choice model (Ben-Akiva et al., 1985). Hence, the probability of observing $Y = 1$ can be expressed as:

$$\Pr(Y = 1) = \Pr(U > \bar{U}) \tag{9}$$

Assume that the utility of parking can be specified by a linear equation:

$$U = \alpha + \beta \cdot P + \gamma \cdot M + \theta \cdot X + e_u \tag{10}$$

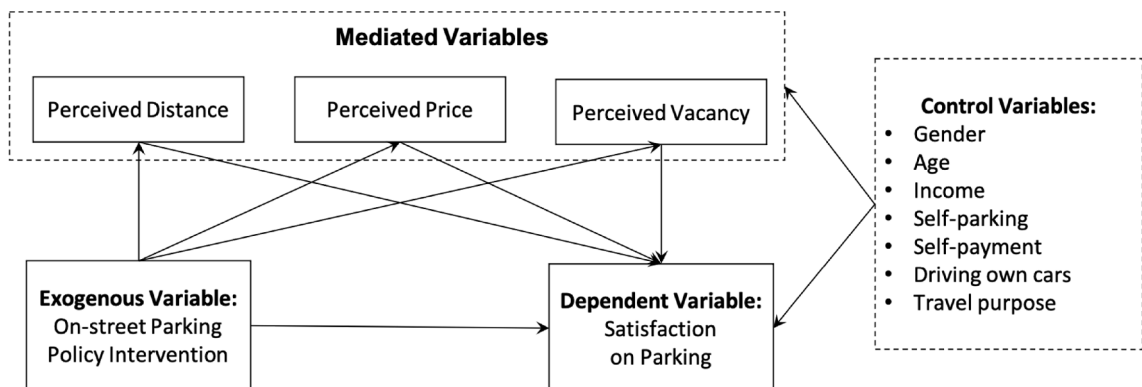


Fig. 7. Structure of the SEM.

where $M = [M_d, M_p, M_v]$ is the vector of the observed perceptions of distance, price, and vacancy. The tilde symbol is used to differentiate these observed values from variables in Section 4.5.1 (i.e., $\tilde{M}_d, \tilde{M}_p, \tilde{M}_v$), where M_d, M_p, M_v are random variables but $\tilde{M}_d, \tilde{M}_p, \tilde{M}_v$ are constants. $\alpha, \beta, \gamma,$ and θ are parameters to estimate. e_u is an error term with a mean of zero. Assume e_u follows a standard logistic distribution, we can express the satisfaction probability as:

$$\Pr(Y = 1) = \Pr(e_u > \bar{U} - \alpha - \beta \cdot P - \gamma \cdot M - \theta \cdot X) = \frac{1}{1 + \exp(\bar{U} - \alpha - \beta \cdot P - \gamma \cdot M - \theta \cdot X)} \tag{11}$$

which has the same form as a BLR model and can thus be easily estimated. The structure of the BLR model is summarized in Fig. 8.

Note that Eqs. (9)–(10) and Eqs. (7)–(8) show that the BLR model and SEM have similar specifications, implying that the estimated effects of $P, X,$ perceived distance, price, and vacancy on user’s satisfaction should be similar. This provides a way to crossly validate the estimation results. The differences between the BLR model and SEM are 1) BLR model only considers the direct effect of policy intervention on user satisfaction (represented by β), but SEM considers indirect effect using mediates of $M_d, M_p,$ and M_v ; and 2) the error term assumptions are different. The BLR model assumes e_u follows a standard logistic distribution while SEM assumes e_y is normally distributed.

5. Effects on parking demand

The impact of policy intervention on parking demand is analyzed from three perspectives: parking volumes, parking duration, and parking costs based on parking meter data. Results are further discussed from the city and subarea (i.e., different parking charging areas) levels.

5.1. Parking volume

5.1.1. City level

The increase in parking prices is expected to decrease the parking volume. Fig. 9 shows the RDD results of parking volume for all areas. It is worth noting that, though the policy is announced at the beginning of December 2014, the actual implementation of the policy requires an additional month (e.g., installing new devices, updating systems, etc.). Therefore, the treatment point is set at the end of December 2014. We observe that the ITE is around 206, which means, the number of parking vehicles in Nanning is decreased by 206 (13.3%) per day on average right after the policy implementation. The TES is also significantly different from 0, indicating that the policy has a continuous long-term impact over 8 months after its implementation. On average, the parking volume is decreased by 0.68 veh/day (after the instantaneous reduction of 206 veh/day). This suggests a long-term behavioral change of drivers such as switching to indoor parking lots and changing travel modes after the policy implementation, which is corresponding to the findings in Wang et al. (2020).

Fig. 10 shows the RDD results for parking volume by weekdays and weekends. Similarly, the ITEs are significant, indicating that the parking volume decreases right after the policy intervention. The reduction in weekdays is 12.5%, which is smaller than that on weekends (14.7%). This is as expected because the on-street parking demands on weekends are usually more elastic. Interestingly, we observe the TES is significant on weekdays but not on weekends. This implies that the continuous policy impact is mostly on weekday trips. Comparing the results of weekdays and weekends, we find that while weekend parking volume shows a higher instantaneous reduction (short-term effect) after the price increase, the long-term effect on weekday demand is stronger.

Though the TES in Figs. 9 and 10 shows the average temporal impact of policy adjustment, to analyze the detailed long-term effect each month after the policy adjustment, we plot the temporal parking volume distribution in Fig. 11. Before the policy implementation, the mean of parking volume was relatively stable over the four months. In Jan 2015, the first month of policy implementation, we

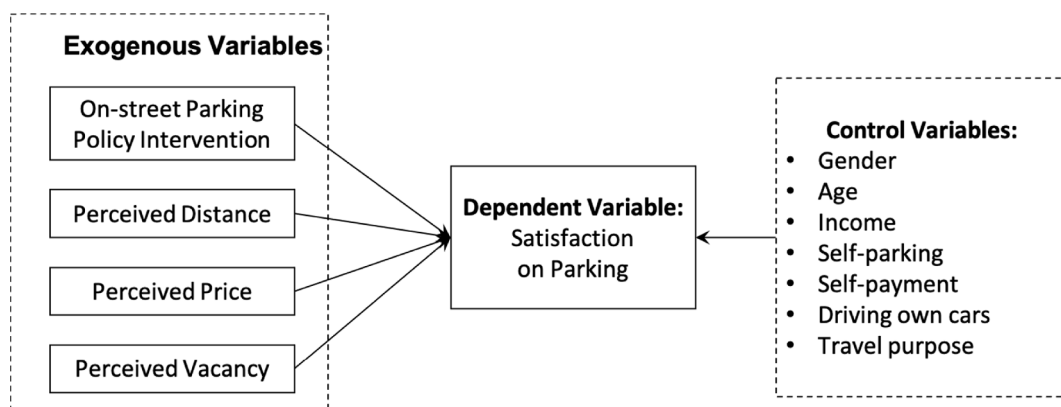


Fig. 8. Structure of the binary logistic regression model.

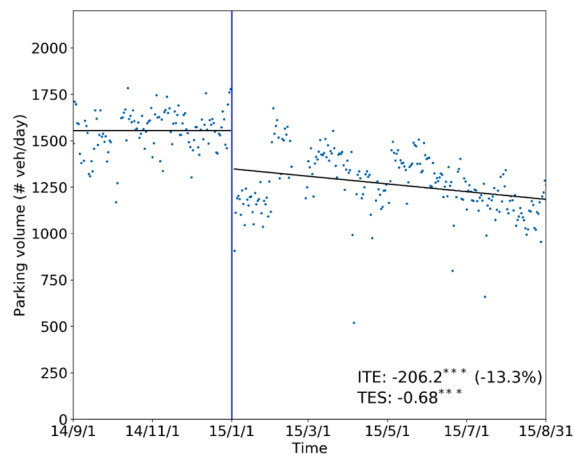


Fig. 9. RDD of parking volume. (***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$, same for the following figures).

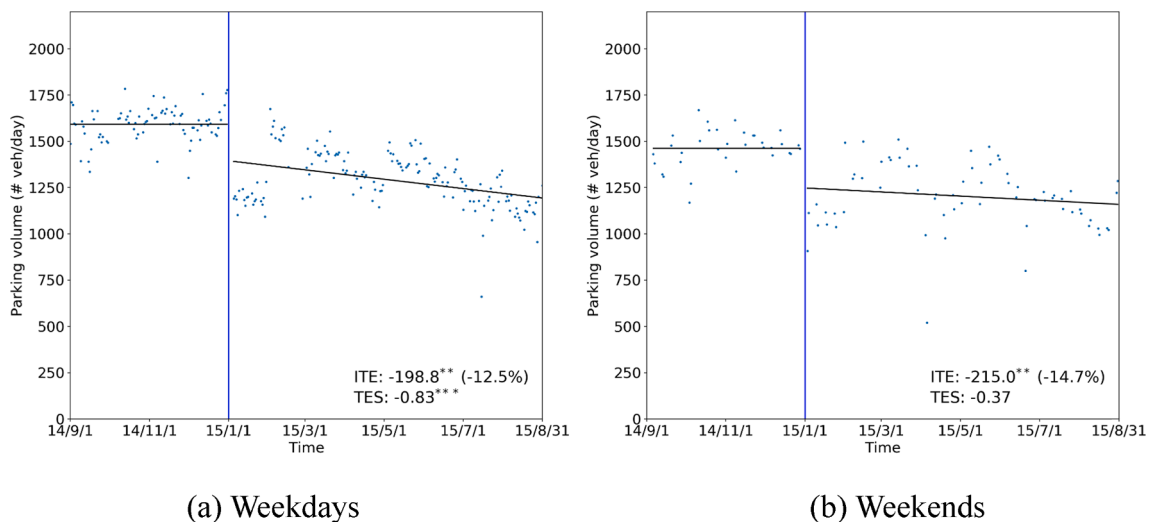


Fig. 10. RDD for parking volume for weekdays and weekends.

observed a plunge in parking volume, while the volume bounced back in the second month. This indicates that people had a dramatic immediate response to the policy, and gradually adapted to the new pricing after that. Similarly, we observe the parking volume continues to decrease over the 8 months after the policy intervention, implying a long-term policy impact.

