POMS

Original Article

Production and Operations Management
2025, Vol. 34(11) 3647–3666

DOI: 10.1177/10591478251344226
journals.sagepub.com/home/pao
Sage

Coins, Cards, or Apps: Impact of Payment Methods on Street Parking Occupancy and Search Times

Sena Onen Oz[1], Mehmet Gumus[1] and Wei Qi[1,2]

Abstract

City dwellers often struggle with on-street parking in many cities, where they generally need to pay for parking in advance. However, drivers usually cannot accurately foresee how much parking time they need. Compared to traditional payment methods, that is, cash and credit card through on-site meters, mobile payment applications provide more flexibility: drivers can adjust their parking sessions remotely if a longer stay is in need. Utilizing data from an online survey and high-resolution transaction records provided by a municipal agency in a densely populated North American city, we analyze how different payment methods and hourly parking prices affect drivers' parking behavior, street parking occupancy, and search time to find an available parking spot. Our findings reveal that mobile payments facilitate shorter parking duration, which in turn improves the turnover rate of parking spaces and reduces the overall search time. Furthermore, we observe that a driver's parking behavior is not solely determined by price or payment method but rather by the interaction of both factors, making it essential for any policy analysis to consider this interplay. In particular, mobile payers are more sensitive to price changes than credit card payers, whereas cash payers are identified as the most sensitive to price changes. To provide further guidance to municipalities, we simulate different pricing mechanisms and show that progressive pricing and mobile payment adoption, along with pricing strategies, significantly impact both search time and occupancy compared to constant pricing.

Keywords

Street Parking, Payment Methods, Online Survey, Regression Discontinuity Design, Survival Analysis

Date received 19 July 2023; accepted 27 October 2024 after two revisions

Handling Editor: Nitin Joglekar

1 Introduction

Driven by patterns in mass migration to urban areas, the world's urban population is projected to reach 6.7 billion in 2050, accounting for 68% of the global population (United Nations and Social Affairs, 2019). As a result, this growth of the urban population substantially strains the urban transportation and mobility infrastructure. One of the urban mobility systems affected by this trend is on-street parking, which has a significant impact on city residents' quality of life and on efficient city operations. Prior studies demonstrate that in large cities, a significant portion of people's driving time is spent searching for on-street parking because of a lack of available parking spaces (Arnott and Rowse, 2013). A review of studies across 15 cities indicates that finding a parking spot takes between 3 and 14 minutes of cruising, and drivers searching for free parking spaces contribute to 8%–74% of traffic (Hampshire and Shoup, 2018). As finding parking spots close to their destinations is difficult, drivers also spend more time walking from the parking lots to their final destinations, thus adding to their hassle costs.

To address these challenges, municipalities are rolling out innovative solutions to provide convenience to drivers so that they can make payments without hassle cost. As an illustrative example, we display the interface of a mobile application used for street parking in one of the most densely populated urban centers in North America. Figure 1 shows the initial screen of the application, which prompts drivers to enter the name of the parking space where they have parked their vehicles.

[1]Desautels Faculty of Management, McGill University, Montreal, Canada
[2]Department of Industrial Engineering, Tsinghua University, Beijing, China

Corresponding author:
Wei Qi, Desautels Faculty of Management, McGill University, Bronfman Building, 1001 rue Sherbrooke Ouest, Montreal, Quebec, H3A 1G5 Canada; Department of Industrial Engineering, Tsinghua University, Shunde Building, Tsinghua University, Beijing 100084, China.
Email: qiw@tsinghua.edu.cn

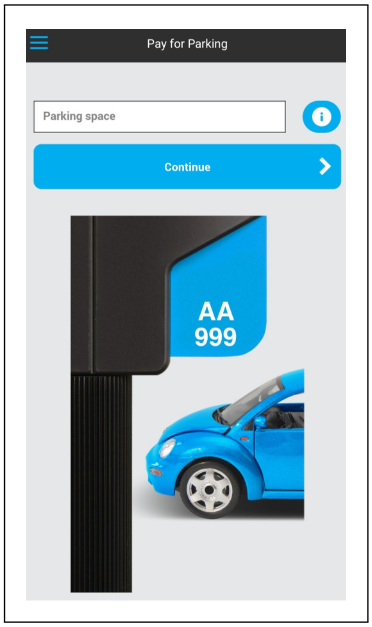

Figure 1. Parking space selection.

