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Research Article

Could the Incentive Policy of Shared Parking Be Sustainable? The Viewpoint of Personal Risk Aversion

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Using an incentive measure to encourage people to share their private parking spaces could be an effective strategy for urban parking problems. This paper discusses an innovative mechanism of shared parking, "FlexPass," which applies a reverse auction in which drivers propose bids in line with their individual expectations to share their idle parking spaces. The auction mechanism, hypotheses on bidding process principles, the competitive environment, and the risk-averse decisions of providers with regard to parking spaces are analysed to explore the sustainability of the economic benefits obtained for FlexPass parking spaces. A total of 216 respondents from the University of California, Berkeley, were invited to participate in bidding in an actual survey during their daily use of parking spaces. The analytical results show that operational rules based on risk aversion can enable profit-seeking with a bounded capability to obtain considerable economic benefits and release parking resources in an environment of demand competition. Particularly in some scenarios, FlexPass would sacrifice a certain monetary income to ensure the perceived benefits of parking space providers. With the improvement of people's enthusiasm for participating in shared parking, the benefits to individuals and parking lots would be further enhanced, suggesting that our mechanism can operate sustainably over the long term. These findings are helpful for policymakers to formulate feasible shared parking policies from the perspective of monetary incentives.

1. Introduction

As an important part of urban transport systems, static traffic, which is an extension of dynamic traffic, can have a positive or negative effect on dynamic traffic, urban mobility, and even human health [1, 2]. With the development of motorization and decreases in available resources in cities, parking is becoming a major challenge for both commuters and transport managers [3]. Previous studies have shown that searching for a parking space can increase urban traffic congestion by 30% and produce large amounts of carbon [4, 5]. According to a report by IBM [6], more than 60% of responding drivers reported that they were so frustrated at least once when searching for a parking space that they eventually gave up, leaving behind only congestion and lost economic opportunity.

Although the governments of several large cities have applied measures to increase parking capacity, increases in parking demand will soon offset the effectiveness of these measures [3]. Parking is a kind of derivative demand created by drivers when they choose to travel by car. This derivative demand can be effectively transformed under the guidance of appropriate policies, such as parking management and pricing regulation. Parking managers hope to improve the effective use of existing infrastructure via methods of economic leverage. The classic case is the SFpark programme, which implements a spatiotemporal price adjustment mechanism to influence parking rates across both the parking period and parking blocks based on presently observed occupancy levels in San Francisco [7]. The goal of this programme is to establish parking prices in real time by evaluating parking demand using the internet to release messages to the public. In addition, with the rise of the shared economy, scholars and enterprises are dedicated to creating proper circumstances for the parking industry and prioritizing the efficient operation of private parking resources. They believe that idle private parking spaces can be efficiently utilized to satisfy the parking demand of neighbouring areas [8–10].

Previous policy efforts have focused mainly on how to guide or realize the spatiotemporal balance between parking demand and supply via personal parking costs. The logic of capacity expansion treats parking only as a fixed or flexible cost added at the end of a car trip. When the law of administrative supervision is enforced, drivers pay parking fees passively, although they have elasticity in choosing their parking time or parking location. Although the policy is easy to implement in cities' parking meter programmes, it may not optimally regulate parking demand, resulting in congestion and the loss of economic potential [11]. To address this problem, some studies have attempted to build a platform of shared parking to solve the urban parking problem by using auction mechanisms [3, 12, 13]. The team of Prof. Raja proposed an innovative measure of shared parking that incentivizes employees at the University of California, Berkeley (UC Berkeley), to reduce their parking demand with an interesting bidding game [14, 15]. Generally, UC Berkeley employees purchase a monthly parking permit for a fixed fee. The participants in the trial of this incentive measure were given access to an extra channel to obtain a monthly cash-out that was proportional to the number of days they did not park. A bidding game in the smartphone app was intended to make them more mindful of parking usage and incentivize the reduction of parking demand. We call this shared parking policy at UC Berkeley "FlexPass."

In the early 1990s, the state of California attempted to promote the cash-out policy to alleviate personal demand for car parking. The law mandates that enterprises provide a parking space for every employee. Alternatively, a special fund can be provided to help people complete their daily commute with parking. As a study by Tscharakschiew [16] revealed, even under this policy, employers lacked sufficient motivation to reduce parking at their workplaces. In implementing this process, the cash-out payment provided by the employer also put great pressure on the company's finances. If FlexPass could be rolled out for the parking market, it would open a channel for people to earn the opportunity cost of sharing parking spaces. This would invisibly reduce personal dependence on car travel and increase the possibility of choosing other travel modes [17]. Compared with other shared parking policies, FlexPass includes a bidding process for individuals, which makes the use rights of parking spaces shareable but carries risks to the economic benefits of the parking lot. This means that in the actual operational process, FlexPass may suffer operational losses due to information asymmetry. However, as rational actors, although parking space providers would not pursue monetary rewards indefinitely under the bidding incentive, they would first attempt to ensure that their basic interests would not be threatened by risks when making decisions about parking space sharing, i.e., to avoid the risk caused by sharing. Therefore, to advance the implementation of FlexPass and spread it to other places, it is necessary to consider the scale and sustainability of the profit space of shared parking policy from the perspective of economic benefits and risks. As the whole operational process involves multiple subjects and behaviours, to our knowledge, there is no existing study that provides an in-depth discussion of the economic benefits of FlexPass considering individual bidding and risk aversion.

Based on the above, this paper puts forward a set of FlexPass operational principles for the reverse auction of parking spaces. We analyse the provider's risk-averse decision-making process and explore the benefits, costs, and parking space utilization of FlexPass in a competitive environment. Determining whether the designed mechanism can bring enough profit for FlexPass is the main purpose of this study, which considers the existence of risk uncertainty in operation. The detailed contributions of this study are as follows. First, the study used the value-at-risk function to describe people's decision-making behaviours in the FlexPass bidding process, and we believe that individuals participating in shared parking pursue perceived benefits rather than pure monetary rewards. Second, by introducing the competition of external parking demand, we discussed the continuity and sustainability of FlexPass based on reverse auction in terms of operating profits. Third, we applied the real-world data survey by UC Berkeley to verify the mathematical model and calculate the corresponding results. A sensitivity analysis of the fluctuations in main factors such as rental pricing, parking space recycling, sublease quantity, and overall policy benefit is put forward based on these principles. The remainder of this paper is organized as follows. Section 2 reviews previous studies that analysed shared parking policies from the perspectives of parking demand management and parking pricing. In Section 3, we illustrate the operational process of FlexPass and propose relevant assumptions to build a mathematical model. A numerical analysis of the UC Berkeley survey is presented in Section 4, which includes a discussion of the economic benefits and the utilization of parking lots. Finally, Section 5 summarizes the main findings of the study and describes possible future work.

2. Literature Review

Shared parking has received increasing attention due to its capacity to deal with parking challenges in metropolises [18]. A well-functioning shared parking policy should enable people to use their parking spaces and to obtain additional benefits by meeting the parking demand of others [19, 20]. To achieve this goal, a series of measures have been attempted in practical applications. Here, we focus on parking demand management and parking pricing.

2.1. Parking Demand Management. As the core of improving the efficiency of parking spaces, scholars have explored several types of management measures, including building land, parking behaviours, and parking demand. Early studies mainly explored how different land types can realize the complementarity of parking demand and supply. The American Urban Land Institute first explicitly discussed the feasibility of using adjacent parking facilities to ease the demand for oversaturated parking facilities [20]. Subsequently, Litman [21] proposed a classification of parking peak hours for different sites based on surveys of shared parking users. Antonson, Hrelja and Henriksson [22] discussed the holistic function of Gothenburg parking and found that policymakers should take shared parking between different parcels more seriously in the concrete application of management approaches. These studies indicated that parking demand for various types of land use facilities (or public buildings) differs over time, and the application of parking space sharing is feasible [23].

Individuals and groups have various preferences for parking facilities that also directly affect and determine the effect of implementing parking space sharing schemes [24]. The behaviours of drivers seeking a parking space and their reactions to changes in external factors to address parking problems should be issues of concern to management [9, 10, 25, 26]. For instance, Golias, Yannis and Harvatis [27] found that despite drivers' individual attributes, parking space cruising time, length of parking time, and walking distance also affected personal parking space selection. If the cruising time is longer than 8 minutes, people's experience of parking space availability is significantly reduced [28]. This has a negative impact on personal participation in shared parking and creates uncertainty in revenue and parking costs [29]. Therefore, it is worth further exploring the decision-making process involved in parking lot selection under the management of shared parking.

With regard to research on parking demand, some studies in this field have been based on a large number of basic data surveys and analyses [30–32]. For example, the fifth edition of the report "Parking Generation Manual," which is published by the Institute of Transportation Engineers on a regular basis, collected survey data on different types of land use, and analysed the parking generation rate with single or multiple independent variables [33]. The reported results provide a good reference for the construction of parking spaces. Alternatively, scholars have explored efficient methods of demand prediction to help manage shared parking systems. Several mathematical models, such as the rate of increment method, classification and regression trees, and the long short-term memory module, have been used to forecast the time-varying fluctuations of shared parking spaces [9, 10, 34–36]. The implementation of management measures also affects the forecasting and analysis results of parking demand [33].

2.2. Parking Pricing. Strictly speaking, parking pricing is a main measure of parking management policy. We listed it here separately because, due to the effectiveness of implementation, many cities and regions have adopted it as an acceptable administrative policy. The earliest research on this topic is Vickrey's study [37] of parking fees, which contributed to the conclusion that it is wise to change parking prices at various times or locations. An increasing number of scholars subsequently began to explore the parking pricing problem [38–40]. For example, in the landmark book *The High Cost of Free Parking* [41], D. Shoup and his coauthors conducted studies to explore how to establish an appropriate price to balance the utilization ratio and velocity rate of parking lots. These authors suggested that a good strategy for parking pricing can ensure that parking lots are well used and readily available and can make the local economy more efficient [8, 42, 43]. Arnott et al. also published an exploration of the effects of parking fees on urban traffic congestion by adopting and expanding the practical model proposed by Vickery [44]. They found that although parking fees could not eliminate urban traffic congestion, raising fees in some areas (such as the central business district with high parking demand) can produce at least three levels of benefits by reducing cruising for parking, local distortionary taxation, and traffic congestion [38, 45, 46].

Although several real-world cases have illustrated the significant effect of price ranges due to the inelasticity of parking difficulty [47–51], these cases have not affected scholars' propositions of a better pricing model to optimize the parking service environment and reduce urban traffic congestion [11, 52, 53]. Scholars have hoped to improve the theoretical development of parking pricing policies and replicate the success of shared parking programmes in other parts of the world [7, 54–57].

Despite the difficulties, academics have an optimistic attitude towards the use of price leveraging to improve the utilization efficiency of urban parking spaces. In addition to the abovementioned SFpark, over recent years, quite a few companies have developed smartphone apps (such as Airparking, Bestparking, and Parkme) to integrate and publish scattered information on parking spaces through online trading methods and help drivers quickly find a suitable parking location. These apps monitor parking availability by deploying a massive network of sensors or encouraging drivers to publish parking space occupancy information. For example, Google's OpenSpot application was developed to help drivers find parking spaces by searching a one-mile radius around their location. Although this application has not become popular due to the complex requirements for user behaviours, the idea of using the power of crowdsourcing and a point incentive system for individuals to promote the effects of shared parking has received increasing attention [58].