Fig. 12 shows the time-of-day distribution of the daily parking volume for weekdays and weekends. The parking start time is used for the calculation. First of all, we observe the peaks of parking demand appear at 10:00 (referred to as morning peak) and 15:00 (referred to as afternoon peak), which is different from peaks of typical commuting trips as on-street parking usually associated with social activities happening in working hours. After the policy intervention, the parking volume is reduced for all billable hours for both weekdays and weekends. The reduction in the day time is larger than that in the early morning and late evening in terms of the absolute volume. Comparing the curves of weekdays and weekends, we find, though the distribution patterns are different (weekend curves have a lower afternoon peak), the impact of policy (i.e., reduction in volume) is similar.

5.1.2. Subarea level

Since the pricing changes for different sub-areas are different (see Table 1), it is worth analyzing the policy influence from the subarea’s perspective. Here we name subareas by X-Y, which means all streets that belong to type X before the policy adjustment and Y after ($X, Y \in \{A, B, C\}$). According to Table 2, only subareas A-A and B-A have enough parking record samples. Hence, we focus on the analysis of these two subareas in this section. Fig. 13 shows the bins of average daily parking volume before and after the policy intervention for different sub-areas. To test whether the changes after policy intervention is significant or not, a Kolmogorov-Smirnov (KS) test on two samples is conducted. We observe that after the policy intervention, there is significant parking volume reduction for both types of subareas. But the reduction in the B-A area is larger than that of the A-A area, which is reasonable because streets from B to A have a higher increase in parking price, hence higher demand reduction. The patterns between weekdays and weekends do not

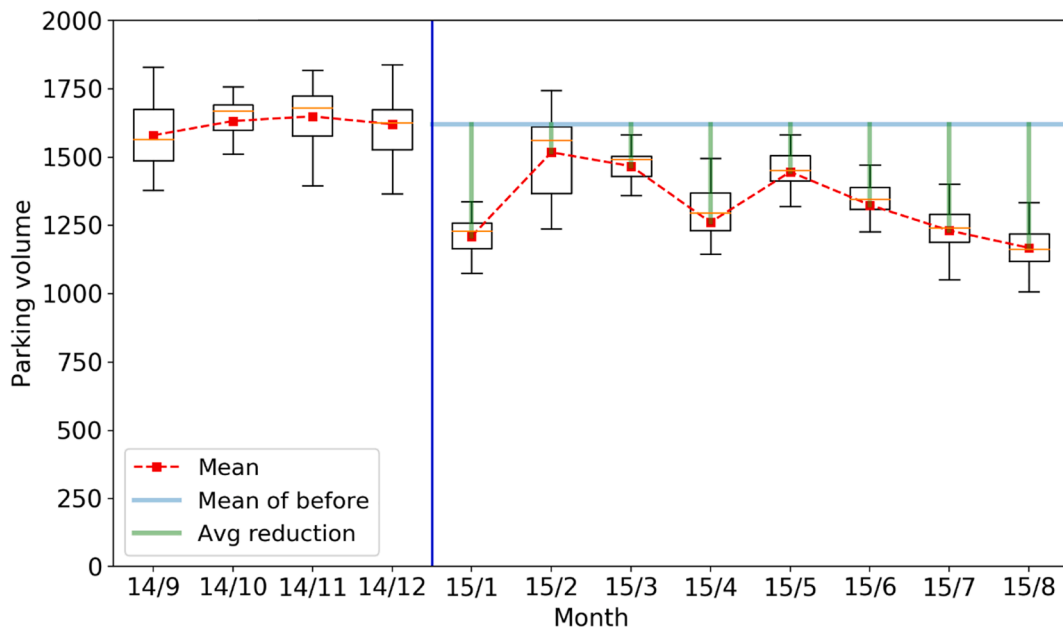


Fig. 11. Temporal distribution of parking volume before and after policy adjustment.

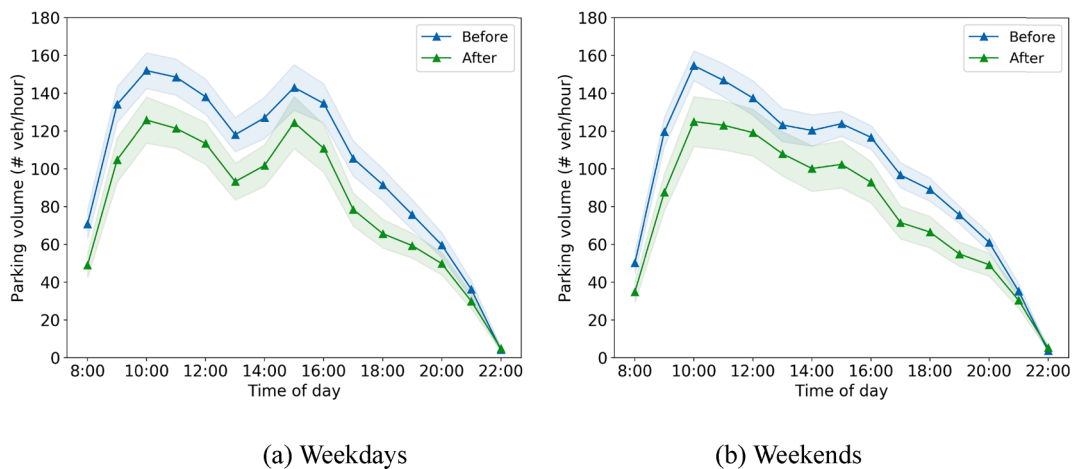


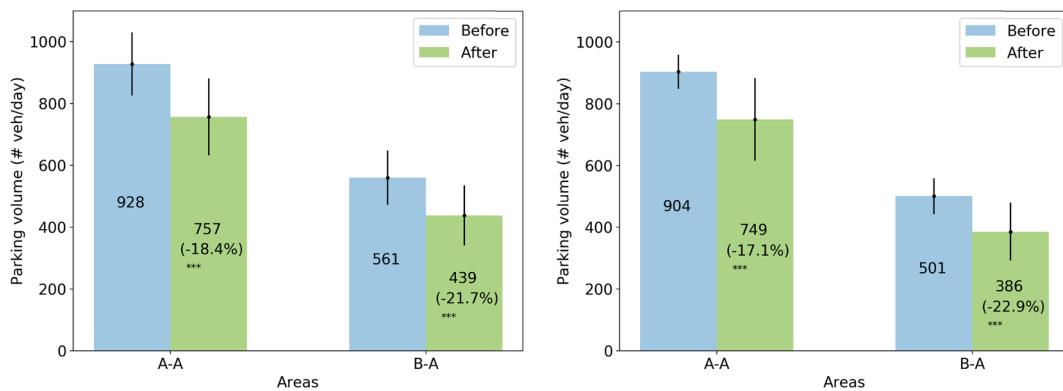
Fig. 12. Time of day distribution of parking volume (Shade: half of the standard deviation, same for the following graphs).

show much difference.

Fig. 14 shows the RDD results for the two types of subareas. For the A-A area, both ITE and TES are significant. And the average instantaneous reduction in parking volume is 127.5 veh/day (13.7%). As for the B-A area, we observe that only TES is significant (ITE not). And the scale of TES in B-A is greater than that of A-A. Recall that in Fig. 13 we observe that the average daily parking volume reduction is higher in B-A than in A-A. Hence, these RDD results imply that though the immediate policy influence in B-A is not significant, the long-term effect plays an important role and leads to a larger final decrease of parking demand than that of the A-A area. In summary, the short-term effect is more significant in the A-A area while the long-term effect is more significant in the B-A area. This may be due to people’s inertia of pricing schemes in the B-A area (i.e. they still have the impression of the low price before), which make drivers take a longer time to adapt.

Fig. 15 presents the time-of-day distribution of parking volume for different subareas. Similar to the results in Fig. 12, the price increment reduced the parking volume for all time periods. In terms of the B-A area, the decreasing amount in the day time (9:00–19:00) is relatively uniform. However, for the A-A area, the decrease in the afternoon peak is less than that in the morning peak, especially on weekdays.