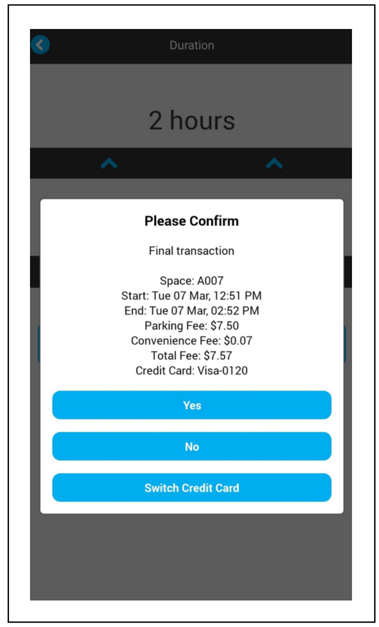

Figure 3. Summary before payment.

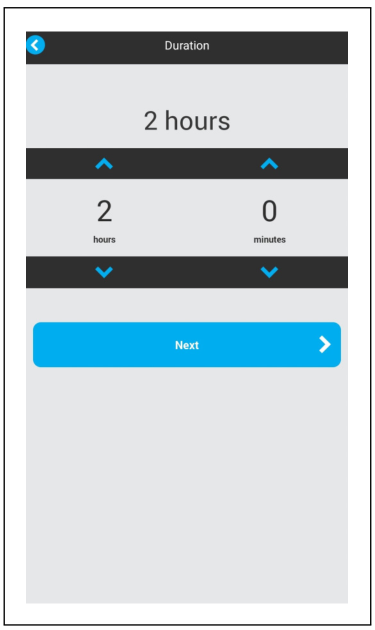

Figure 2. Payment duration selection.

Once this information is submitted, the next screen (Figure 2) requires the drivers to enter the duration of their parking. After the duration is entered, the final screen (Figure 3) presents a summary of the user's inputs and awaits their approval.

While these innovative solutions are being launched by the municipalities, it is not clear how these new payment methods ultimately affect drivers' payment behavior. Even though it is shown in the literature that introducing a mobile payment method reduces the pain of payment, these results are shown in the retail context, where the consumers' utility trade-off is influenced by the price of the product and willingness to pay (WTP) (Boden et al., 2020; Liu et al., 2021). However, the payment behavior in the street parking context is fundamentally different. Specifically, when a driver opts for a specific payment method, they encounter a trade-off akin to a newsvendor's dilemma. If they pay below the required amount for their parking duration, they may need to make an extra payment to avoid penalties. Conversely, if they pay too much, they lose the excess amount since the payment is non-refundable. Due to the varying payment methods and pricing options involved, the central trade-off faced by the drivers stems from the interplay between these factors. For example, changes in parking fees impact the overpayment aspect of the equation, whereas the introduction of convenient payment methods, such as mobile payments, affects the underpayment side. Since a driver's payment behavior, such as overpaying or underpaying and to what extent, depends on how this trade-off is balanced, it is essential to not only evaluate the individual effects of payment methods and pricing but also comprehend how they together influence payment behavior.

Considering the numerous different payment options and driver preferences, we collaborated with a densely populated North American city to analyze their real-life parking data to understand drivers' parking payments. Sixty-eight percent of more than five million transactions come from mobile application users. This is followed by cash and credit card payers with 21% and 11%, respectively. Our partner introduced its mobile application in 2012, and it is seen that people have adapted to using this system for their parking payments. We also observe that payment methods are associated with distributional shifts in the payment amounts. Specifically, those who pay with credit cards pay 62% and 21% longer, on average, than those who pay with cash and mobile applications, respectively. Motivated by the differences between payment methods in terms of flexibility and these apparent descriptive differences in payment amounts, we pose our first research question: *RQ1: How does a driver's payment amount change across different payment methods (i.e., cash, credit card, and mobile)?*