In subsequent studies, scholars have considered sharing platforms for urban parking spaces based on smartphone technology that involves renting personal parking spaces through a peer-to-peer market with new e-sharing methods in which the core business plan is to match parking demand and parking space pricing [18, 59]. Shao, Yang, Zhang et al. [60] proposed a linear 0-1 programming model to maximize operating revenue while attempting to minimize loss due to request rejection via the first-booked-first-served sequence. Xiao et al. [3, 61] used a truthful double-auction mechanism to address the price issue of shared parking and ensure fairness for all participants. These authors found that the auction mechanism based on the principle of fairness could improve the turnover rate of shared parking spaces and market trading volume. Furthermore, they compared the platform's payoff and participants' utility in different auction-based pricing strategies (e.g., a uniform price strategy and differential price strategy) and discovered the advantages of unified pricing for shared parking spaces. Other technologies, such as location tracking, parking reservation, parking space allocation, and dynamic parking permits combined with pricing principles, have been used to address the potential space and efficiency of existing shared parking infrastructure [18, 19, 59, 62, 63].

Overall, the literature has made great contributions to the study of shared parking policies, and these studies have provided strong support for specific measures to reduce or eliminate regional parking pressure. These measures can assist local governments in identifying other mandatory or incentive methods to optimize the efficiency of shared parking spaces using smartphone apps. Although previous studies have explored several interesting economic features, including pricing, shared infrastructure, and parking management, to help shared parking policy succeed in the context of scarce resources, we hope to answer the following questions by exploring the effects of policy implementation considering the current situation of excessive car usage:

(i) How can we describe the judgement process of individual risk and benefit perception when users participate in FlexPass bidding, and how can we distinguish bids for shared parking spaces in the environment of parking demand competition?

(ii) How does the bidding incentive affect the economic benefit of parking lots, and what is the correlation among the incentive intensity, utilization efficiency of parking spaces, and policy effectiveness of FlexPass?

3. Survey Data and Modelling Approach

3.1. Survey Design. The FlexPass survey was conducted from Sep. 21, 2015, to Oct. 16, 2015, among parking users at UC Berkeley. The campus can be likened to a small town, and its parking lots are used mainly by parking permit holders of the university. Therefore, our survey targeted the current annual C permit and F permit holders, who have the right to use the parking lots. A parking permit allows the holder to park in a garage or parking lot according to the permit type. C permits are normally used only by faculty and senior staff, while F permits are available to other people. In 2015, the parking price for a C permit was \$131 per month, and the price for an F permit was \$95 per month. During the survey process, the volunteers who participated installed a FlexPass app on their smartphones and could be paid up to \$15 to sell their parking rights on campus for the day. Figure 1 shows the interfaces of the FlexPass app.

In the volunteers' daily travel, a subsidy price could be submitted through the bidding interfaces of the smartphone app, as shown in Figure 1(a), if they did not need to use campus parking lots (e.g., no use of parking rights held). The smartphone app produced a randomly generated amount (RGA) from 0 to 15 dollars for comparison to allow the user to decide whether to accept the individual bidding price. To incentivize the volunteers, if the bidding price was lower than the RGA, the smartphone app provided information on the bidding success, and the users could obtain a monetary reward equal to their bidding price. Otherwise, the app prompted the bidding to fail, and the volunteers still reserved their right to park on campus on that day. The default choice every day was "park on campus," as shown in Figure 1(b). It could be changed from the app interface or from the app calendar if the volunteer did not plan to use the parking. Before bidding prices were submitted, two questions had to be answered: the alternate mode of transportation the user would be taking and whether the user would be coming to campus (as shown in Figure 1(c)). The deadline for the return of parking rights was 12 noon every day. After the end of our survey, each volunteer could obtain the quota of subsidies they had earned through the app statistics (as shown in Figure 1(d)).

3.2. Process Execution Description and Modelling Theory. Figure 2 illustrates how parking lot providers, demanders, and managers cooperated to implement FlexPass. The shared parking policy helped the use rights of parking lots form a closed loop among the participants. Parking lots' recycling and leasing based on cash-out measurements were a decision-making behaviour process with risk. Drivers who held F and C permits were the original owners of parking spaces at UC Berkeley. They could freely propose bidding prices within a reasonable range according to their use of their parking spaces and could obtain the corresponding subsidies. Although promoting FlexPass could improve the utilization of parking lots, the possibility of cashing out could also make users face uncertainty and risk when reclaiming their use rights for parking spaces. Fortunately, management controls the pricing power and may be able to hedge certain risks and obtain an objective benefit by renting parking spaces.

Note that our study does not include the concrete allocation for parking spaces in the evaluation scope of the model, although many excellent studies have provided profound discussions of this topic [64, 65]. Instead, we focus on determining what kind of external leasing strategy is beneficial to shared parking considering the competition between parking lots and people's risk perception of sharing. In particular, the bidding process in FlexPass is essentially incentive guidance for people to share parking spaces. Whether the slots are traded or not, the cash-out scheme will be included in the cost and paid by the parking lot management to the parking space providers. Obviously, the transaction price approval standard here should depend on the external parking demand, people's parking supply decisions and the competitive pressure between parking lots. In addition to the distance from the parking space to the destination, the economic cost of parking is the core focus of demanders. This can be expressed as different parking lots competing in rental pricing to attract various demanders if we do not consider the parking distance. Therefore, from a rational

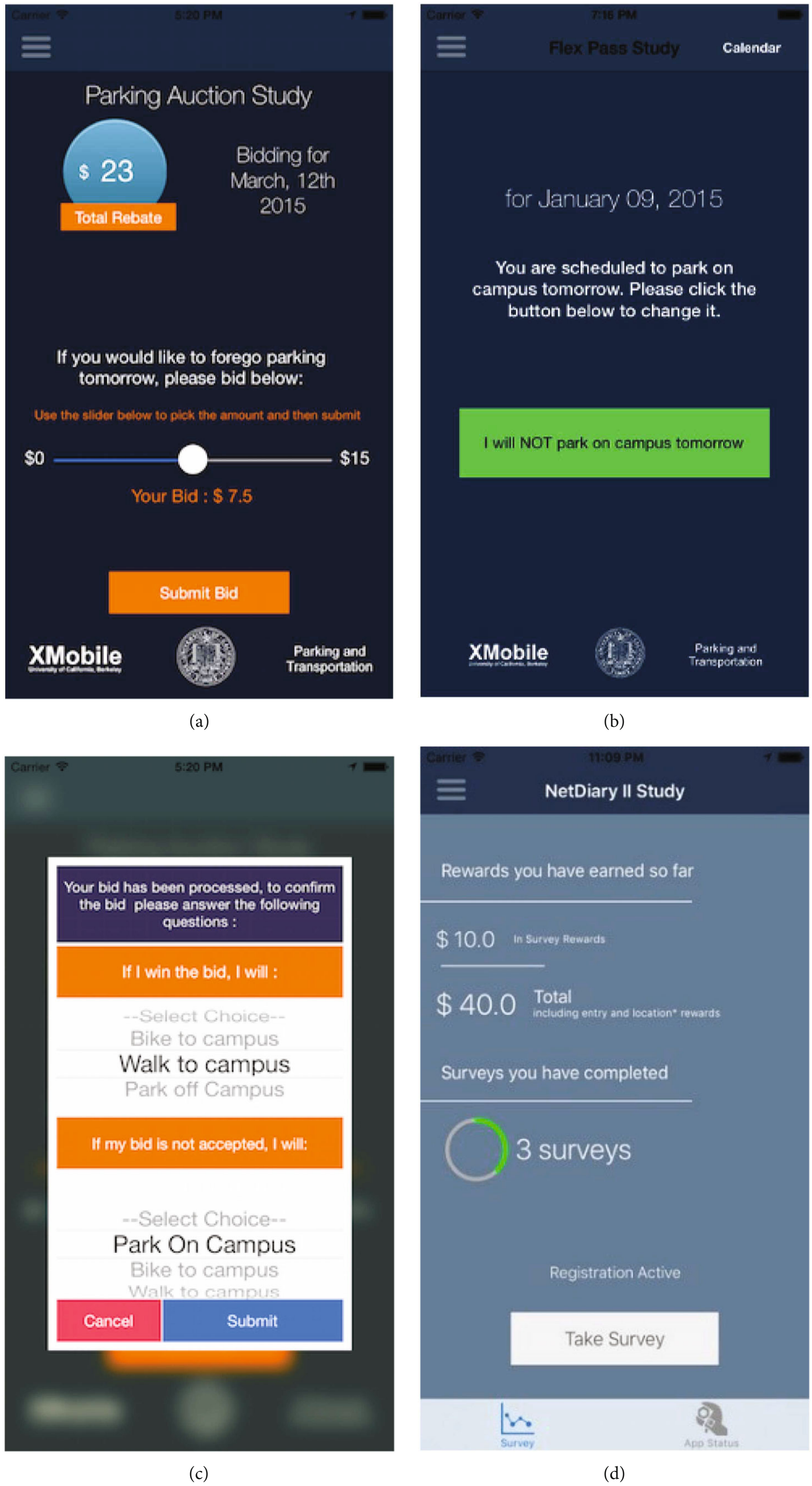

Figure 1: The interfaces of the FlexPass app.

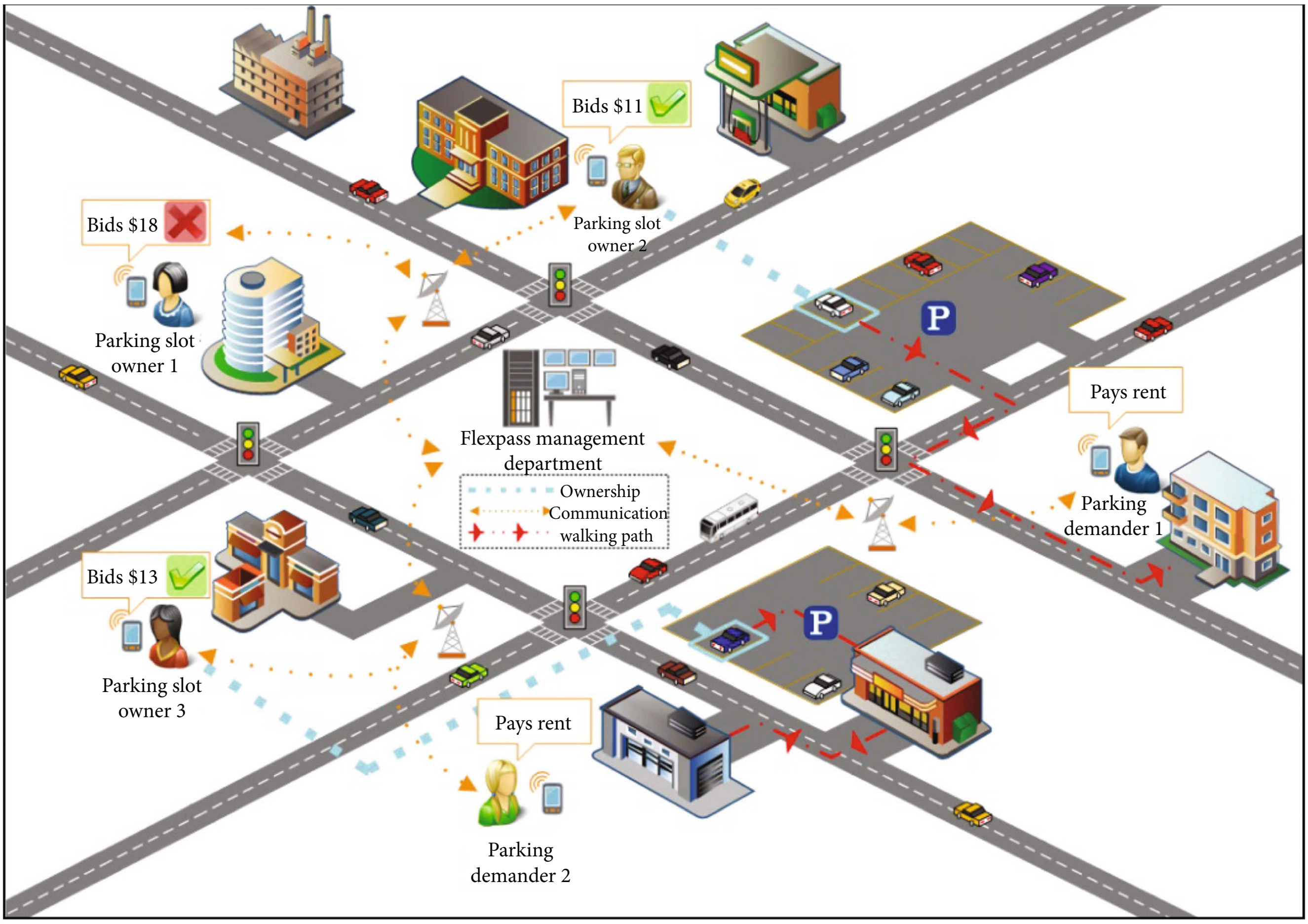

Figure 2: The operational process of FlexPass.