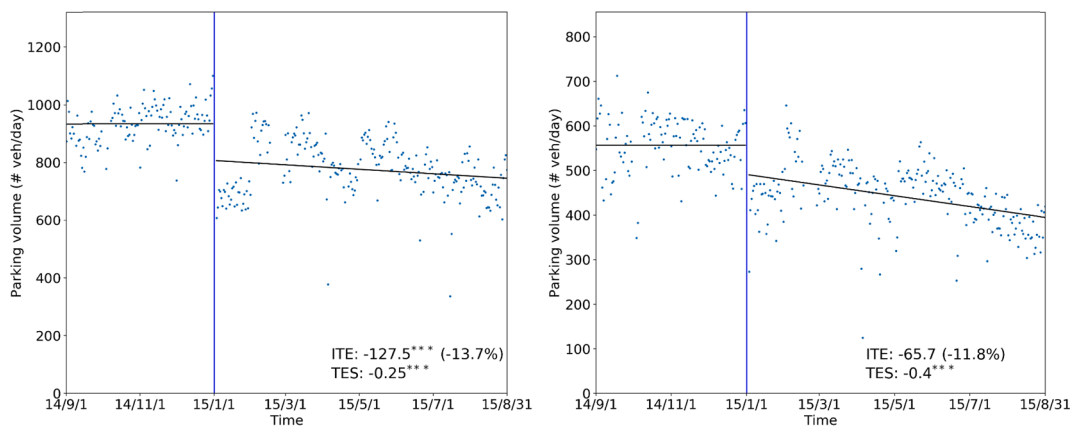
To better visualize the policy influence geographically, we plot the parking volume percentage change on the street level (Fig. 16). It is found that most of the streets have a reduction in parking volume, implying that policy intervention has a large scope of effect.



(a) Weekdays

(b) Weekends

Fig. 13. Average daily parking volume before and after policy adjustment (Black lines are standard deviation. The inner numbers are the values of each bin. Percentages are the changes after the policy adjustment. Stars indicate the p-values of the KS test, where ***: $p < 0.01$. Meanings of these labels are the same for the following figures with the same format).



(a) A-A

(b) B-A

Fig. 14. RDD results of parking volume for different subareas.

Roads with the highest decrease in parking volume are mostly located in the B-before area (i.e. B-A). Notably, area ① is a major residential area in Nanning and shows the highest volume reduction. This may be because there are usually alternative indoor parking lots (or garages) in the residential area that drivers can switch to. Area ② is a major business area where people highly relied on on-street parking. Thus, the parking volume reduction is relatively small (or even slightly increased). The high percentage of increase of road near area ① is mainly due to its low parking demand before (only 6.7 veh/day).

5.1.3. Trip level

The trip purpose is another important variable that affects the parking volume change. As the HPS and LPS trips are inferred based on the parking location and price adjustment is also related to parking locations, it is essential to control the price adjustment scheme when examining the impact of trip purpose. Hence, A-A and B-A areas should be analyzed separately such that within the same group all trips have the same parking price before and after the policy change.

Fig. 17 shows the comparison of parking volume for HPS and LPS trips. We observe that there are more HPS trips in the A-A area but less in the B-A area, which is reasonable because the A-A area is the CBD of Nanning with more shopping POIs. Notably, the relative parking volume reduction for HPS trips is higher than that of LPS trips, especially in the A-A area (-16.8% vs. -8.7%). This is as expected because shopping trips are generally more flexible and easier to be influenced by the price increase compared to other trips.

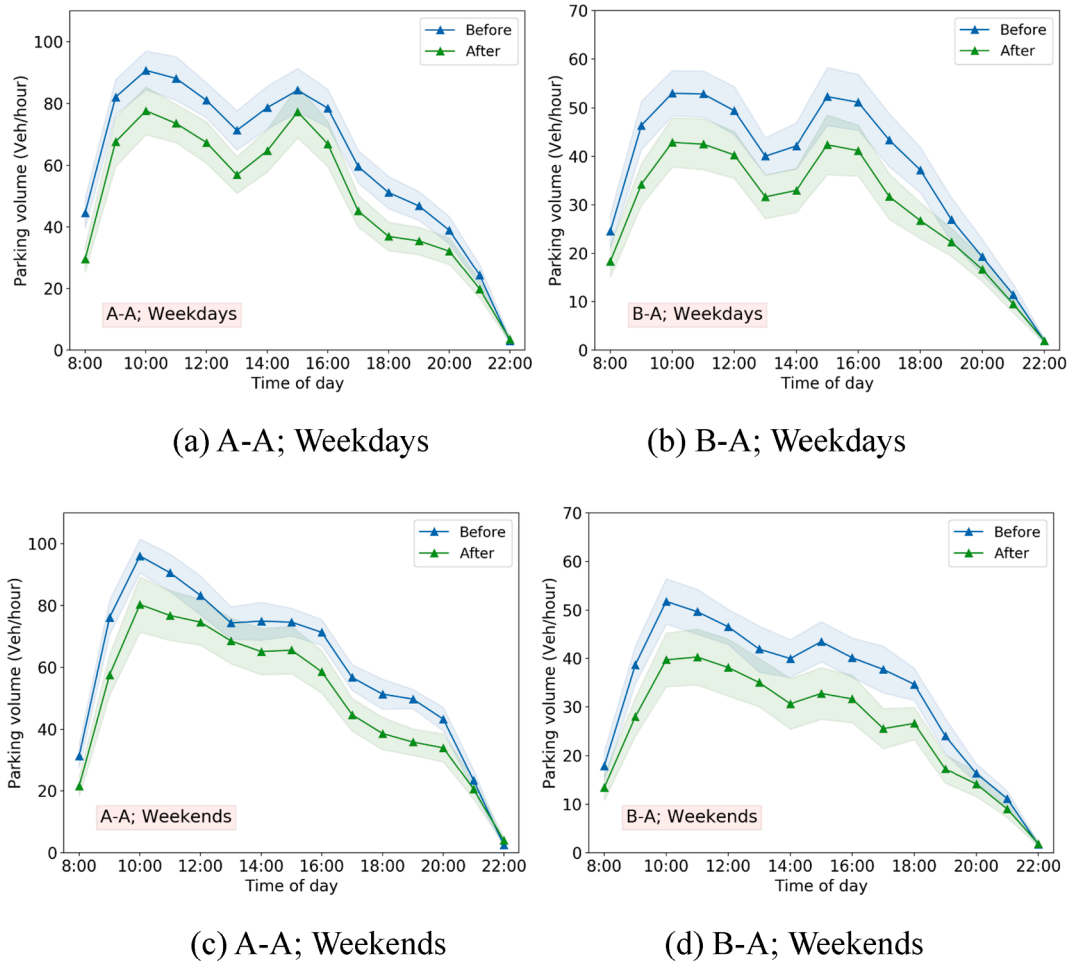


Fig. 15. Time of day distribution of parking volume for different subareas.

5.2. Parking duration

5.2.1. City level

Fig. 18 shows the RDD results of parking duration. It is observed that the ITE is significant while TES is not, indicating that the short-term effect is more prominent. On average, the parking duration was reduced by 6.3 min (10.7%) right after the policy intervention and got stable over the following months. However, we also find the decreasing trend starts in Dec 2014. This may be because the announcement of the policy started in Dec 2014. And during the time of infrastructure installation and updating, people began to respond to the policy and reduce the parking duration (while the parking volume does not show apparent reduction). The discrepancy of people’s behavioral responses on parking volume and duration indicating that at the early stage of policy implementation, people are more flexible in shortening their parking time than canceling the parking trips. However, in the long-term, they gradually canceled the parking trips but the average parking duration is not shortened.

Fig. 19 shows the temporal distribution of parking duration for each month. Similarly, we observe that the decrease of parking duration started in Dec 2014, and continued to decrease in Jan 2015, while slightly bounced back in Feb 2015. This may indicate that people usually have an immediate response to the policy, and gradually adapted to the new pricing after that (similar to the results of parking volume). After March 2015, the parking duration is relatively stable, implying the long-term effect is not significant. This may reflect that the reduction of average parking duration is limited due to the requirement of corresponding social activities.

Fig. 20 shows the time-of-day distribution of parking duration for weekdays and weekends. Firstly, the peaks of parking duration appear at 13:00 and 18:00, which is different from those of parking volume. These two peaks may correspond to the lunch and dinner activities, implying that dining may be the activity with the highest demand of duration for on-street parking. After the policy intervention, the parking duration for all time periods is reduced by around 5–10 min on average for both weekdays and weekends. We also find that the reduction in the morning is higher than that in the afternoon.

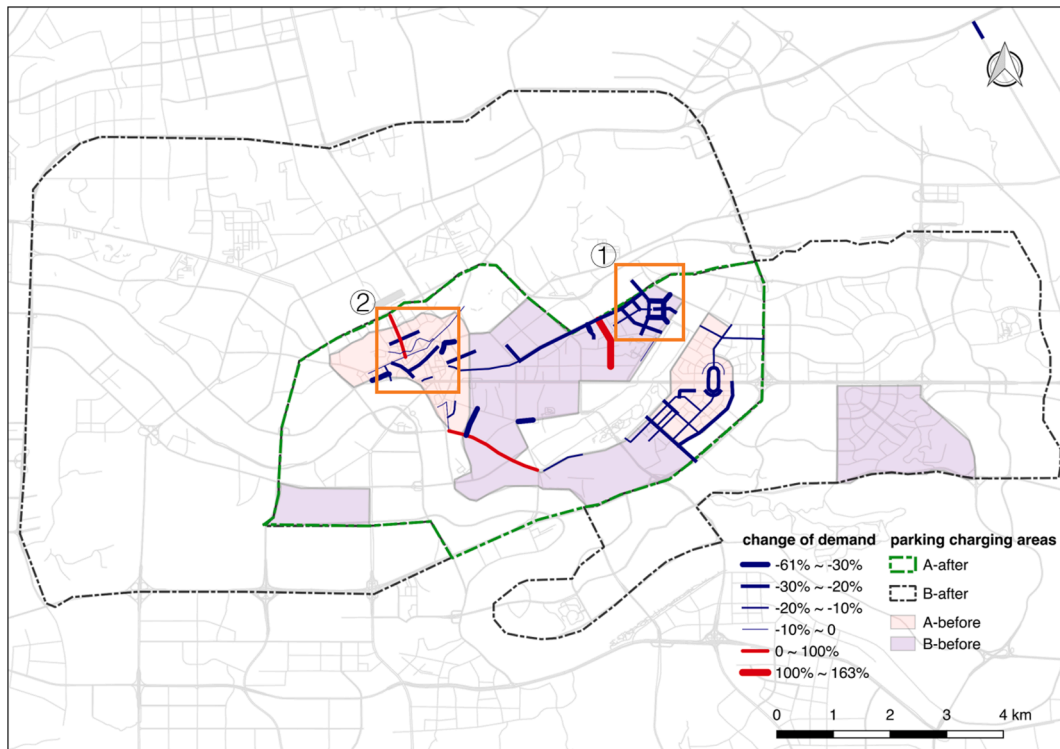


Fig. 16. Street-level parking volume percentage change.