The aforementioned newsvendor trade-off suggests that adjusting parking prices directly affects the cost of overpayment from the drivers' perspective. Furthermore, the effect of price will also differ depending on the preferred payment method used by the driver. This interplay between payment methods and prices leads to our second research question: *RQ2: How does the price of parking affect the payment amounts of drivers across different payment methods?*

Changes in pricing and the differences in payment methods could significantly affect how efficiently drivers can find and utilize parking spaces. Therefore, it is also important to examine the implications of these factors on urban mobility and parking management. This raises the following third question: *RQ3: What is the impact of price changes and payment methods on occupancy levels and search times to find an available parking space?*

In this study, we aim to understand and explain the patterns in drivers' payment behaviors that may occur according to different payment methods and prices to help municipalities adjust their pricing policies and balance street parking occupancy rates. To do so, we conduct an online survey to find an answer to our first research question. In this survey, participants were assigned to different conditions based on the specified payment method and hourly parking price, and each participant makes payment decisions under various hypothetical situations that vary depending on the distance to the destination, the reason for parking, and the duration of parking. Furthermore, to answer RQ2, we use a real-life transaction dataset to observe the interaction of price and payment method on payment amounts. In this dataset, each transaction includes the start date and time of parking, the location of the parking spot, and the payment amount. Although the parking spot prices in this city are the same as those in other areas within the region, there are differences between regions. To diminish the risk of omitted variable bias, we use the regression discontinuity design (RDD), which assumes that the parking spots located in region boundaries are similar in all aspects except for price changes. However, even after finding answers to our first two research questions, the impact of differences created by each payment method and pricing on parking occupancy and search time remains unknown. To answer our third research question, we conduct a discrete event simulation study in the last step using findings from our survey and empirical analysis of transaction data.

This study has several research contributions. First, our survey findings support our main hypothesis, which posits that, all else being equal, mobile payment results in a smaller payment amount compared to the other payment methods due to its reduced hassle cost. Specifically, our analysis revealed that participants using the mobile payment method paid on average 79.18 minutes (SE = 1.356) for parking, whereas those using credit cards and cash paid on average 83.58 minutes (SE = 1.424) and 82.94 minutes (SE = 1.317), respectively. This suggests that the average payment duration under the mobile payment method was 3.44 standard errors less than that under credit card payment and 3.21 standard errors less than that under the cash payment method, indicating a significant difference ($p < 0.01$). Consequently, this difference, which arises from mobile payment, will improve the turnover rate of parking spaces and decrease the overall search time for available parking. Second, our RDD analysis enables us to estimate both the main impact of price adjustments and how this impact is moderated by the parking payment method. Our findings show that a driver's parking behavior is influenced not only by price or payment method but also by the interaction of both. Namely, the analysis of the price change around the RDD boundary indicates that a \$1 decrease in the hourly parking fee results in an average increase of 16% in the total payment amount. Furthermore, the analysis of moderation indicates that the positive impact of the price reduction is most significant when using the cash payment method, with an increase of 37%, and second most significant with the mobile payment method, with an increase of 26%, compared to credit card payment. Third, combining these results with a simulation study, we measure the impact of parking fees and payment methods on key metrics such as street parking occupancy levels and search times—a critical aspect influencing urban life quality. We find that changes in both parking fees and payment methods have the greatest impact on streets with moderate levels of utilization. Our findings also reveal asymmetric effects resulting from a \$1 change in the hourly parking rate. In addition to constant pricing, we simulate the impact of a progressive pricing policy where the hourly parking rate changes based on the total duration of parking. Our simulation study shows that progressively increasing pricing policy used in many North American cities (Shoup, 2018) decreases the average search time for drivers. Finally, our study reveals that as the number of mobile app users increased, both operational metrics showed improvement. These findings strongly emphasize the potential benefits for a municipality to implement different pricing policies and introduce mobile payment options.

The rest of the article is organized as follows. The following section reviews related studies. We then construct the hypotheses based on the previous discussions and analytical findings in Section 3. We present our online survey design and analysis of the observations in Section 4. Following this section, we introduce the real-life dataset, describe the econometrics model constructed to answer our second research question, and discuss the empirical findings with policy implementations in Section 5. The simulation study and its results are provided in Section 6. Finally, concluding remarks, managerial implications, and future research directions are discussed in the last section.