viewpoint, the actors in FlexPass are making a risk decision based on a cost–benefit analysis. To describe the operational process of FlexPass more carefully, we propose four model assumptions from the perspective of the aforementioned risk decision theory.

Assumption 1. "All-or-nothing" principle for drivers and "one-to-many" principle for parking managers.

Parking space providers who can share their parking spaces and parking managers who can establish the reclamation prices are established as rational actors. The "all-or-nothing" principle for drivers implies that when they want to share their use rights for parking spaces, they are bound to propose a satisfactory bidding price. The "one-to-many" principle means that parking managers must face the bidding decisions of many drivers within a certain period. This differs from Xiao et al.'s research [3] in that one occupied parking space cannot be redistributed to multiple parking demanders during the available time. Although this setting sacrifices part of the mobility of resource utilization and reduces the flexibility of supply-demand matching, it avoids disputes over shared parking, such as parking time allocation conflicts or overtime parking, in the actual operational process. In FlexPass, the parking lot also determines the reclamation of parking spaces. Managers need to pay the agreed-upon bids and make profits by subletting the use rights of parking spaces to parking demanders. Rejecting unnecessary bidding applications at the right time will help parking managers maintain their profit margins.

Figure 3 is the game tree diagram of the bidding process under this assumption. In the figure, player 1 is the parking lot and player 2 is the provider. $f_i (i = 1, 2, \cdots)$ is the incentive intensity scheme of the parking lot, and u and v refer to the single benefits of players 1 and 2, respectively. Y means that the provider's bidding is successful, and N refers to failed bidding or retaining the use right for a parking space.

If the parking manager successfully recovers the parking right of provider i and subleases it to the surrounding demanders at a certain price, the parking lot can obtain economic benefits $u(f_i)$. The corresponding subsidy of provider i is $v(f_i)$. If the parking manager rejects the bidding application of provider i or decides to keep the use rights for the parking space that day, then the benefits of both parties are zero. In Figure 3, the right forms of the node for player 2 are a subgame tree with only one provider i. Let ω_i denote the behavioural state of the individual bidding of provider i. If the person is rational, the decision must depend on the

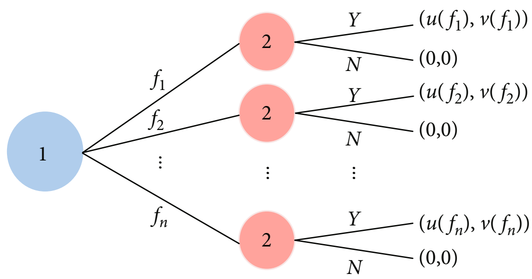

Figure 3: Game tree of the bidding process between parking managers and car users.

size of the second component in brackets; i.e., the optimal decision is as follows:

$$\omega_i = \begin{cases} Y, & v(f_i) > 0, \\ N, & v(f_i) \leq 0, \end{cases} \tag{1}$$

where Y and N can be numerically recorded as 1 and 0, respectively.

On the other hand, the parking manager can obtain profits depending on whether the individual initiates the bidding and successfully returns the parking right. Consequently, when FlexPass becomes a mature policy, we can imagine that it would be an interactive process similar to a nonconfrontational game between the providers and the parking manager. The ideal result of this game is to make the income of parking managers as large as possible on the basis of ensuring that the economic benefits of drivers returning parking rights are greater than 0.

Under this assumption, parking lots must bear most of the day-to-day trading risk. In addition to the cost of reclamation, the income from FlexPass must be considered in terms of the external demand for and leasing smoothness of shared parking spaces. Only after subletting the recovered parking spaces to external parking demanders can the parking lot obtain economic benefits with the help of FlexPass. Therefore, the incentive intensity to meet the optimal decision of the manager should be in accordance with

$$U(f) = \max\{u(f_i)\}, \quad v(f_i) > 0. \tag{2}$$

Unlike in previous studies, the operation of FlexPass is divided into two independent stages by the principles of this assumption. In the first stage, the providers of shared parking spaces propose the bidding prices. In the second stage, the parking lot makes the decision of whether to accept the bidding by evaluating the rental income of shared parking. For both parties, the pure strategy of the game (f, Y) is not the best strategy for people to follow. The reason is that in real life, providers do not focus only on economic benefits when they make bidding decisions, and there is no way for parking lots to make a fully informed decision regarding whether to accept bids. This will be further discussed in the following assumptions of this paper.

Assumption 2. The operation of FlexPass will compete with traditional parking lot operations, and the market allocation of parking demand will be linked to the external rental price of parking spaces.

The utilization efficiency of shared parking lots is uncertain in this study because shared parking policies such as FlexPass interfere with many factors during the operational process, such as a lack of punctuality in the arrival and departure of vehicles, traffic congestion, and individual policy compliance [29, 59]. Fortunately, it seems that market competition with limited resources has a positive influence on managerial incentives and avoids the risk of uncertainty [66]. Therefore, our study considers the overall parking demand to be allocated to two parking lots, denoted parking lot A and parking lot B, that compete for market share via the rental pricing of parking spaces. Parking lot A implements the traditional parking service mode with a certain supply capacity, while parking lot B implements the mode with FlexPass. To focus on the problem of the sustainability of the benefit, we assume that the proximity between the parking position and the demander's destination as well as the cost are not considered. For parking lots, the risk of uncertainty in parking demand is related to the rental prices they set.

Due to intensive competition in the parking market, parking lots A and B both need to face the potential risk of business loss due to resource vacancies. This result is in line with our previous assumption that parking managers are sufficiently rational to implement the "one-to-many" principle. In the whole process of competition, a company such as parking lot B would make risk-averse decisions in a timely manner as a rational actor [67]. In other words, the flexible incentive strategy of parking lot B is to find the dynamic equilibrium between the parking price and parking demand in competition. As in some previous studies [48–50, 68], the relationship between parking price and parking demand is defined as a linear model, as shown in the following equations:

$$\begin{aligned} D_{\mathrm{A}} &= (1-\theta)\xi - a_{\mathrm{A}}(p_{\mathrm{A}} - p_0) + r_{\mathrm{A}}(p_{\mathrm{B}} - p_{\mathrm{A}}), \\ D_{\mathrm{B}} &= \theta \cdot \xi - a_{\mathrm{B}}(p_{\mathrm{B}} - p_0) + r_{\mathrm{B}}(p_{\mathrm{A}} - p_{\mathrm{B}}), \end{aligned} \tag{3}$$

where D_{A} refers to the portion of the forecast parking demand ξ allocated to parking space A and D_{B} refers to the parking demand allocated to parking space B. p_{A} and p_{B} represent the rental price set by parking lots A and B. p_0 is the governmental guidance price set for parking. a_{A} and a_{B} refer to the demander's price sensitivity for parking spaces based on the government guidance price; correspondingly, r_{A} and r_{B} represent the competition intensity of the rental price. The parameter θ is used here to introduce the demand shares between these two parking lots, which may be determined by other simplified factors in our study, such as travel purpose, payment method, and parking convenience. Its value ranges from 0 to 1, and the value 0.5 can be used as a judgement value to identify which parking space has an advantage in demand allocation. Note that the parameter θ can also be regarded as the preference or the choice habits of parking demanders for the parking space.

The parameters r_A and r_B represent the demand for parking spaces from competitors by adjusting prices and explain the total utility of price to parking demand together with a_A and a_B. The advantage of this assumption is that the allocation of parking demand cannot be guaranteed to be very susceptible to the parking price compared with the other assumptions of nonlinear relationships [67].

Due to the finite absorptive capacity, parking lot B can earn only constrained revenue from the fulfilled demand because its unmet demand is assumed to be lost. Thus, the possible profits π of parking lot B can be given by

$$\pi = p_B \cdot \min (C, D_B) - O, \tag{4}$$

where C refers to the capacity of parking lot B, which is related to personal bidding behaviours and the reclaimed number of parking spaces, and O refers to the reclaimed cost for the parking space providers. Note that D_B is a random variable, and $\min (C, D_B)$ refers to the minimum value of C and D_B. It describes three scenarios: (1) if the value of C is smaller than the parking demand D_B, the results of min (C, D_B) will be equal to C; (2) if the value of C is greater than the parking demand D_B, the result will be D_B itself; (3) if the value of C lies within the distribution of D_B, the result of $\min (C, D_B)$ will also be a random variable. Denoting $(g)^+ = \max (g, 0)$, $\min (C, D_B)$ will be recorded as $C - (C, D_B)^+$. The profit function of parking lot B can be written as

$$\pi = p_B \cdot [C - (C, D_B)^+] - O. \tag{5}$$

In a competitive environment, the parking lot manager's aim is not just to rent out all the existing parking spaces. The operational process of FlexPass also needs to consider the impact on its revenue of reclaiming parking spaces. The parking lot must pay for the purchased spaces in advance regardless of whether the parking spaces are utilized.

Assumption 3. In bidding, providers often submit a price higher than their real earnings to avoid the risk associated with the FlexPass policy.

We can imagine that if the FlexPass policy is carried out smoothly, the shared parking business will be a service market, and its pricing frameworks will be developed in the context of parking space utilization. To optimize cost contingency in service pricing, the expectation of risk aversion is still the main reason for people's decision-making regarding travel choices [69–73]. Therefore, combined with the rational actor setting in Assumption 1, we have reason to believe that when people share their parking spaces, they also make decisions that involve risk aversion.