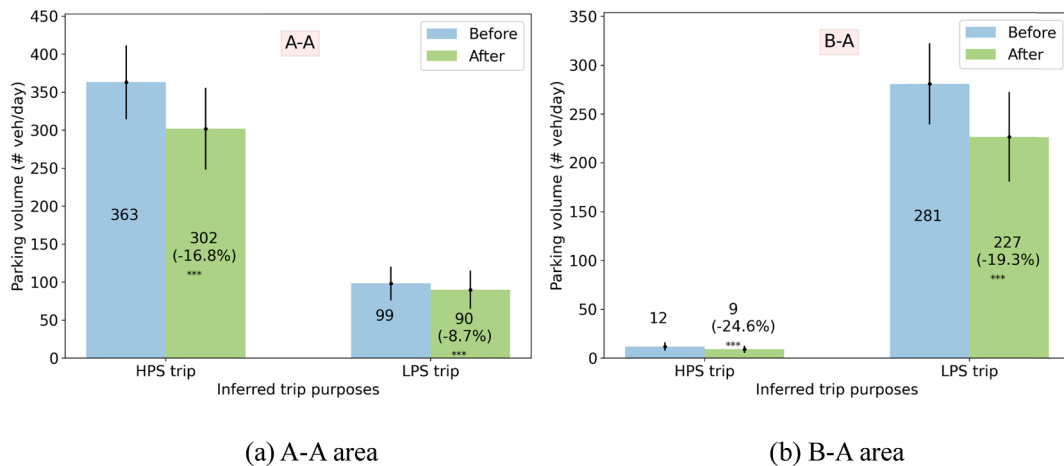


Fig. 17. Parking volume change by inferred trip purposes.

5.2.2. Subarea level

Fig. 21 shows the comparison of the average parking duration before and after the policy adjustment. Firstly, we observe that there is a significant reduction in average parking duration after the policy for all subareas. Similar to the results of parking volume, the reduction in the B-A area is larger than that of the A-A area, which is as expected because the pricing increment in B-A areas is higher. From the comparison between weekdays and weekends, we observe that the parking duration has a higher percentage reduction on weekends. This may be because activities on weekends are usually more flexible in terms of duration.

Fig. 22 presents the RDD results for the two types of subareas. Similar to the results at the city level, the ITE is significant while TES not. The ITE for the A-A area (-6.5 min) is slightly larger than that of the B-A area (-5.6 min). The street-level parking duration percentage change is shown in Fig. 23. What stands out in the graph is that the parking duration of most of the streets decreases due to the policy intervention. And the reduction in residential areas (area ①) is higher than that of business areas (area ②), probably owing to the alternative indoor parking sources provided in area ①.

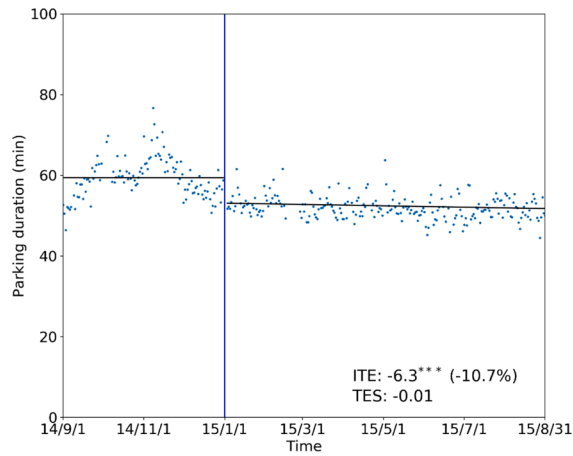


Fig. 18. RDD of parking duration.

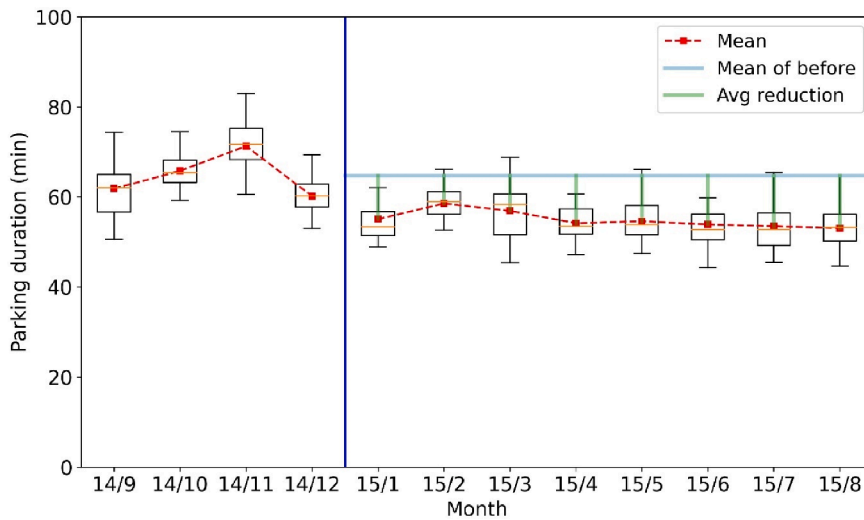
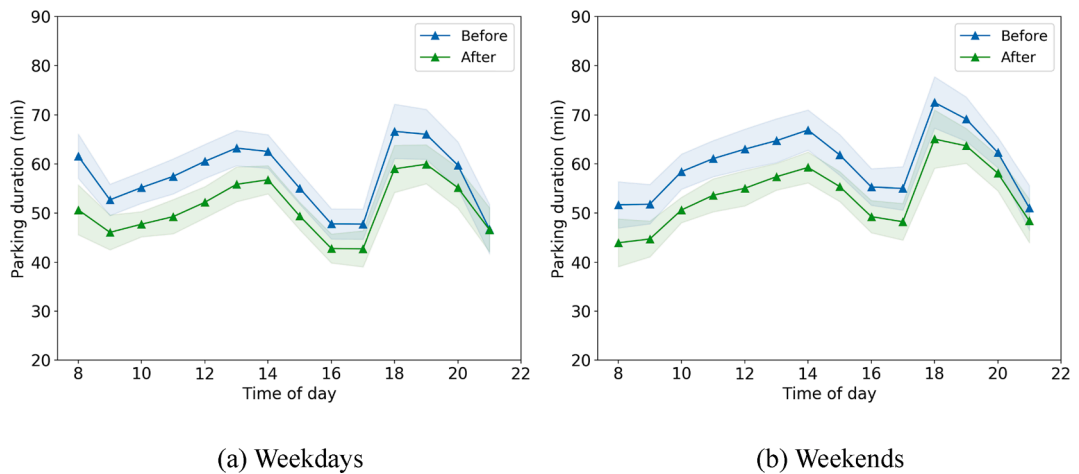


Fig. 19. Temporal distribution of parking duration before and after policy adjustment.



(a) Weekdays

(b) Weekends

Fig. 20. Time of day distribution of parking duration.

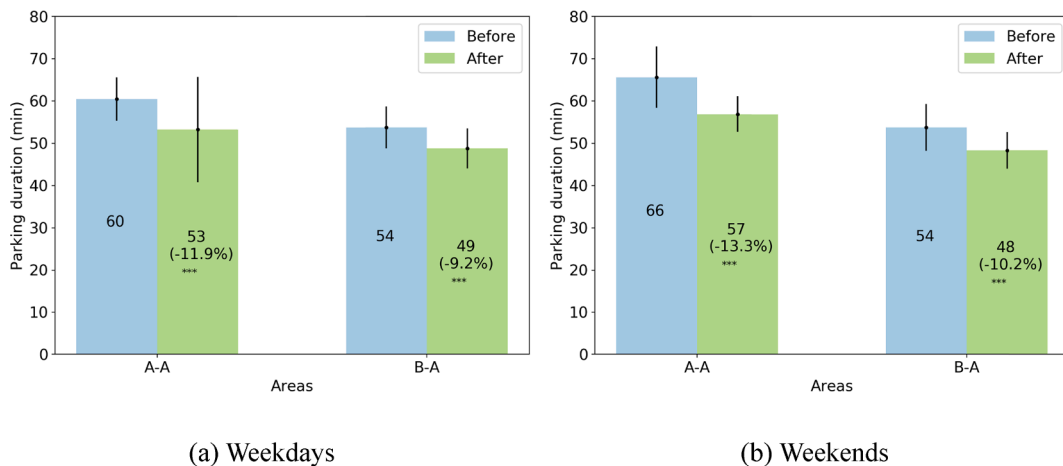


Fig. 21. Average parking duration before and after policy adjustment.