2 Literature Review

Smart city design has become a remarkable focus area within operations management (OM), exploring various aspects such as vehicle sharing (Benjaafar and Shen, 2023; Jin et al., 2023; Qi et al., 2022), bike sharing (He et al., 2021; Jin et al., 2024), and ride-sharing (Castro and Frazelle, 2024; Li et al., 2022; Naumov and Keith, 2023; Siddiq and Taylor, 2022; Yu et al., 2024). Considering that there is a significant overlap between the interests of the OM and transportation research communities (Mak, 2022), it is not surprising that a significant portion of recent transportation literature is related to smart city OM. Although primarily published in transportation journals, research on street parking, including our study on the effects of payment methods and pricing on parking behavior, aligns well with both OM and transportation, contributing to insights on urban life quality.

This section, therefore, examines two key research areas that are relevant to our investigation of payment methods and parking prices. We review each of these areas, summarizing relevant research findings and highlighting aspects where our research aims to contribute new insights.

2.1 Payment Methods

Traditional payment methods for goods and services include cash, physical credit cards, and debit cards. A service that uses mobile devices and mobile network technology to enable users to pay is called mobile payment. Soman (2001) showed that consumers' buying behaviors are affected differently by various payment methods. When discussing the reasons for these differences, researchers focus on the concept of *pain of payment* (Zellermayer, 1996), which refers to the emotional response customers have when they spend money. While the amount of payment can influence how painful the experience is, research suggests that the mode of payment may also have an impact on this emotional response. Prelec and Loewenstein (1998) claimed that consumers experience lower pain of payment when the actual payment is decoupled from the purchase, as in the case of credit cards. In another study, the transparency of payment methods, defined as the "relative salience of the payment both in terms of form and amount" (Soman, 2003: 175), is considered as the principle behind the pain associated with payment. In this context, the salience of the form explains how simple it is to experience how money is spent, while the salience of the amount indicates how simple it is for consumers to track how much money is spent. For example, according to Soman (2003), credit cards are less transparent than cash because there is no physical money outflow, which indicates that the pain of payment arising from credit cards is lower than that associated with cash payments. Also, (Boden et al., 2020) stated that mobile payments also rely on built-in payment tools, such as credit cards or direct debit. Thus, the pain of payment associated with mobile payments should be similar to that of credit cards.

The study of consumer payment behavior has long been of interest to researchers, with a particular focus on the two key decision variables of WTP and basket value (payment amount). Table 1 summarizes the existing studies in the literature. Although most of the reported studies include more than one empirical analysis, we only reported those that use dependent variables similar to our focus in this article. Prelec and Simester (2001) empirically established the credit card premium on consumers' WTP over cash payments. Lie et al. (2010) also observed that the WTP of credit card payers might be less than that of cash payers if there is no personal experience with credit cards. Similar results have been observed when the dependent variable is the basket value instead of the WTP, meaning that credit card payers tend to spend higher amounts than do cash payers (Soman, 2003; Thomas et al., 2011). Although behavioral comparisons of credit card and cash payments have previously drawn researchers' attention, empirical research on the potential effects of mobile payment use on consumers' purchase behaviors has recently started with the increasing use of mobile payments. The first study to include mobile payment among the analyzed payment methods was conducted by Falk et al. (2016). Although they could not find a significant mobile payment premium compared with credit card payment, they showed this effect over cash. Boden et al. (2020) found that consumers' WTP is increased with the adoption of mobile payment compared with credit card payment, with convenience as the mediator. Liu et al. (2021) showed consistent results with Falk et al. (2016) regarding the comparison of mobile and cash payments. However, Liu and Dewitte (2021) stated that the credit card effect on either WTP or basket value may have been lost, as they could not find a significant difference between credit card and cash payments. In one of their studies, they also showed a significant difference between mobile and cash payments in terms of basket value but not in the WTP measure. Recently, Yang et al. (2023) and He et al. (2024) also showed that mobile payments increase household spending. Apart from the spending amount, the study by Ho et al. (2022) also highlighted how price incentives can significantly shift consumer behavior from cash to mobile payments, illustrating a potential increase in efficiency and customer satisfaction in retail environments.