According to the mechanism of flexible incentives, the cost of reclaiming is directly related to the bidding of parking providers. Because bidding behaviour is only the first step in parking space sharing, whether revenue is obtained also depends on the reclamation decision of parking space B from a personal viewpoint. Note that β_i refers to the bidding price of provider i, and c_i is the cost after sharing the parking space. Thus, the profit ε_i of driver i can be written as

$$\varepsilon_i = (\beta_i - c_i) \cdot [\omega_i - (\omega_i - \chi_i)^+], \tag{6}$$

where χ_i represents the reclamation state of this parking space. When provider i initiates bidding β_i, parking lot B will determine whether to reclaim by examining the number of parking spaces currently recovered. If the current recovery quantity is less than the forecast demand, parking lot B will agree to the bidding price, and χ_i should be recorded as 1. Otherwise, the value of χ_i should be recorded as 0. The expected profit π_i for parking lot B produced by individual bidding is

$$\pi_i = (p_B - \beta_i) \cdot [\omega_i - (\omega_i - \chi_i)^+] \cdot \frac{D_B}{C}. \tag{7}$$

In this assumption, we first introduce the value-at-risk function to depict the risk-averse behaviours of parking lot providers during the bidding process. In traditional studies, the value-at-risk function is defined as the η-quantile of profit ε_i, i.e., $P\{\varepsilon_i \leq V^\eta(\varepsilon_i)\} = \eta$. The risk-averse indicator η of the value-at-risk function $V^\eta(\varepsilon_i)$ takes a value in the interval [0,1]. When the indicator η equals 1, the risk people feel during bidding is neutral. The closer the value of η is to zero, the stronger the feeling of risk people have and the weaker their willingness to bid for parking space sharing (because people tend to be more risk averse). Therefore, the focus of FlexPass should shift from the pursuit of the economic benefit of parking lot B to protecting people's bidding enthusiasm.

However, the value-at-risk function cannot represent the tail distribution characteristic of people's bidding enthusiasm. In our study, we use the function of conditional value-at-risk $V_C^\eta(\varepsilon_i)$ as an extension of the value-at-risk function $V^\eta(\varepsilon_i)$ to overcome the tail-end shortcoming [74, 75]. The mathematical formula is

$$V_C^\eta(\varepsilon_i) = \int_{-\infty}^{+\infty} z dF_\varepsilon^\eta(z), \tag{8}$$

where z is an auxiliary dummy variable and $F_\varepsilon^\eta(z)$ refers to the cumulative distribution function of $V^\eta(\varepsilon_i)$. If $z \geq V^\eta(\varepsilon_i)$, the function $F_\varepsilon^\eta(z)$ equals 1; if $z < V^\eta(\varepsilon_i)$, then $F_\varepsilon^\eta(z) = F_\varepsilon(z)/\eta$. Thus, we can intuitively see that $V_C^\eta(\varepsilon_i)$ is the conditional expectation function of ε_i subject to z. In other words, $V_C^\eta(\varepsilon_i)$ refers to the perceived benefits of provider i after considering the risk in a shared parking policy, which can be defined as follows [67, 76]:

$$V_C^\eta(\varepsilon_i) = \max \left\{ \nu + \frac{1}{\eta} E[\min (\varepsilon_i - \nu, 0)] \right\}, \tag{9}$$

where ν is an auxiliary dummy variable and its range is in the interval [0, +∞]. Under this condition, the function $V_C^\eta(\varepsilon_i)$ reaches its maximum when ν takes the value of $V^\eta(\varepsilon_i)$. Let $\Lambda = a_B(p_B - p_0) - r_B(p_A - p_B)$. We can deduce the following result if we substitute Equation (6) into Equation (9):

$$V_C^\eta(\varepsilon_i) = \begin{cases} \dfrac{\pi_i(\beta_i - c_i)\left[\Phi^{-1}(\eta)\theta - \Lambda\right]}{D_\mathrm{B}(p_\mathrm{B} - \beta_i)}, & \text{if } \Phi^{-1}(\eta)\theta - \Lambda \leq C, \\ \dfrac{\beta_i - c_i}{\eta}(\eta\omega_i - \omega_i + 1), & \text{if } \Phi^{-1}(\eta)\theta - \Lambda \geq C, \end{cases} \tag{10}$$

where $\Phi^{-1}(g)$ refers to the inverse function of forecast parking demand ξ. The detailed proof process of this function is provided in Appendix A.

Assumption 4. The parking lot will comprehensively consider the current number of recovered parking spaces and the self-estimated parking demand for each provider's bidding price and then determine whether each parking space is profitable under the bidding price.

As in previous studies, the auction mechanism of FlexPass in this study establishes a direct connection between parking space providers and demanders via an internet platform, and the parking manager needs to buy back parking rights before leasing to demanders [14, 15]. During the operational process, the parking manager takes risks and earns profits, which inevitably makes the parking manager adopt rational behaviour of risk aversion when making decisions. The only risk that leads to a profit is a unique uncertainty resulting from an exercise of ultimate responsibility, which by its very nature cannot be insured, capitalized, or salaried [77]. This makes the manager consider the risk when recycling shared parking spaces. Therefore, we establish that the bidding prices $B = \{\beta_1, \beta_2, \cdots, \beta_n\}$ are provided in a discrete form for the parking manager. Each bidding price β_n corresponds to a cost $c_n \geq 0$ of sharing the parking space in FlexPass, which means there is a relationship $\beta_n - c_n \geq 0$ and that the behavioural state ω_n of individual bidding should be recorded as Y according to previous assumptions. For ease of exposition, our study refers to all providers who would bid the price as agents when we do not distinguish them specifically. Due to the sealing characteristic of FlexPass biddings, the price offered by providers is known only to the parking manager, and no provider is aware of the prices offered by others.

To hedge against risk, the management would estimate the possible number of bidders K and the external parking demand D_K. The bidding orders could be processed under the first-come-first-served principle; we cannot consume too much computing power and time in judging whether to receive them. The proportion of bidding and reclaiming that we consider is characterized by the following formula:

$$0 \leq \sum_{n=1}^{i} \frac{\chi_n}{\omega_n} \leq 1. \tag{11}$$

Under this policy, at any time, the distribution of reclaiming maintains a reasonable state in determining these bidding prices. Therefore, we establish that the parking manager could comply with the following utility rule:

$$\sum_{n=1}^{i-1} \chi_n \beta_i (K - i + 1) - \sum_{n=1}^{i-1} \omega_n p_0 \left(D_K - \sum_{n=1}^{i-1} \chi_n \right) \leq 0. \tag{12}$$

The constraint condition here is used to guarantee that this decision rule is initiated only after a person has filed a bidding application. The parking guidance price p_0 represents the driver's stereotype of parking pricing to assist managers in reclamation decisions. The first item of this formula makes a simple calculation when the bidding price β_n is received. If, within the estimated number K, someone submits a bidding price β_i, the first item reflects the expected total cost of recovering under the accepted probability at that moment, while the second item calculates the income that can be obtained by subletting the parking space at the guidance price p_0. The constraint condition is that the deviation between these two items is less than zero, which means that the recovery by bidding price β_i is profitable. As a real-time allocation process, the winner would gradually emerge with the bidding pushed out of the model. It is worth mentioning that, according to our model assumptions, we have made some appropriate amendments for the incentive properties referenced in the research of Myerson and Satterthwaite [78] as follows:

(1) Computational efficiency: the calculation involved in the operation of FlexPass should be able to be determined in polynomial time.

(2) Rationality of participants: the participants expect a non-negative utility of trading in FlexPass when they take action to share or sublet parking spaces

(3) Approaching truthfulness: the providers of parking spaces will behave truthfully in setting their bidding prices. If a provider offers a high price, he or she will also bear a high risk of bidding rejection

(4) Budget balance: if FlexPass continues to operate for a long time, its revenue should be at least in surplus

In general, although formula (10) that we derived to describe people's risk perception benefit is a piecewise function, the forms of both formulas are linear under their corresponding conditions. Therefore, bidding, which is a distributed concurrent process, has a faster calculation speed. Meanwhile, the objective function in our model is set as $\sum \chi_i \cdot V_C^\eta(\varepsilon_i)$ to ensure the maximization of personal perceived benefits while chasing the effectiveness of the parking lot. Formula (12) is provided to help determine the trading price and satisfy the rapid response of recovery judgement for the parking manager. Our allocation of winning bids does not have a complete monotonic, although each winner would receive a threshold payment. However, it is close to meeting the state of truthfulness because the piecewise function representing the personal perceived benefit could be monotonic under the condition of the respective segments (proved in Appendix B). The last property provided by Myerson's research is the target of this paper, which focuses on exploring the economic benefit of parking spaces by applying the FlexPass shared parking policy. Obviously, the model presented is mixed integer quadratic programming (MIQP), and for this kind of problem, the branch-and-bound algorithm would be used in our study because of its ability to quickly find the optimal solution.

4. Results

4.1. Case Description and Parameter Setting. This study selects the bidding data on working days for analysis and assumes that the parking spaces of our survey respondents are in a parking lot in Berkeley. The parking lot has 225 parking spaces, and among them are 25 redundant parking spaces left over when implementing the incentive policy to deal with the sudden pressure of parking demand (i.e., ensuring that the peak rate of daily parking occupancy is approximately 0.9). As mentioned earlier, a parking lot with the same number of parking spaces and the same demand evolution rules is included for competition. That is, external parking demanders can park their cars in these two parking lots without considering factors other than parking fees. To quickly respond to bids, a program that generates random contrast numbers is preinstalled in the FlexPass app to provide people's cash-out claims under the incentive mechanism. According to the parking situation in Berkeley at that time, we set the respondent to submit a bidding application of US \$0 to US \$15 to the parking lot, and the app produced an RGA for bidding judgement. If the bid submitted was lower than the RGA, the parking lot would automatically receive it. In this setting, if drivers bid at a higher price, they will bear a greater risk of failure. However, if the bidding is too low, it cannot offset their travel cost, although it can be accepted more easily. Thus, people's ideal bidding strategy is to propose a reasonable bid for the actual situation.

To facilitate the analysis, we divided the entire bidding process into 13 time periods. This is because when testing FlexPass, UC Berkeley established that respondents could decide whether to bid for returned parking spaces before 12:00 at the latest, and the earliest time to bid was pushed forward 36 h. The respondents' bidding during the whole investigation is illustrated in Figure 4. The total number of people who initiated bidding showed a two-peak fluctuation feature in the bidding periods and reached the maximum 2–4 h and 16–18 h before the bidding deadline (i.e., the peak period of bidding was from 8:00 AM to 10:00 AM and from 6:00 PM to 8:00 PM). If we divide the total number of people bidding by the days, we can obtain the average bidding number.

Figure 5 shows the number and prices of bids during the survey period. The bidding approval rate of individuals in the UC Berkeley survey was between 54.35% and 83.58%. The maximum approval prices ranged from US \$6 to US \$13, which was significantly lower than people's highest bids. This is because during the actual operational process, FlexPass could enable the parking manager to not blindly follow people's irrational bidding prices when recovering the use rights of parking spaces, which reflected the "strategy-proof" characteristic of the incentive mechanism. Since the survey obtained bidding information initiated by providers based on their own wishes, it was difficult to measure the cost c_i after they shared the parking spaces. In our study, the provider's cost was iterated in the model formulas in the form of coefficients for each survey sample. According to the parking environment around UC Berkeley, we used the linear function $\Phi(\xi) = q_1\xi + q_2$ as the fitting result of the parking demand distribution, and the values of the coefficients were 0.01951 and -0.6939, respectively. The setting and descriptions of other model parameters are illustrated in Table 1.