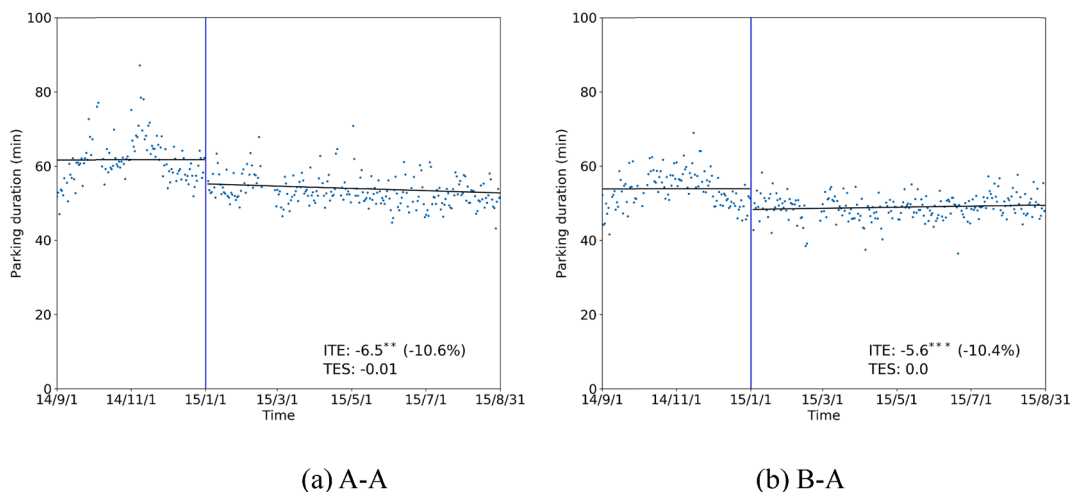


Fig. 22. RDD results of parking duration for different subareas.

5.2.3. Trip level

We evaluate the impact of trip purpose on parking duration (Fig. 24). We observe that for both A-A and B-A areas, the relative parking duration reduction for HPS trips is higher than that of LPS trips, which is as expected with the same reason as Section 5.1.3.

At the trip level, we plot the parking duration distribution before and after the policy adjustment (Fig. 25). Fig. 25(a) is plotted using the full meter data set (i.e., 4-month trips before and 8-month trips after), showing the general duration distribution patterns. We observe that the parking duration follows a single-peak and long-tail distribution, similar to many other real-world distribution patterns such as commute travel time (Mo et al., 2021). The distribution patterns before and after the policy adjustment are similar. The mean average parking time is decreased from 56.4 min to 49.9 min. Besides, the peak of parking duration after the policy intervention moves slightly forward to a time just smaller than 15 min. This is due to the 15-minute step-wise pricing scheme (see Table 1) where drivers tend to shrink their parking time such that they don't pay for too much unused time.

The effect of parking duration clustering just under each pricing time interval should exist for multiple pricing boundaries. However, due to the randomness of parking duration patterns across different days (caused by exogenous factors such as day of the week, weather, drivers' behavioral uncertainty, etc.), the clustering effect in Fig. 25(a) is not obvious. Therefore, in Fig. 25(b), we plot the parking duration distribution using a weekday in 2014 Sep (before adjustment) and a weekday in 2015 Aug (after adjustment). We observe that before the price adjustment, there are many duration concentrations just under each 30-minute boundary. As the price before is step-wise based on 30-minute intervals. After the price adjustment, the step-wise pricing is on a 15-minute basis. Many small peaks are observed at the times just under each 15-minute boundary.

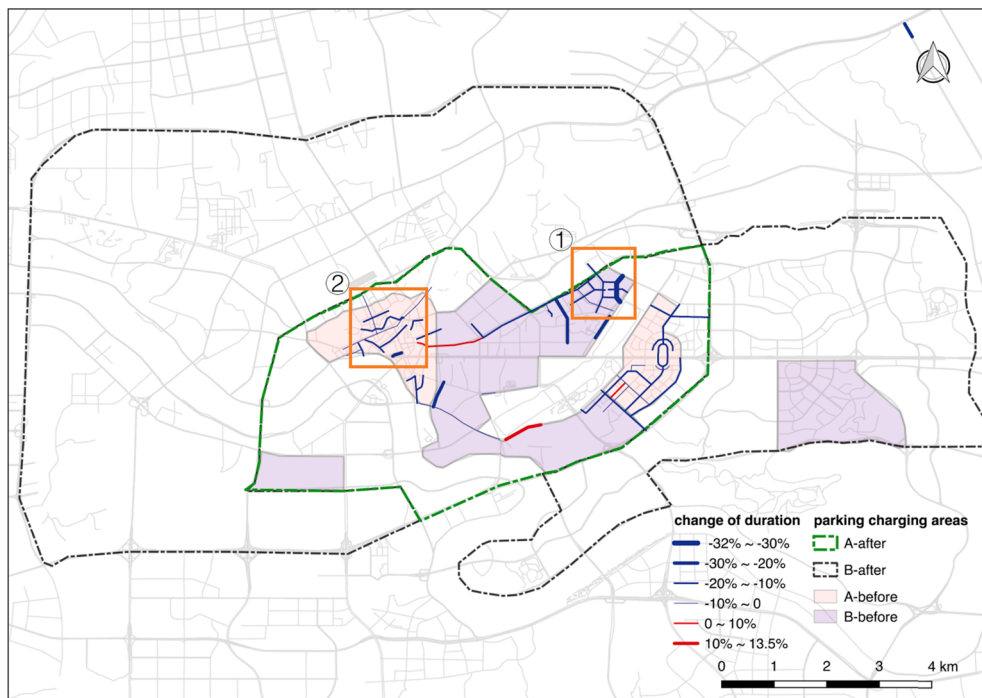


Fig. 23. Street-level parking duration percentage change.

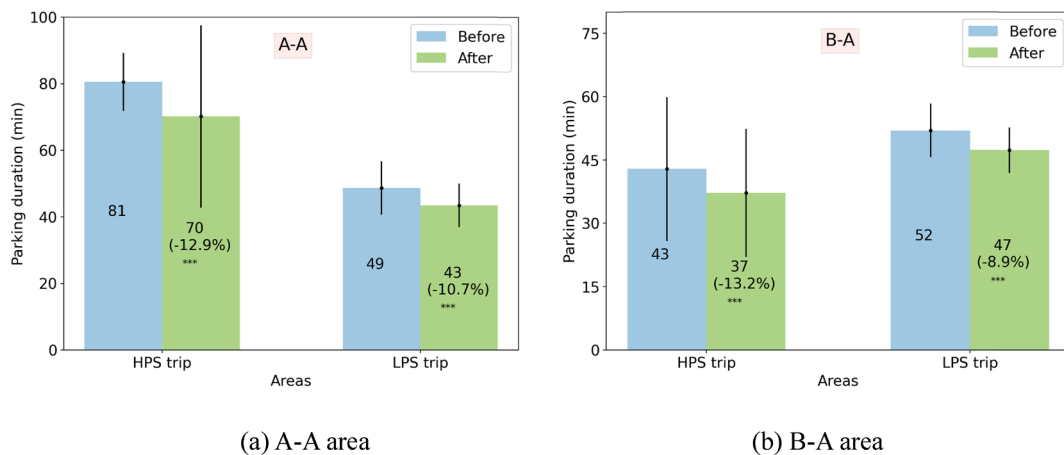
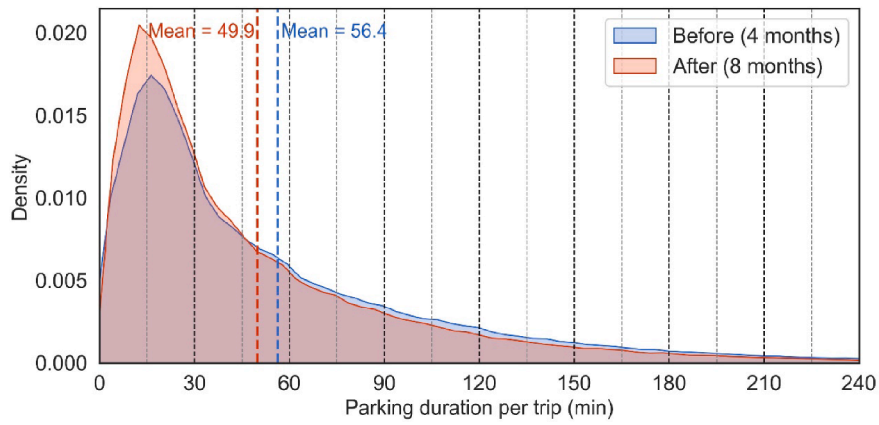


Fig. 24. Parking duration change by inferred trip purposes.

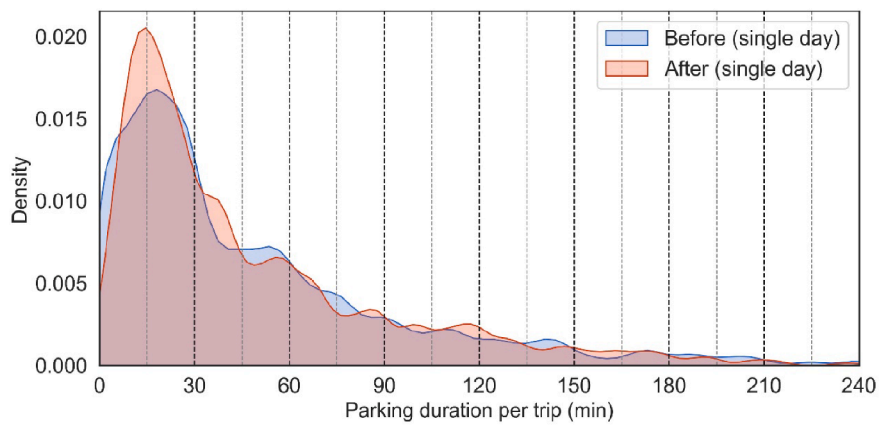
5.3. Parking costs

The parking cost (per trip) distribution is shown in Fig. 26. Generally, drivers need to pay more for parking after the price adjustment. The mean parking cost before the policy is RMB 6.7, while after is RMB 9.5. Combining the results in Section 5.2, we may conclude that the price adjustment harms the benefits of drivers who rely on on-street parking. These drivers parked for a shorter duration and paid a higher price for each trip.