Table 1 draws attention to three points. First, while existing literature has primarily focused on examining the impact of payment methods on consumer products, the domain of recurring payment activities such as street parking remains largely unexplored. Second, the literature presents conflicting or insignificant results when comparing mobile payments with credit card and cash payments. Lastly, although comparisons between credit card and cash payments have been extensively reported, recent research suggests that the observed effects may be diminishing (Liu and Dewitte, 2021). Drawing on these

Table 1. Literature review on the effect of payment methods on consumers' spending behavior.

Authors	Payment methods				Decision variable	Business context
	Cash	CC	Mobile	Other		
Prelec and Simester (2001)	x	x			WTP	Event ticket
Soman (2003)	x	x		x	Basket value	Grocery shopping
Lie et al. (2010)[a]	x	x			WTP	Consumer product
Moore and Taylor (2011)	x	x		x	WTP	Gift items
Thomas et al. (2011)	x	x			Basket value	Food products
Falk et al. (2016)	x	x	x		WTP	Household products
Boden et al. (2020)	x	x	x		WTP	Food products, gas refill Phone charger, repair
Liu et al. (2021)	x		x		WTP	Specific product
Liu and Dewitte (2021)	x	x	x		WTP Basket value	Household products
Yang et al. (2023)			x		Basket value	Household expenditure
He et al. (2024)			x		Basket value	Household expenditure
This study	x	x	x		*Basket value*	*Street parking*

WTP = willingness to pay.
[a]This is the only study that showed an adverse effect on the WTP of credit card.

findings from the literature, our study aims to contribute to the literature by examining how various payment methods affect consumer spending on street parking, consequently, parking occupancy and search time. With evidence supporting the benefits of mobile payment (Ho et al., 2022), we also explore the potential benefits of introducing mobile payment for parking in municipalities.

2.2 Parking Pricing Policies

To understand the impact of hourly parking pricing and payment methods on street parking payments, we review the literature on parking price policies and their effects on parking demand, availability, and duration. Although this literature often overlooks how payment methods interact with parking prices to influence drivers' behavior, it offers valuable insights into pricing strategies. Accordingly, we categorize relevant studies into two streams. The first stream refers to price elasticity, which has been a popular research topic in the field. Many studies have explored how changes in parking prices affect consumer behavior. Using transaction data from parking payment stations in Seattle, Ottosson et al. (2013) demonstrated that the price elasticity of parking occupancy varies depending on the time of day and neighborhood-related variables. Pierce and Shoup (2013) examined parking price elasticity at different places and times of the day using data obtained from the SFpark project. They investigated the variations in occupancy for thousands of changes and found mostly negative elasticities. In their study, Millard-Ball et al. (2013) used the RDD to address potential endogeneity concerns. In a similar vein, our study uses this approach to minimize internal validity issues. Notably, Millard-Ball et al. (2013) discovered different price elasticities compared with those reported by Pierce and Shoup (2013). Pu et al. (2017) revealed a significant negative relationship between parking demand and price, as well as a regional variation in the sensitivity of on-street parking demand to price changes. Building on this prior work, Ostermeijer et al. (2022) demonstrated that a citywide parking policy in Amsterdam resulted in a 17% decline in hourly on-street parking demand, with a corresponding price elasticity of demand of -0.37.

The second stream focuses on the effects of parking price policies on various performance indicators, such as availability and parking duration. For availability-related questions, Chatman and Manville (2014) suggested that a price increase slightly improves parking availability. Millard-Ball et al. (2014) simulated street parking to estimate changes in cruising and found a reduction of about 50%. Alemi et al. (2018) showed that SFpark results in a reduction of ~15% and 12% in the average parking search time and distance, respectively, in the pilot areas compared with the control ones. On the other hand, for parking duration-related changes, Milosavljević and Simićević (2014) used data from central Belgrade, Serbia, and found that an increase in parking rates resulted in a drop in parking volume, garage occupancy, and typical parking time. Wang et al. (2020) and Mo et al. (2021) examined the impact of parking policy change on parking turnover, parking volume, and duration using parking meter data. Both studies revealed that parking duration decreases as the parking price increases. Also, recent studies have explored how differentiated parking fees can influence drivers' parking choices (Rodríguez et al., 2022; Zhou et al., 2023). All these studies are relevant to our investigation into how pricing affects payment amounts and, subsequently, parking occupancy and search times. However, they do not address the impact of payment methods on parking duration. Our study diverges from previous research by considering how drivers' payment method choices combined with the hourly parking prices may influence their parking duration behaviors. We also conduct a simulation study to investigate how the various driver behaviors affect occupancy and search times.