4.2. Solution and Sensitivity Analysis. In this paper, we use the branch-and-bound algorithm solver of Cplex 12.9 software to program the numerical experiment. When analysing the sensitivity of an indicator, the other parameters are temporarily fixed, as shown in Table 1. For example, when we discuss the impact on parking demand of the change in the competition coefficient between the two parking lots, although the proportion between r_A and r_B may change from 1 : 1 to 1 : 3.5 (i.e., people are becoming increasingly sensitive to the rental price of parking lots), the psychological value of people's sensitivity to the guidance price is still set as 1 : 1. To avoid the nonconvex nature of the linear programming and ensure that the model can quickly respond to individual bidding behaviour, we record the constraint condition $\Phi^{-1}(\eta)\theta - \Lambda \le C$ as scenario 1 (i.e., due to the erroneous judgement, the number of reclaimed spaces is excessive under the risk-aversion level η and the preference θ of parking demanders, and the parking demand allocated to parking lot B is limited) and constraint condition $\Phi^{-1}(\eta)\theta - \Lambda \ge C$ as scenario 2 (i.e., there is a shortfall in spaces for shared parking, and the demand for parking lot B is strong) according to the derivation of Assumption 3. The research model supports a remarkable illustration of rental price setting, parking turnover, and policy effectiveness.

4.2.1. Price Setting for Leasing. Using the FlexPass survey data as our model input, we obtain the optimal pricing strategies for leasing. Figure 6 shows the optimal pricing for leasing and FlexPass net profits under competition with the traditional parking lot. The rental prices differ between scenarios 1 and 2. In general, the optimal prices in scenario 1, in which the assigned demand is limited, are higher than those in scenario 2. This is because our method allows parking lots to adopt the operational strategy of "high pricing and high revenue." It enables the parking lot to reduce the competition for the sublease volume and instead customize a higher price to offset the economic cost of reclaiming too many spaces and pursuing a certain benefit in the situation of limited demand. Conversely, if the parking demand is sufficient (i.e., in scenario 2), our method tends to formulate a lower rental price for stealing market share competition and ensuring people's perceived benefits.

Obviously, the allocation of parking demand in our model is affected by the pricing of competitive parking lots and government guidance. FlexPass considers these two factors when setting prices. As shown in Figure 7, if the opponent's parking price or the government's guidance price

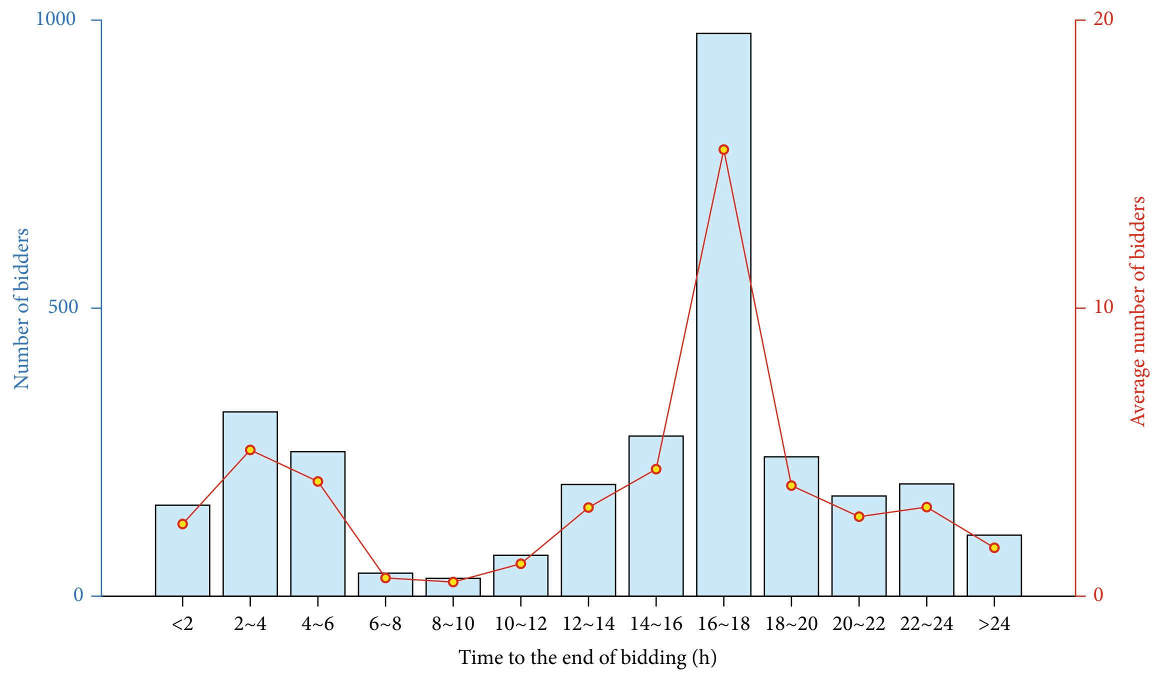

Figure 4: The number of people bidding.

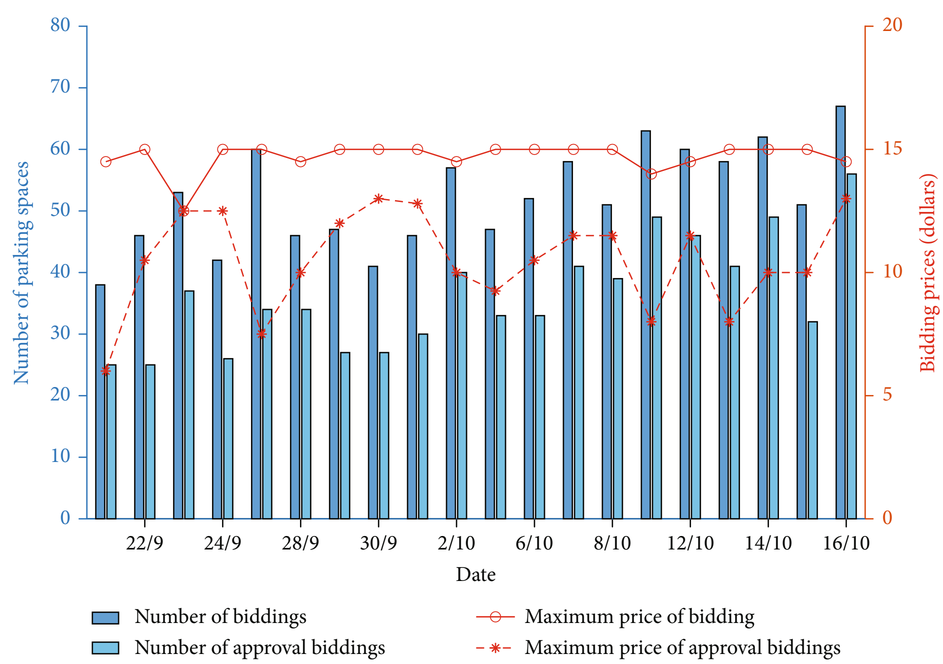

Figure 5: The bidding survey of the University of California, Berkeley.

increases by 5 dollars to 10 dollars, the optimal prices of FlexPass increase accordingly in both scenarios. From the results that we calculated based on the actual data, the optimal price of scenario 1 is more stable than that of scenario 2. This is reasonable because in the context of limited demand, rental prices must be anchored at a high-order position to hedge the monetary costs of excessive recovery. In the environment of sufficient demand, our method has more pricing space to win the competition for parking demand allocation. Note that the trend of this change is equivalent to the government guidance price and the rival price due to the default setting having the same weight.

4.2.2. Turnover Situation of Parking Spaces. Exploring the turnover of parking spaces under an incentive strategy is one of the main purposes of a shared parking policy. Figure 8 shows the statistical results of the recovery number under these two scenarios based on the model's berth

Table 1: The default setting of other model parameters.

Name	Parameter symbol	Value
Default setting of government guidance price	p_0	15
Default rental price of competitor	p_A	20
Competition coefficient of parking demand	$r_A : r_B$	1 : 1
Psychological sensitivity to government guidance price	$a_A : a_B$	1 : 1
Conversion coefficient of personal travel cost	c_i	0.5
Initial distribution proportion of parking demand	θ	0.5
Risk aversion indicator	η	0.3

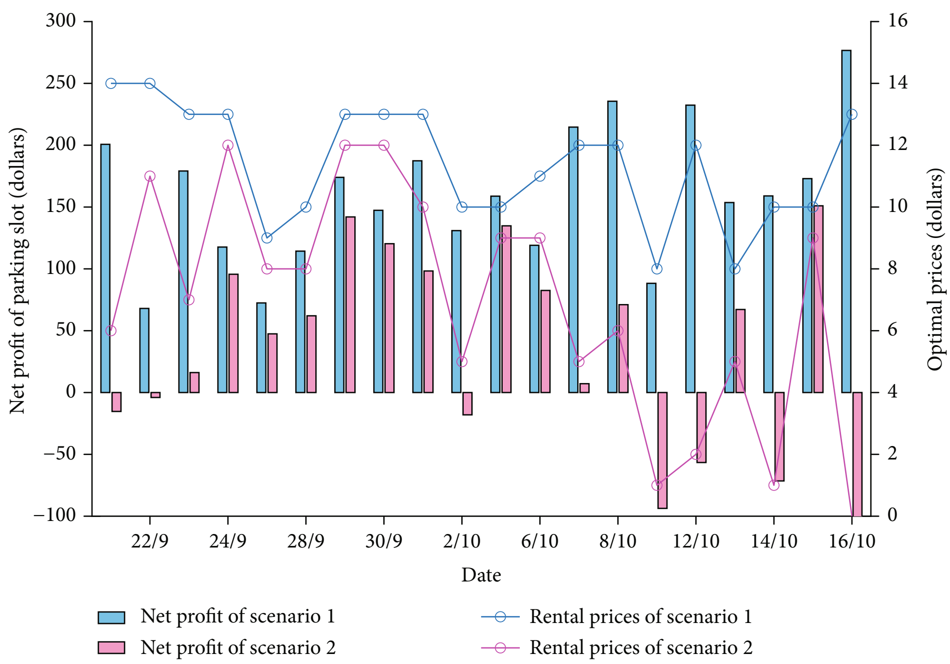

Figure 6: Optimal pricing and net benefit under different scenarios.

recovery decision rules mentioned above. The recovery decision rules considering the proposed risk aversion will be more radical to enable agreement on the recovery of parking spaces and to ensure providers' benefits from participating in shared parking. Compared with the number of bidding applications, the decision rules enable FlexPass to bear at least 70% of the recovery rate during the survey period, and the recovery rate can be maintained at a relatively equal proportion under these two scenarios.

Figure 9 shows the fluctuation in attracted demand and occupancy rate of parking spaces if the providers who win the bidding do not fail to keep their appointments. Although the attraction of the rival may reduce the occupancy rate of parking spaces in some demand environments of scenario 1, in general, it ensures that the parking spaces for FlexPass are used effectively. The reason is that in addition to considering the parking demand attracted from competitors, the overall utilization efficiency of parking spaces depends on the number of people's bidding applications and the number of FlexPass spaces reclaimed. If the parking lot recovers too many parking spaces and there is not enough external demand, some of the recovered spaces will inevitably be idle during the operational process. On the plus side, the method we propose can occupy a favourable position in the competition and obtain one part of the parking demand that was originally assigned to the opponent. Regarding the attraction effect, due to the lower pricing, scenario 2 can win a larger parking share than scenario 1, which was at the expense of the parking lot's net profits.