Since the average parking cost per trip increased and the parking volume decreased after the policy, it is worth analyzing the total daily parking cost (i.e., parking volume per day multiplied by parking cost per trip) because it reflects the total revenue of the government. Fig. 27 presents the daily parking cost comparison before and after the policy intervention by different subareas. We observe that the total parking costs per day increased despite there being fewer parking trips per day and a reduction in average parking duration. Owing to the higher price increase in B-A areas, the daily parking cost increase in B-A areas is higher than that in A-A areas.



(a) Full data set



(b) Selected weekdays

Fig. 25. Parking duration distribution (The dashed lines indicate every 15 and 30 min).

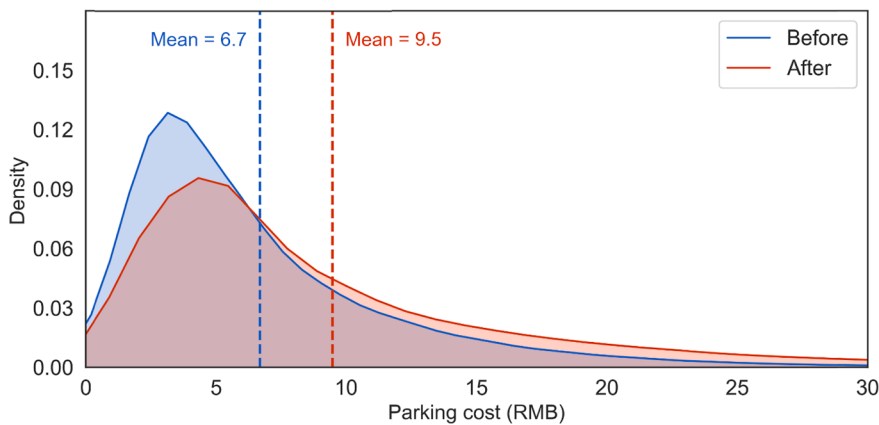


Fig. 26. Parking cost (per trip) distribution before and after the policy adjustment.

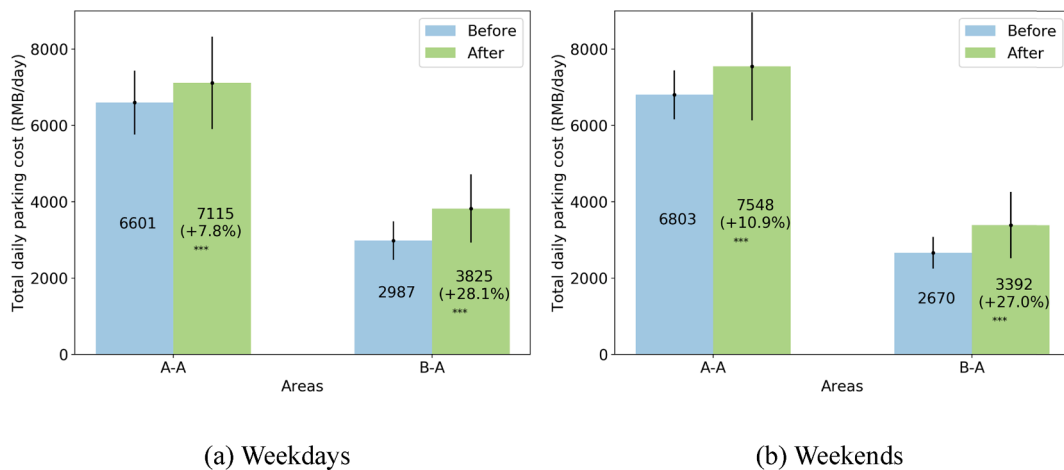


Fig. 27. Total daily parking costs before and after policy adjustment.

Table 5
Results of the SEM model.

| | Model 1: SEM | | | | Model 2: BLR |
|---|--------------------|-----------------|-------------------|--------------|--------------|
| | Perceived distance | Perceived price | Perceived vacancy | Satisfaction | |
| Policy intervention (Yes = 1) | -0.249*** | 0.073* | 0.075** | 0.126*** | 0.198*** |
| Perceived distance | - | - | - | -0.403*** | -0.392*** |
| Perceived price | - | - | - | 0.146*** | 0.149*** |
| Perceived vacancy | - | - | - | 0.227*** | 0.269*** |
| Male (Yes = 1) | -0.026 | -0.016 | -0.040 | 0.030 | 0.037 |
| Age < 40 (Yes = 1) | -0.005 | 0.042 | 0.132*** | -0.003 | -0.007 |
| Monthly income (RMB) | 0.089** | -0.014 | 0.059* | -0.020 | -0.040 |
| Private parking space ownership (Yes = 1) | -0.091** | -0.085** | 0.035 | -0.097** | -0.111** |
| Self-payment (Yes = 1) | 0.014 | 0.041 | -0.003 | 0.218*** | 0.359*** |
| Working trip (Yes = 1) | 0.000 | -0.030 | -0.025 | -0.047 | -0.060 |
| Driving your own car (Yes = 1) | -0.133*** | 0.077* | 0.119*** | 0.241*** | 0.318*** |
| R ² | 0.084 | 0.016 | 0.043 | 0.461 | 0.253 |

Note: *** = significant at 0.001 level; ** = significant at 0.01 level; * = significant at 0.05 level.

6. Effects on parking satisfaction

This section discusses the influence of policy adjustment on drivers' parking satisfaction based on the survey results. SEM and BLR models are applied to analyze the survey data. Since all variables used in this study are directly observed, the SEM construction is a simple mediation path model (without any latent variables). Hence, there is no need to conduct the Confirmatory Factor Analysis (CFA) as the model is just-identified. The results of the SEM (model 1) and BLR (model 2) are represented in Table 5. Standardized coefficients are reported for both models to enable the comparison of results, and the equation-by-equation R² is reported as an indicator of the model predictability.

Several conclusions could be drawn from the SEM results. First, the coefficients of the on-street parking price policy intervention on users' general satisfaction are positive and significant at the 0.001 level. Therefore, the direct effect of the change of parking price on satisfaction is positive. This is corresponding to the findings from Fig. 5. The possible reason is that as price increases, the remaining drivers generally have higher income and are more sensitive to service quality (i.e., distance and vacancy) instead of price.

Second, the parking price policy intervention is negatively correlated with drivers' perceived distance from parking space to the final destination, and the standardized coefficient (-0.249) is greater than that of the price (0.073) and vacancy (0.075), indicating that as the parking charging increases, drivers perceive that their parking location is closer to the final destination than before. This finding is in accordance with Fig. 6b, which may be because the increase in parking price reduced parking demand and it was easier for drivers to find close on-street parking lots. On the other hand, the association between perceived distance and overall satisfaction is significantly negative (-0.403), indicating that the longer distance from the parking space to the final destination is associated with lower satisfaction towards parking. Therefore, the indirect effect of the parking price policy intervention on user satisfaction via perceived distance is positive ((-0.249) × (-0.403) = 0.100), indicating the change of parking price is also indirectly associated with higher user satisfaction via the mediated effect of reducing perceived distance.

The coefficient of parking price policy intervention on drivers' perceived price is positive (0.073) and significant at 0.05 level, indicating that after the implementation of price change, drivers tend to feel that the parking price is higher than before. This result

makes sense as the policy increases the cost of parking in most areas. On the other hand, the coefficient of the perceived price's direct effect on the overall satisfaction is significantly positive (0.146). Therefore, the indirect effect of the parking price policy intervention on user satisfaction via perceived price is positive ($0.073 * 0.146 = 0.011$).

The association between the parking price policy intervention and drivers' perceived vacancy of parking space is positive (0.075) and significant at 0.01 level. This implies that after the policy intervention, people tend to feel that there are more vacant parking spaces. The reduction of parking volume and duration as a reaction to the increase of parking charge, as has been demonstrated in Sections 5.1 and 5.2, may explain the perception of higher parking vacancy after the policy intervention. This finding is also in line with Fig. 6c. Also, the perception of higher parking vacancy is associated with higher satisfaction, illustrated by the positive coefficient of the perceived vacancy on satisfaction (0.227). Therefore, the indirect effect of policy intervention on satisfaction via perceived vacancy is positive ($0.075 * 0.227 = 0.017$), indicating that the increase of parking charging is indirectly associated with higher satisfaction mediated by the perception of higher parking vacancy.

As for the associations between other socio-demographic variables and the perceived distance, price, and vacancy, results reflect that respondents younger than 40 are more likely to feel that the parking space is vacant. This may be because finding a vacant parking place is less costly for younger people. Monthly income is positively correlated with drivers' perceived distance and vacancy, indicating that respondents with higher income tend to feel that the distance of the parking space is far away from their final destination, but there is enough vacant space available. This finding also indicates that the high-income population may have higher requirements for the quality of parking, especially for the distance. The correlations between private parking space ownership with distance and price are negative. This indicates that respondents who own a private parking space tend to feel that the distance of parking space is closer to their final destination and the parking price is lower, compared to the respondents that do not own any private parking space. Respondents who drive their own cars tend to have a lower perceived distance of parking space to their final destination and a higher parking vacancy, but they are also more likely to have a higher perceived parking price.