3 Hypothesis Development

In this section, we first develop an analytical model to investigate the impact of payment methods, parking pricing, and their interaction on the street parking payment amount. Following our analytical model, we then present our hypotheses drawing on insights from the existing literature on parking management and transportation economics. Overall, this section serves as a foundation for our subsequent empirical analysis and helps justify the theoretical mechanisms that underlie our research questions.

3.1 Analytical Model

Determining the parking payment amount is difficult for drivers, as they are often unable to predict their parking durations in advance accurately. This uncertainty presents a challenge akin to the newsvendor problem. To address this challenge, we have developed an analytical model that leverages the newsvendor approach to determine the optimal payment amount.

When it comes to street parking, overpaying for a longer period than necessary leads to a loss of money equal to the cost of the additional time that was not used. While this overpayment is primarily a function of the price, p, its perceived impact on drivers can vary based on the pain of payment, ω, which drivers experience differently depending on their preferred payment method. Therefore, we state that this overage expense is directly related to the cost of parking and pain of payment, $C_o = p \times \omega$. On the other hand, underpaying for a shorter amount of time than necessary puts drivers at risk of being caught by enforcement personnel and being fined for unpaid parking time. To avoid getting tickets, drivers may have to either take a break from their activities to pay again or retrieve their vehicles from where they are parked, which leads to hassle cost, h. When deciding on the payment amounts, drivers must consider both the hassle cost and the expected ticket price, which is calculated by multiplying the probability of being caught, β, with the parking violation fee, f. The cost of underpaying is then determined by taking the minimum value between the hassle cost and the expected ticket price, represented by the formula $C_u = \min\{h, \beta f\}$. It is worth noting that even if we do not have data regarding the expected ticket price, our hypothesis development remains unaffected by this lack of information. Specifically, the results will remain the same in both scenarios: where the minimum value between the hassle cost and the expected ticket price is either the hassle cost or the expected ticket price itself.

The newsvendor approach can be used to understand their decision-making processes for parking payments. If we assume that the demand follows a cumulative distribution $F(\cdot)$, the optimal payment amount by the driver, represented as Q^*, can be expressed as follows:

$$Q^* = F^{-1}\Big(\frac{C_u}{C_u + C_o}\Big) = F^{-1}\Big(\frac{\min\{h, \beta f\}}{\min\{h, \beta f\} + p \times \omega}\Big), \quad (1)$$

where $C_u/(C_u + C_o)$ is the critical ratio. As the newsvendor model has been well analyzed in the OM literature, our focus here is on examining how the different parameters of the newsvendor model can impact drivers' payment decisions.

3.2 Hypotheses

As $F^{-1}(\cdot)$ is non-decreasing, we know that an increase in the critical ratio will result in an increase in the payment amount. Therefore, to determine the impact of payment methods, parking pricing and their interaction on the payment amount, we study how these factors influence the critical ratio in the following sections.

3.2.1 Impact of Payment Methods on Payment Amount. We start this section by comparing credit card and mobile payments and identify two factors for this comparison: the pain of payment and the hassle cost. Regarding the pain of payment, previous studies have shown that credit card usage can reduce it, resulting in a higher WTP and a higher basket value (Falk et al., 2016; Prelec and Simester, 2001; Soman, 2003). Note that mobile payments also rely on built-in payment tools, such as credit cards or direct debit. This implies that the pain of payment for mobile payments should be similar to that of credit cards (Boden et al., 2020). However, in terms of the hassle cost, these two payment methods differ significantly. More specifically, thanks to mobile payment applications, drivers can increase their payment amounts remotely if their initial payments are insufficient before their parking permits expire. On the other hand, a driver who uses a credit card to pay needs to stop what they are doing, walk to the parking place where they parked their cars, and pay using a nearby street parking payment machine. As a result, we assert that the hassle cost associated with credit cards, h_{cc}, is likely to be larger than that associated with mobile payments, h_m. Considering that the partial derivative of the critical ratio with respect to the hassle cost is non-negative, we can draw the following hypothesis:

$$\frac{\partial \frac{C_u}{C_u + C_o}}{\partial h} = \begin{cases} \frac{p\times\omega}{(h+p\times\omega)^2} > 0 & \text{if } h \le \beta f, \\ 0 & \text{if } h > \beta f. \end{cases}$$

Hypothesis 1a: Mobile payers pay less than drivers who pay with credit cards.