4.2.3. Effects of Policy Benefits. During the operation of FlexPass, there may be some differences in policy benefits between individuals and parking lots when the individual perceived benefit is analysed separately, as shown in Figure 10. Compared with scenario 1, the lower pricing of scenario 2 will make the overall perceived benefits of providers higher. This may be because individuals' perceived benefit is affected mainly by their own subjective value judgement. When a parking lot that implements FlexPass has a lower leasing price, it is equivalent to transmitting a

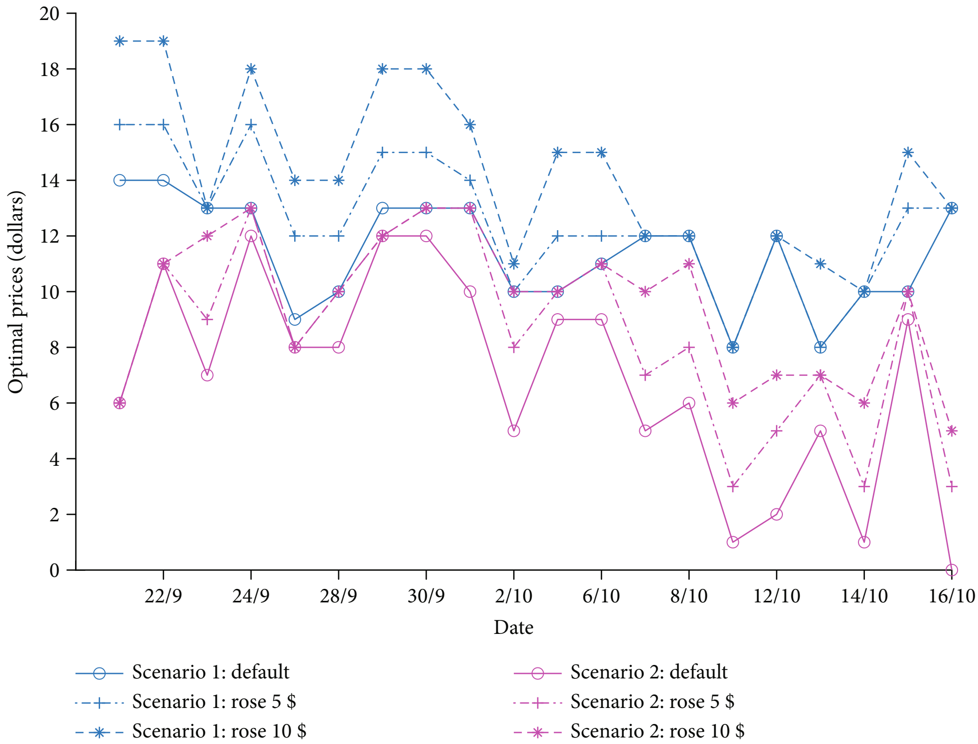

FIGURE 7: Trend chart of optimal pricing with the upticks of the government or competitor.

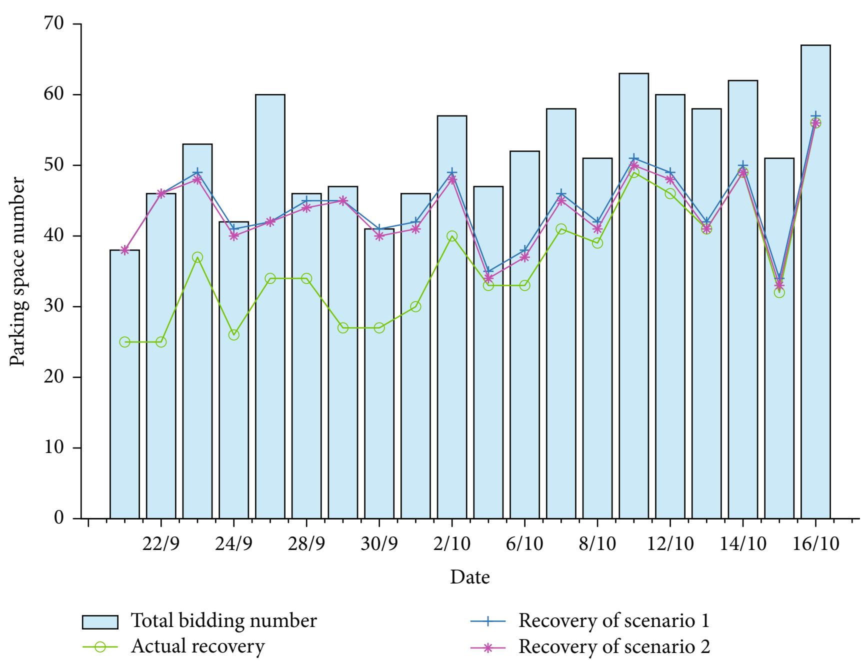

FIGURE 8: Quantity of recovery between these two scenarios and actual judgement.

signal that sharing the parking spaces will not make app users feel put upon. This will partially offset people's underestimation of space reclamation and improve their enthusiasm for participating in shared parking. It is worth mentioning the trade-off relationship between the individual perceived benefit and net profits of the parking lot by comparing the variation between Figures 6 and 10. Whether we pursue individual perceived benefits or parking lot benefits, all come at the cost of neglecting the other. This result is similar to many research findings that apply the truthful auction method to realize the incentive mechanism of mobile crowdsourcing service; i.e., it is considered difficult

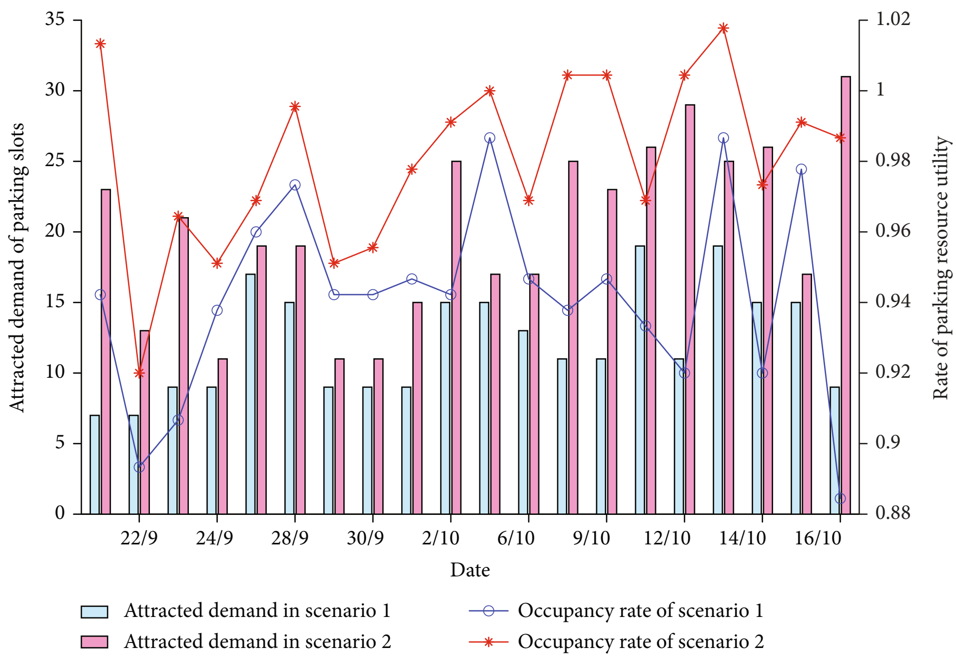

Figure 9: Demand attracted from competitors and the parking space utility.

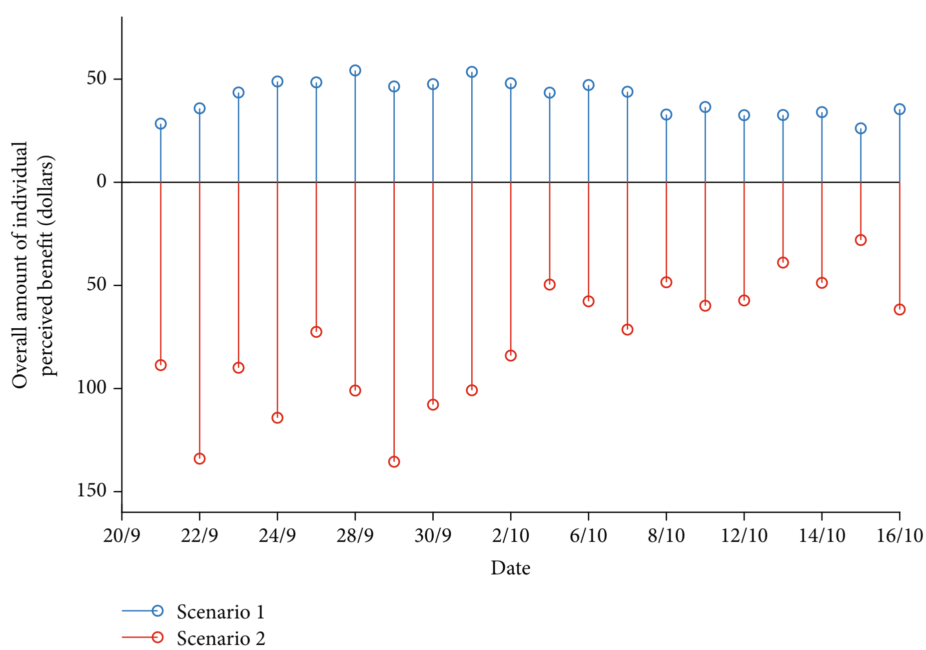

Figure 10: Stem leaf diagram of individual perceived benefits.

to design a system that simultaneously satisfies individual rationality, budget balance and system efficiency [79–83].

In our model, people's enthusiasm for participating in policies can be reflected in their perception of risks (refer to formulas (8) and (9)). It is not difficult to imagine that if FlexPass operates smoothly with the incentive mechanism, the risk associated with sharing parking spaces will be reduced. This is specifically reflected in the fact that compared with the initial stage of FlexPass operation, the perceived benefit tends towards its real income when people make a bid (i.e., the maximum value of the risk aversion quantile will approach 1 in the model). To analyse the impact of risk aversion behaviour on the operation of FlexPass, we choose October 14 as the target day, which has a significant difference in net benefit under the two scenarios for the sensitivity analysis (as shown in Figure 11). On this day, the respondents submitted 62 bids in total, and 25 applications were approved by the smartphone app. The maximum amounts of bidding and system approvals were US $15 and US $10, respectively. As the risk aversion quantile increases, our method will gradually shift from taking care of individual perceptions to chasing profits and formulate a rising price for external leasing. Under this effect, the net profit of the parking lot also shows a gradual upwards trend, whether profitable or not. When the provider's enthusiasm for participating in shared parking increases, people's perceived benefits increase under different risk aversion levels. Our pricing strategy will help parking lots make more favourable reclamation decisions in a negative return environment and maintain the price advantage in a positive income environment. If the personal benefit and parking lot benefit are added together as the policy benefits of FlexPass, we can obtain the results shown in Figure 12, which reflects the positive effect of shared parking policy to some extent.

5. Discussion

In this section, we analyse how FlexPass sets a competitive rental price by our model and how the utilization efficiency and monetary incentive of shared parking spaces evolve in this study. Two different scenarios, which are divided by the predicted number of recovered spaces based on prior experience, were calculated and discussed here in depth. As stated in the report of Minnesota University [17], FlexPass is promoted to reduce single-occupancy vehicle travel and increase the commuting accessibility of parking spaces. It is hoped that it will change the pattern of car travel and encourage people to use alternative methods of high-occupancy transportation. Fortunately, together with previous studies, our research verifies the effectiveness of parking cash-out schemes in encouraging people's enthusiasm for sharing their parking spaces [16, 84]. This is because exiting from the bidding process could influence people's parking decision-making despite the power of economic leverage, which is a hidden function compared with the traditional shared parking policy. In terms of behaviours, FlexPass generates an incentive for providers to recover the cost of their parking spaces and helps people flexibly set a time period for shared parking according to their travel schedules [14, 15].