Regarding the associations between other socio-demographic variables and the overall satisfaction, an interesting finding is that respondents who own the private parking space tend to have a lower satisfaction towards the on-street parking compared to those who do not have private parking space. This makes sense as people who have private parking spaces are more likely to have a higher expectation of parking. On the other hand, drivers who pay for the parking by themselves and who drive their own cars tend to have a higher satisfaction towards parking. This may be because these drivers have more options for parking locations than drivers getting parking reimbursement from employers or not driving their own cars, as the latter group of drivers usually have to park at fixed parking spaces or at parking lots that can provide the receipt for their reimbursement.

The BLR model (model 2) returns similar results to SEM. All the variables have the same significance level and the same direction effects as the SEM results, with only a slight difference in the magnitude of the coefficients. This indicates the robustness of our findings from the two models.

7. Discussion and implications

7.1. Discussion for the policy adjustment

An on-street parking charging scheme with stratified prices is a powerful tool for parking management (Barter, 2010). Careful considerations are required for new pricing policies. The study case in Nanning provides us an opportunity to empirically analyze the impact of price increment on on-street parking and is enlightening for future related policy makings.

From the driver's perspective, as the results in Section 5, the parking volume and duration decreased significantly after the new policy application, and total parking costs became higher. The benefits of drivers are sacrificed and transferred to the revenue of the supply (i.e., government) side. Considering the heterogeneous demand elasticity with respect to price among drivers, a shift of parking demand to people with higher incomes is observed (see Fig. 4). This suggests that low-income people may be forced to change parking places, or even change their travel modes, which may lead to some equity concerns. We also observe a significant increase in perceived

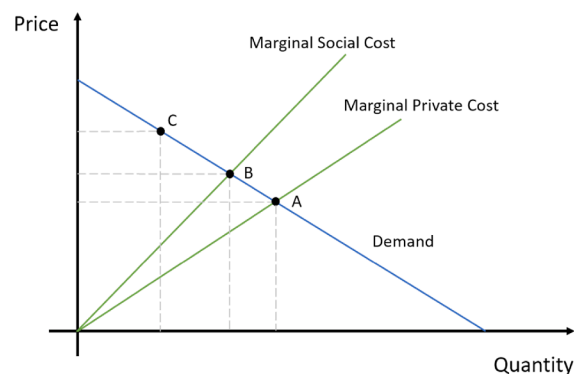


Fig. 28. Illustration diagram of the parking market.

parking prices. Therefore, on the consumer side, the new policy does harm their benefits with increased parking costs and decreased parking duration.

However, every coin has two sides. From the government perspective, the increased parking price brings more direct revenues from providing public services (see Section 5.3). More importantly, since most of the drivers tend to park for a shorter time (see Section 5.2), it may have the potentials to separate the function of on-street parking facilities and off-street parking facilities (e.g., underground garage), where the on-street facilities mainly serve for short-term parking and off-street parking mainly serve for long-term parking, hence enhancing the operational efficiency of both services. Service quality can also be increased as the result of the price increase as we observe a closer distance from parking lots to final destinations and a more vacant parking space. In the meanwhile, the decreased on-street parking demand may also result in a decrease in the number of vehicles entering the central area, which thereby reduces traffic congestion, emissions, noise, and increases traffic safety. These positive externalities may compensate for the loss of drivers' benefits and lead to better total social welfare.

The tradeoff between social equity and efficiency has been revealed in many transportation-related fields (Shi and Zhou, 2012). The parking service is not an exception. Based on the above analysis, the new pricing policy pushed the balance to the side of efficiency. However, whether this adjustment is socially effective or not depends on the comprehensive evaluation of social welfare. It is possible that the market condition before the policy adjustment is around the intersection of the marginal *private* cost curve and demand curve (point A in Fig. 28), while the market condition after the policy adjustment is around the intersection of the marginal *social* cost curve and demand curve (point B in Fig. 28). The increase of price pushing the market from point A to point B, which improves the total social benefits. However, it is also possible that the new market condition is pushed beyond the optimal point (the price increment is too high, e.g., point C in Fig. 28), resulting in social ineffectiveness. Future research could be done to quantify the impact of the new policy in terms of social welfare.

7.2. Implications for practice

The results of this study have several policy implications. First, because there are benefits transferred from drivers to governments, future actions could be done to transfer the benefits back to citizens. For example, the additional revenue from providing parking services could be used to improve the quality of public transit, construct the bike and passenger lanes, build more off-parking facilities, and improve urban greening. In this way, the use of private cars could be reduced, which is usually the goal of the parking price increase, while at the same time people are provided with better transportation facilities and more alternative travel modes. Second, though we observe that the overall satisfaction is increased, this is mostly due to sampling bias as low-income drivers may not use on-street parking after the policy adjustment. Therefore, considering the need to improve social equity and preserve the benefits of the low-income population, some subsidy policies should be implemented for low-income drivers. Moreover, as the demand for parking varies across times of a day, the current time-fixed pricing change policy may not be the best match for the dynamic parking demand. A temporally dynamic pricing scheme can be designed based on demand prediction to better utilize on-street parking sources.

8. Conclusions

Understanding the pricing policy effect is important for on-street parking management. This study investigates the impact of the on-street parking price adjustment with a case study in Nanning. Parking meter data and survey data are used to analyze the impact of the policy intervention on parking demand and parking satisfaction, respectively. Results show that the increase in pricing significantly decreases the parking volume (by around 20%) and parking duration (by around 10%). Drivers' parking costs are also increased. The influence varies across different sub-areas and days of the week. After the policy adjustment, people generally feel that the parking price is higher, the distance of parking lots to the final destination is closer, and the parking lots are more vacant. Parking drivers after the policy intervention have higher incomes. As they are less sensitive to the price but more on quality, the overall parking satisfaction is increased.

Some limitations exist in this study. First, the satisfaction score is collected with a yes/no question, which may cause information loss of users' attitudes. Future research may have a better survey design and collect indicator questions to better estimate the model. Second, there is a tendency to sample more high-income people after policy adjustment. Future research can collect samples using off-street parking and control the sample's demographic distributions for two surveys to avoid sample bias. Third, this study did not control some external factors for RDD (such as GDP, city car ownership) due to lack of data. This may cause estimation errors to policy effects. Future studies can collect more data to better quantify policy influence. Fourth, the surveys analyzed in this study were conducted five years ago, which may reduce the timely effectiveness of this article. Though the discussion and implications are still helpful for today's policy design, follow-up research can be done using more recent pricing policy cases.

Based on the results of the study, future studies can explore the following directions. 1) Quantify the social welfare changes of the policy. As we discussed in Section 7.1, there are benefits transferred from drivers to the government, but we are unaware of the change of total social welfare. More data can be collected to calculate the externalities brought by the policy and better evaluate the policy. Specifically, the reduction in congestion and emissions can be measured by the traffic flow data, such as license plate recognition data (Mo et al., 2020, 2017) and GPS data (Gately et al., 2017), etc. 2) Design demand-based dynamic pricing strategies. Results in the study indicate the various demand elasticity and flexibility by the time of days. A dynamic pricing scheme can help to better utilize the resources and improve user satisfaction. 3) Conduct a stated preference survey to examine the effects of a parking price change and some parking characteristics (e.g., vacancy rate) on drivers' parking location choice. The policy intervention may affect drivers' parking location choice, which then changes the vacancy rate in on-street parking facilities. However, the changes in vacancy rate may

in turn influence the driver's location choice. The interaction and endogeneity between these two variables need careful survey design techniques to uncover the causality. Moreover, their relationship to drivers' parking satisfaction may also be incorporated in the future.

CRedit authorship contribution statement

Baichuan Mo: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Hui Kong:** Methodology, Software, Formal analysis, Data curation, Visualization, Writing - original draft, Writing - review & editing. **Hao Wang:** Investigation, Resources. **Xiaokun (Cara) Wang:** Conceptualization, Writing - review & editing. **Ruimin Li:** Conceptualization, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The authors thank the National Natural Science Foundation of China (71361130015) and the Collaborative Innovation Center for Capital World City's Smooth Traffic Construction for sponsoring and supporting this study.