In regard to the characteristic analysis of our study, the integration of FlexPass and the pricing rules based on risk aversion effectively releases parking resources and improves the service level of parking spaces by guiding drivers to voluntarily share their parking rights. Figures 6 and 7 reveal that when all the parking resources can be allocated in a competitive environment, our approach dares to make aggressive pricing decisions, although the net profit of the parking lot will temporarily fall to a negative value. This aggressive "sacrifice" in economic benefits is in return for the positive control of the individual risk perception of parking space providers. It is not explicitly calculated in our model but can affect the number of parking spaces shared by providers. A supporting phenomenon is that the number of recovered parking spaces and the parking demand attracted from the rival are both presented as positive fluctuations, as shown in Figures 8 and 9. In particular, compared with the original results of RGA judgement in the UC Berkeley survey, whether the demand prediction of parking spaces reclaimed by the parking lot was accurate or not, FlexPass would maintain a stable high quantity for recovery to ensure the continuity of people sharing their parking spaces. Meanwhile, the analysis results of individual perceived benefits, net profits of parking lots, and policy benefit of FlexPass shown in Figure 10 to Figure 12 illustrate that the operation of FlexPass has a characteristic of profit seeking, which enables it to strive for a positive benefit of shared parking in the competitive environment of parking demand. This feature enables FlexPass not only to keep the positive revenue of individuals and society to the greatest extent possible but also to have the ability to turn losses into profits for the parking lot with the strengthening of risk preference psychology.

In contrast to previous studies, we anticipate that the outcome of our study will alleviate the dilemma of urban parking supply and demand by setting a reasonable channel for bidding incentives in shared parking policy. Our empirical results are consistent with the research of Tscharaktschiew and Reimann [16], who found that cashing out for bidding incentives could serve as a corrective strategy and guarantee economic efficiency. Since we eliminated the need for platform fees, the positive behaviour of providers following the incentive to share their parking spaces would be further expanded, which would also make people participate in the design of FlexPass [17, 29]. From the perspective of commercial operation, our method is not like SFpark in implementing a purely performance-based pricing strategy but rather adjusts the flexibility of the price gradient in real time by observing the change in external parking demand to maintain the occupancy rate and demand attraction ability of parking lots at a high level [7, 54]. This can avoid setting too-high prices due to the overheated demand, which only changes the composition of parkers and creates more vacancies. Note that although studies have shown that there is a consistent trend in the system cost and profitability of shared parking policy under some threshold conditions [85], our research found that a reasonable recovery and release mechanism of sharing parking spaces can also enable parking lots to obtain sustainable benefits during long-term operation, even if the economic income may be negative. In other words, for local governments or policy makers, the shared parking policy can try to promote first and then gradually pursue the development of profit, which may be an effective way to alleviate the pressure of urban parking.

In fact, the introduction of FlexPass has transformed commuters' parking spaces, which were originally "durable goods," into a public resource with the day-to-day characteristics of "consumables." The use rights of these parking spaces can be drawn into market competition through the mode of reverse auctions, which further encourages people to flexibly share parking spaces. Unlike tradable parking permits [86, 87], the cash-out scheme of FlexPass is focused on improving individual awareness of subjective initiatives and alleviating urban static and dynamic traffic problems. Collecting discrete parking spaces into a management centre via the bidding mode can not only provide more stable parking spaces but also prevent market-oriented parking rights

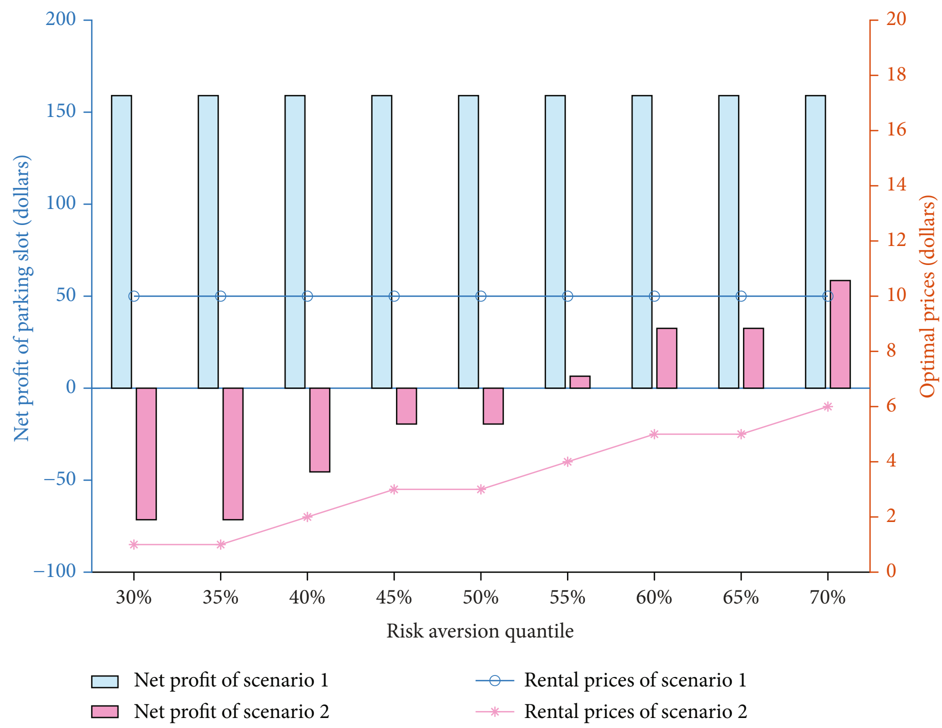

Figure 11: Optimal pricing and net benefit under different risk perceptions.

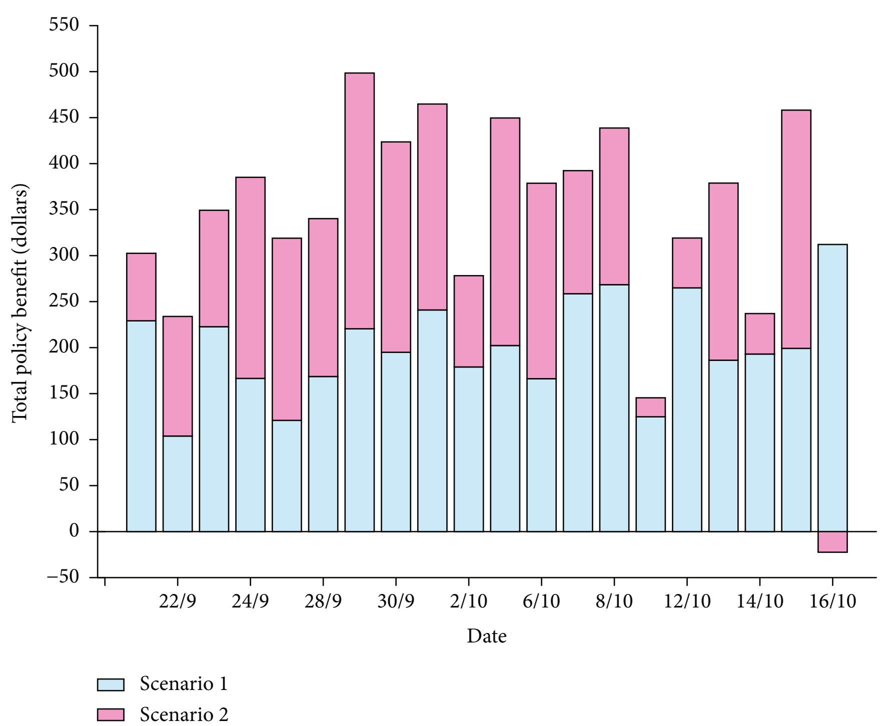

Figure 12: Total policy benefit of FlexPass during the survey period.

from falling into the hands of individuals who hoard and resell them. In summary, the integration of FlexPass and the pricing rules based on risk aversion could effectively release parking resources and improve the service level of parking spaces by guiding drivers to voluntarily share their parking rights. Although to protect the provider's perceived benefits against competition, the parking lot may also risk a loss in setting a low price when the number of parking spaces is insufficient, our method can sustainably maintain a positive external income through individual perceived expectation.

6. Conclusions

Monetary incentives, as an embodiment of economic leverage, have been increasingly applied in related fields of transportation. For the urban parking problem, a sharing economy strategy based on monetary incentives is continuing efforts to implement new opportunities to relieve the pressure of urban parking. In this study, we introduced FlexPass, which uses incentives in shared parking via the mode of bidding prices. A flexible pricing method with a cash-out scheme was proposed to guide commuting drivers to share their personal parking spaces and ensure a reasonable profit for parking management under different parking demand scenarios. To make the calculation more realistic, we used four model assumptions to describe this pricing procedure. First, we set up the bidding game and the decision-making behaviours between the rational parking lot and parking space providers. Second, the demand competition between parking lots caused by rental pricing was integrated into the profit assessment of shared parking policy. Third, a function of conditional value-at-risk induced by the unrepresentative characteristic for individual bidding perception was numerically simulated to explore the evolution process of people's shared revenue expectation. Last, we provided a utility rule to meet the rapid response requirement of individual bidding and reflect parking managers' decision-making power over parking space reclamation when the external demand became clearer. In this research, we used survey data of 216 drivers obtained from UC Berkeley in a common unit with 225 parking spaces to analyse the change in operational revenue of FlexPass and included another parking lot, treated as a competitor, to simulate the demand competitive environment. A mixed integer nonlinear programming model was built, and the branch-and-bound algorithm was applied to solve for the optimal solution. The results show that when the relationship between the total parking demand and the number of reclaimed parking spaces is considered, our method cannot only formulate a more competitive price in different scenarios and earn a higher demand distribution proportion from a competitor but also enable the utilization efficiency of parking lots to be maintained at a good and stable level. In particular, if the bids are used as the criterion to distinguish people's enthusiasm for parking space sharing, the implementation of FlexPass would help parking lots pursue their own net profits due to the increase in shared parking spaces. Therefore, the economic benefits of our mechanism would be further expanded as the operation time is extended.

Although this study represents a practical attempt at a new incentive mechanism, we assumed that the rental process of the bidding survey took place in a single parking lot of UC Berkeley, and the model parameters were limited to a fixed value or a certain range to explore the economic benefits and avoid volatility in the operational process of FlexPass. Some settings of this study still differ from real-world applications. For example, major holidays and important citizen events that may lead to a significant imbalance between the demand and supply of parking spaces are not considered in this paper. Additionally, the parking cash-out of the UC Berkeley survey set a lower limit of 0 dollars and an upper limit of 15 dollars, which may lead to uncertain revenues and affect people's willingness to share their private spaces. The behavioural evolution caused by bidding prices controlled with a fixed value or without a certain boundary was not considered in the model construction and analysis. Furthermore, this study did not consider the detailed allocation of shared parking spaces, which could be an independent and important issue in future research.

Appendix A

In this appendix, we derive the optimal bidding strategy for parking lot providers, and we analyse how the behavioural tendency of risk aversion influences personal bids.