References

- Adebambo, S., Adebayo, I.T., 2009. Impact of bus rapid transit system (BRT) on passengers' satisfaction in Lagos Metropolis, Nigeria. *Int. J. Creat. Tech. Dev.* 1, 106–119.
- Albert, G., Mahaleh, D., 2006. Congestion tolls and parking fees: A comparison of the potential effect on travel behavior. *Transp. Policy* 13, 496–502.
- Ali, F., Dey, B.L., Filieri, R., 2015. An assessment of service quality and resulting customer satisfaction in Pakistan International Airlines. *Int. J. Qual. Reliab. Manag.*
- Amer, A., Chow, J.Y.J., 2017. A downtown on-street parking model with urban truck delivery behavior. *Transp. Res. Part A Policy Pract.* 102, 51–67.
- Angrist, J.D., Pischke, J.-S., 2008. *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.
- Barter, P.A., 2010. Parking policy in Asian cities. *Lee Kuan Yew Sch. Public Policy Res. Pap. No. LKYSPP 10–15*.
- Becker, N., Carmi, N., 2019. Changing trip behavior in a higher education institution: The role of parking fees. *Int. J. Sustain. Transp.* 13, 268–277.
- Beijing Municipal Commission of Transport, 2017. *Beijing parking resource survey report*.
- Ben-Akiva, M.E., Lerman, S.R., Lerman, S.R., 1985. *Discrete choice analysis: theory and application to travel demand*. MIT Press.
- Bollen, K.A., 1989. A new incremental fit index for general structural equation models. *Sociol. Methods Res.* 17, 303–316.
- Budiani, S.R., Iffani, M., Novianti, I., Alfana, M.A.F., Harini, R., Roñi, A., 2018. User satisfaction level of parking space facility: a case of Faculty of Geography, Universitas Gadjah Mada, Indonesia. *E&ES* 148, 12012.
- Cain, A., Burris, M.W., Pendyala, R.M., 2001. Impact of variable pricing on temporal distribution of travel demand. *Transp. Res. Rec.* 1747, 36–43.
- Calthrop, E., Proost, S., Van Dender, K., 2000. Parking policies and road pricing. *Urban Stud.* 37, 63–76.
- Carpio-Pinedo, J., 2014. Urban bus demand forecast at stop level: Space Syntax and other built environment factors. Evidence from Madrid. *Procedia-Social Behav. Sci.* 160, 205–214.
- Cats, O., Zhang, C., Nissán, A., 2016. Survey methodology for measuring parking occupancy: Impacts of an on-street parking pricing scheme in an urban center. *Transp. Policy* 47, 55–63.
- Clemes, M.D., Gan, C., Kao, T.-H., Choong, M., 2008. An empirical analysis of customer satisfaction in international air travel. *Innov. Mark.* 4, 50–62.
- Eboli, L., Mazzulla, G., 2015. Relationships between rail passengers' satisfaction and service quality: a framework for identifying key service factors. *Public Transp.* 7, 185–201.
- Flora, D.B., Curran, P.J., 2004. An empirical evaluation of alternative methods of estimation for confirmatory factor analysis with ordinal data. *Psychol. Methods* 9, 466.
- Fosgerau, M., De Palma, A., 2013. The dynamics of urban traffic congestion and the price of parking. *J. Public Econ.* 105, 106–115.
- Gately, C.K., Hutyra, L.R., Peterson, S., Wing, I.S., 2017. Urban emissions hotspots: Quantifying vehicle congestion and air pollution using mobile phone GPS data. *Environ. Pollut.* 229, 496–504.
- Givoni, M., Rietveld, P., 2007. The access journey to the railway station and its role in passengers' satisfaction with rail travel. *Transp. Policy* 14, 357–365.
- Gumasing, M.J.J., Atienza, C.A.V., 2018. A design of automated parking system for shopping centers in Metro Manila. In: 2018 5th International Conference on Industrial Engineering and Applications (ICIEA). IEEE, pp. 415–419.
- Hensher, D.A., King, J., 2001. Parking demand and responsiveness to supply, pricing and location in the Sydney central business district. *Transp. Res. Part A Policy Pract.* 35, 177–196.
- Jöreskog, K.G., 2005. *Structural equation modeling with ordinal variables using LISREL*.
- Kaplan, D., 2008. *Structural equation modeling: Foundations and extensions*. Sage Publications.
- Kelly, J.A., Clinch, J.P., 2009. Temporal variance of revealed preference on-street parking price elasticity. *Transp. Policy* 16, 193–199.
- Kelly, J.A., Clinch, J.P., 2006. Influence of varied parking tariffs on parking occupancy levels by trip purpose. *Transp. Policy* 13, 487–495.
- Liu, Z., Li, R., Wang, X.C., Shang, P., 2018. Effects of vehicle restriction policies: Analysis using license plate recognition data in Langfang, China. *Transp. Res. Part A Policy Pract.* 118, 89–103.
- Mashhoodi, B., Berghauer Pont, M.Y., 2011. Studying land-use distribution and mixed-use patterns in relation to density, accessibility and urban form. ISUF 2011: 18th International Seminar on Urban Form: Urban Morphology and the Post-Carbon City, Montreal, Canada, 26–29 August 2011.
- Miloslavjević, N., Simićević, J., 2014. Revealed preference off-street parking price elasticity. In: *Proceedings of 5th Annual Meeting of the Transportation Research Arena*. Citeseer, pp. 1–10.
- Mo, B., Feng, K., Shen, Y., Tam, C., Li, D., Yin, Y., Zhao, J., 2021. Modeling epidemic spreading through public transit using time-varying encounter network. *Transp. Res. Part C Emerg. Technol.* 122, 102893.
- Mo, B., Li, R., Dai, J., 2020. Estimating dynamic origin–destination demand: A hybrid framework using license plate recognition data. *Comput. Civ. Infrastruct. Eng.* 35, 734–752.
- Mo, B., Li, R., Zhan, X., 2017. Speed profile estimation using license plate recognition data. *Transp. Res. Part C Emerg. Technol.* 82, 358–378.
- Muthén, B., 1984. A general structural equation model with dichotomous, ordered categorical, and continuous latent variable indicators. *Psychometrika* 49, 115–132.

- Muthén, B.O., 1993. Goodness of fit with categorical and other nonnormal variables. *SAGE Focus Ed.* 154, 205.
- Olsson, U., 1979. Maximum likelihood estimation of the polychoric correlation coefficient. *Psychometrika* 44, 443–460.
- Ottoson, D.B., Chen, C., Wang, T., Lin, H., 2013. The sensitivity of on-street parking demand in response to price changes: A case study in Seattle. *WA. Transp. Policy* 25, 222–232.
- Pu, Z., Li, Z., Ash, J., Zhu, W., Wang, Y., 2017. Evaluation of spatial heterogeneity in the sensitivity of on-street parking occupancy to price change. *Transp. Res. Part C Emerg. Technol.* 77, 67–79.
- Rosseel, Y., 2012. **lavaan** : An R Package for Structural Equation Modeling. *J. Stat. Softw.* <https://doi.org/10.18637/jss.v048.i02>.
- Samorodnitsky-Naveh, G.R., Geiger, S.B., Levin, L., 2007. Patients' satisfaction with dental esthetics. *J. Am. Dent. Assoc.* 138, 805–808.
- Shen, W., Xiao, W., Wang, X., 2016. Passenger satisfaction evaluation model for Urban rail transit: A structural equation modeling based on partial least squares. *Transp. Policy* 46, 20–31.
- Shi, J., Zhou, N., 2012. A quantitative transportation project investment evaluation approach with both equity and efficiency aspects. *Res. Transp. Econ.* 36, 93–100.
- Sidorchuk, R.R., Skorobogatykh, I.I., Mkhitarian, S.V., Voronova, T.A., Ivashkova, N.I., 2020. Clustering Megacity Districts upon Customer Satisfaction on Parking Services. *Montenegrin J. Econ.* 16, 69–86.
- Suksanguan, W., 2018. Study on the use of parking spaces and satisfaction of Thai people using Don Mueang Airport in Bangkok Metropolis. *Thailand. ABAC J.* 38, 147–160.
- Syed, S., Golub, A., Deakin, E., 2009. Response of regional rail park-and-ride users to parking price changes: systemwide results and a detailed study of two stations. *Transp. Res. Rec.* 2110, 155–162.
- Thompson, R.G., Richardson, A.J., 1998. A parking search model. *Transp. Res. Part A Policy Pract.* 32, 159–170.
- Tin-Oo, M.M., Saddki, N., Hassan, N., 2011. Factors influencing patient satisfaction with dental appearance and treatments they desire to improve aesthetics. *BMC Oral Health* 11, 6.
- Tsafarakis, S., Kokotas, T., Pantouvakis, A., 2018. A multiple criteria approach for airline passenger satisfaction measurement and service quality improvement. *J. Air Transp. Manag.* 68, 61–75.
- Turner, G.A., Paech, M., 1991. A comparison of oral midazolam solution with temazepam as a day case premedicant. *Anaesth. Intensive Care* 19, 365–368.
- Wang, H., Li, R., Wang, X.C., Shang, P., 2020. Effect of on-street parking pricing policies on parking characteristics: A case study of Nanning. *Transp. Res. Part A Policy Pract.* 137, 65–78.
- Whitty, P.M., Shaw, I.H., Goodwin, D.R., 1996. Patient satisfaction with general anaesthesia: Too difficult to measure? *Anaesthesia* 51, 327–332.
- Wilson, R.W., 1992. Estimating the travel and parking demand effects of employer-paid parking. *Reg. Sci. Urban Econ.* 22, 133–145.
- Xiao, H., Xu, M., Gao, Z., 2018. Shared parking problem: A novel truthful double auction mechanism approach. *Transp. Res. Part B Methodol.* 109, 40–69.
- Xue, Y., Fan, H., Guan, H., 2019. Commuter departure time choice considering parking space shortage and commuter's bounded rationality. *J. Adv. Transp.*
- Yang-Wallentin, F., Jöreskog, K.G., Luo, H., 2010. Confirmatory factor analysis of ordinal variables with misspecified models. *Struct. Equ. Model.* 17, 392–423.
- Yang, Y., Diez-Roux, A.V., 2012. Walking distance by trip purpose and population subgroups. *Am. J. Prev. Med.* 43, 11–19.
- Zheng, N., Geroliminis, N., 2016. Modeling and optimization of multimodal urban networks with limited parking and dynamic pricing. *Transp. Res. Part B Methodol.* 83, 36–58.