According to Assumption 3, the perceived benefits $V_C^{\eta}(\varepsilon_i)$ of provider i considering risk aversion can be given as

$$V_C^{\eta}(\varepsilon_i) = \max\left\{v + \frac{1}{\eta}E[\min(\varepsilon_i - v, 0)]\right\}. \tag{A.1}$$

To simplify the narrative, let $\varepsilon_i = (\beta_i - c_i)\cdot[\omega_i - (\omega_i - \chi_i)^+]$ for each provider and $\Lambda = a_B(p_B - p_0) - r_B(p_A - p_B)$ for parking space B, which is operating with FlexPass. Therefore, the personal perceived benefit $V_C^{\eta}(\varepsilon_i)$ can be rewritten as follows:

$$V_C^{\eta}(\varepsilon_i) = \max\left\{v + \frac{1}{\eta}E[\min((\beta_i - c_i)\cdot[\omega_i - (\omega_i - \chi_i)^+] - v, 0)]\right\}. \tag{A.2}$$

Then, we set $V_C^{\eta}(\varepsilon_i) = \max G(v)$, and $G(v)$ can be written as

$$G(v) = v + \frac{1}{\eta}E[\min((\beta_i - c_i)\cdot[\omega_i - (\omega_i - \chi_i)^+] - v, 0)]. \tag{A.3}$$

To further discuss the expression of perceived benefit $V_C^{\eta}(\varepsilon_i)$, we consider the following two cases.

Case 1. If $v \geq (\beta_i - c_i)\cdot\omega_i$, then,

$$G(v) = \frac{1}{\eta}E[-(\beta_i - c_i)\cdot(\omega_i - \chi_i)^+] + \frac{(\beta_i - c_i)\cdot\omega_i}{\eta} + \frac{\eta - 1}{\eta}\cdot v = \frac{\eta - 1}{\eta}v + \frac{\beta_i - c_i}{\eta}. \tag{A.4}$$

Note that $dG(v)/dv < 0$, which means $G(v)$ would decrease with v; thus, $G(v)$ reaches a maximum at the lower boundary point when v equals $(\beta_i - c_i)\cdot\omega_i$.

Case 2. If $v \le (\beta_i - c_i)\cdot\omega_i$, then,

$$C = \frac{D_B\cdot(p_B-\beta_i)\cdot[\omega_i-(\omega_i-\chi_i)^+]}{\pi_i},$$

$$\begin{aligned}G(v) &= v + \frac{1}{\eta}E[\min((\beta_i-c_i)\cdot\omega_i-(\beta_i-c_i)\cdot(\omega_i-\chi_i)^+-v,0)]\\ &= v-\frac{1}{\eta}E[\max((\beta_i-c_i)\cdot(\omega_i-\chi_i)^+-(\beta_i-c_i)\cdot\omega_i+v,0)]\\ &= v-\frac{1}{\eta}E[(\beta_i-c_i)\cdot(\omega_i-\chi_i)^+-(\beta_i-c_i)\cdot\omega_i+v]^+\\ &= v-\frac{1}{\eta}E[(\beta_i-c_i)\cdot[(\omega_i-\chi_i)^+-\omega_i]+v]^+\\ &= v-\frac{1}{\eta}E\left[v-\frac{\pi_iC(\beta_i-c_i)}{D_2(p_2-\beta_i)}\right]^+ = v-\frac{1}{\eta}\int_{-\infty}^{\Delta}\left[v-\frac{\pi_iC(\beta_i-c_i)}{D_2(p_2-\beta_i)}\right]^+ d\Phi(\xi),\end{aligned} \tag{A.5}$$

where the integral upper Δ would be determined if we record the variation Λ of parking demand on parking lot B as $a_B(p_B-p_0)-r_B(p_A-p_B)$. If parking demand D_B equals, C, then all parking spaces, including those that providers bid to reclaim, are leased. At this time, the operation of FlexPass is in an ideal state. Let $\xi_{\max}$ be the total parking demand at this moment, i.e., $\xi_{\max}=\Delta$. Therefore, the formulation is

$$\begin{aligned}\Delta &= \xi_{\max} = \frac{C+\Lambda}{\theta},\\ G(v) &= v-\frac{1}{\eta}\int_{-\infty}^{(C+\Lambda)/\theta}\left[v-\frac{\pi_iC(\beta_i-c_i)}{D_B(p_B-\beta_i)}\right]^+ d\Phi(\xi),\\ \frac{dG(v)}{dv} &= 1-\frac{1}{\eta}\cdot\Phi\left(\frac{C+\Lambda}{\theta}\right).\end{aligned} \tag{A.6}$$

Obviously, $\beta_i - c_i > 0$ and $v \le (\beta_i-c_i)\cdot\omega_i$. If v reaches its maximum at ε_i, we can deduce that

$$\begin{aligned}[\omega_i-(\omega_i-\chi_i)^+] &= \frac{v}{(\beta_i-c_i)},\\ \frac{C+\Lambda}{\theta} &= \frac{D_B(p_B-\beta_i)[\omega_i-(\omega_i-\chi_i)^+]+\Lambda\pi_i}{\pi_i\theta}\\ &= \frac{1}{\pi_i\theta}\left[D_B(p_B-\beta_i)\frac{v}{\beta_i-c_i}+\Lambda\pi_i\right]\\ &= \frac{1}{\pi_i\theta}\left[\frac{(p_B-\beta_i)D_B}{\beta_i-c_i}v+\Lambda\pi_i\right],\\ \frac{dG(v)}{dv} &= 1-\frac{1}{\eta}\cdot\Phi\left\{\frac{1}{\pi_i\theta}\left[\frac{(p_B-\beta_i)D_B}{\beta_i-c_i}v+\Lambda\pi_i\right]\right\}.\end{aligned} \tag{A.7}$$

Note that $d^2G(v)/d^2v<0$ and $G(v)$ are concave. Therefore, when $dG(v)/dv=0$, $G(v)$ reaches its maximum and $\bar{v}$ is

$$\bar{v} = \frac{\pi_i(\beta_i-c_i)\left[\Phi^{-1}(\eta)\theta-\Lambda\right]}{D_B(p_B-\beta_i)}. \tag{A.8}$$

Thus, when v equals $\bar{v}$ under the condition $v \le (\beta_i-c_i)\cdot\omega_i$, the value of $G(v)$ reaches the maximum; otherwise, the maximum is reached at $(\beta_i-c_i)\cdot\omega_i$. That is,

$$v = \begin{cases}\bar{v}, & v\le(\beta_i-c_i)\cdot\omega_i,\\ (\beta_i-c_i)\cdot\omega_i, & v\ge(\beta_i-c_i)\cdot\omega_i.\end{cases} \tag{A.9}$$

Note that under the condition of $v\le(\beta_i-c_i)\cdot\omega_i$, $G(\bar{v})$ can be deduced as follows:

$$\begin{aligned}G(\bar{v}) &= \bar{v}-\frac{1}{\eta}\int_{-\infty}^{\Delta}\left[\bar{v}-\frac{\pi_iC(\beta_i-c_i)}{D_B(p_B-\beta_i)}\right]^+ d\Phi(\xi)\\ &= \bar{v}-\frac{1}{\eta}\int_{-\infty}^{\Delta}\left[\frac{\pi_i(\beta_i-c_i)\left[\Phi^{-1}(\eta)\theta-\Lambda\right]}{D_B(p_B-\beta_i)}-\frac{\pi_iC(\beta_i-c_i)}{D_B(p_B-\beta_i)}\right]^+ d\Phi(\xi)\\ &= \bar{v}-\frac{1}{\eta}\int_{-\infty}^{\Delta}\left[\frac{\pi_i(\beta_i-c_i)\theta}{D_B(p_B-\beta_i)}\left[\Phi^{-1}(\eta)-\frac{\Lambda+C}{\theta}\right]\right]^+ d\Phi(\xi).\end{aligned} \tag{A.10}$$

Therefore, due to the relationship $(\Lambda+C)/\theta=\Phi^{-1}(\eta)$, the formula of personal perceived benefit $V_C^{\eta}(\varepsilon_i)$ can be deduced as

$$V_C^{\eta}(\varepsilon_i) = \begin{cases}\dfrac{\pi_i(\beta_i-c_i)\left[\Phi^{-1}(\eta)\theta-\Lambda\right]}{D_B(p_B-\beta_i)}, & \text{if } \Phi^{-1}(\eta)\theta-\Lambda\le C,\\ \dfrac{\beta_i-c_i}{\eta}(\eta\omega_i-\omega_i+1), & \text{if } \Phi^{-1}(\eta)\theta-\Lambda\ge C.\end{cases} \tag{A.11}$$

Appendix B

Now, we prove that FlexPass satisfies the three properties mentioned in Section 3.

Lemma 1. *FlexPass is computationally efficient.*

Proof. Let n be the total bidding number on the target date. To ease the exposition, we assume that the parking lot determines the bidding prices individually according to the order offered by the parking space providers. The loop of information interactions and judgements takes a maximum of $O(n)$ time complexity in FlexPass; i.e., the proposed method of the reclamation rule can be computed in polynomial time. Therefore, the shared policy of FlexPass is computationally efficient. □

Lemma 2. *FlexPass is individually rational.*

Proof. During the operation of FlexPass, the manager needs to pay provider i the bidding price β_i if it has decided to reclaim the parking space. Under this condition, the utility of provider i is $V(f_i)=\beta_i-c_i$, which we define as $V(f_i)\ge 0$ in Assumption 1. Although in subsequent hypotheses we know that the perceived benefits of individuals will be lower than their real benefits due to the existence of risk aversion, profit ε_i of provider i who has won the bidding application is also greater than 0. Therefore, FlexPass is individually rational for parking space providers. □

Lemma 3. *Biddings of FlexPass are close to truthfulness.*

Proof. Since FlexPass has not yet been implemented, the truthfulness of biddings here refers to providers behaving truthfully in parking space sharing by participating in more bidding prices. Let c_i and β_i be the provider's cost and bidding price, respectively. $\varepsilon_i = \beta_i - c_i$ is the utility if bidding price β_i is accepted by the parking space provider. Even considering people's risk-averse bidding behaviour, as presented in Appendix A, the perceived benefit $V_C^{\eta}(\varepsilon_i)$ under the condition $\Phi^{-1}(\eta)\theta - \Lambda \leq C$ equals $(\pi_i(\beta_i - c_i)[\Phi^{-1}(\eta)\theta - \Lambda])/(D_B(p_B - \beta_i))$, which is greater than zero within acceptable values. Therefore, the personal utility of the provider becomes $V_C^{\eta}(\varepsilon_i) \geq 0$. On the other hand, we deduce that under the condition $\Phi^{-1}(\eta)\theta - \Lambda \geq C$, the perceived benefit $V_C^{\eta}(\varepsilon_i)$ is greater than zero because its terms in expression $((\beta_i - c_i)/\eta)(\eta\omega_i - \omega_i + 1)$ are all positive. That is, people will not raise a false bidding price, especially when the risk of parking space sharing is taken into account under these two conditions. With the increment of FlexPass implementation time, the parking space provider's experience in bidding will gradually mature, and the personal incentive rewards will be close to their perceived value of inner expectation. □

Data Availability

The FlexPass data used to support the findings of this study are restricted by the UC Berkeley in order to protect the personal privacy of respondents. Data are available from Dounan Tang (dounan.tang@berkeley.edu) for researchers who meet the criteria for access to confidential data.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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