Next, we compare credit card payments with cash payments. As drivers who pay with credit cards or cash will face the same requirement to return to their vehicles to avoid parking tickets, the hassle costs associated with these payment methods are expected to be the same for street parking. However, as explicitly stated by Soman (2003) and Thomas et al. (2011), cash payers experience the pain of payment, ω_c, more and thus tend to have smaller basket values. Given the higher pain of payment that cash payers experience compared with credit card users, ω_{cc}, and considering that the critical ratio decreases with the increase in the pain of payment, we propose the following hypothesis:

$$\frac{\partial \frac{C_u}{C_u+C_o}}{\partial \omega} = \begin{cases} -\frac{h \times p}{(h+p\times\omega)^2} < 0 & \text{if } h \leq \beta f, \\ -\frac{\beta f \times p}{(\beta f+p\times\omega)^2} < 0 & \text{if } h > \beta f. \end{cases}$$

Hypothesis 1b: Cash payers pay less than drivers who pay with credit cards.

Finally, when comparing mobile and cash payments, we can reasonably argue that both the pain of payment and the hassle costs differ between these payment methods. As those who pay in cash tend to feel the pain of payment more, it is expected that their payment amounts will be lower than those who use mobile payments. However, cash payers incur more hassle costs than mobile payers, since cash payers experience the same problems as credit card payers. Therefore, we expect cash payers to pay more than those who use mobile payments. As a result, these two conflicting points lead us to the following two hypotheses:

Hypothesis 1c(d): Cash payers pay less (more) than mobile payers.

3.2.2 Impact of Parking Price on Payment Amount. When we keep the payment method fixed, the pain of payment and the hassle cost are expected to remain constant. Therefore, to answer the research question about the effect of parking price on the payment amount, we take the partial derivative of the critical ratio with respect to price.

$$\frac{\partial \frac{C_u}{C_u+C_o}}{\partial p} = \begin{cases} -\frac{h \times \omega}{(h+p\times\omega)^2} < 0 & \text{if } h \leq \beta f, \\ -\frac{\beta f \times \omega}{(\beta f+p\times\omega)^2} < 0 & \text{if } h > \beta f. \end{cases}$$

Regardless of the condition, the sign of the partial derivative is always negative, which implies that the payment amount will decrease with the increase in parking price. Therefore, our hypothesis on the effect of parking price on the payment amount is as follows:

Hypothesis 2: Given the payment method, the payment amount is greater for parking spaces located in regions with lower unit parking prices.

3.2.3 Effect of Payment Method on the Effect of Parking Price. In this subsection, we consider how the impact of price on the payment amount varies with respect to the payment method. By comparing the payment amounts of different payment methods, we can determine which method is more sensitive to changes in parking prices, providing insights that can be used to optimize the parking payment system.

Our previous sections suggest that mobile payers experience a pain of payment similar to that of credit card payers, due to the integration of payment tools such as credit cards or direct debit in mobile applications. However, there is a notable difference between these two payment methods when it comes to hassle costs. Taking the partial derivative of the critical ratio with respect to the hassle cost and price, we obtain the following equation:

$$\frac{\partial^2 \frac{C_u}{C_u+C_o}}{\partial h \partial p} = \begin{cases} \frac{\omega\times(h-p\times\omega)}{(h+p\times\omega)^3} > 0 & \text{if } h > p\times\omega \text{ and } h \leq \beta f, \\ \frac{\omega\times(h-p\times\omega)}{(h+p\times\omega)^3} \leq 0 & \text{if } h \leq p\times\omega \text{ and } h \leq \beta f, \\ 0 & \text{if } h > \beta f. \end{cases}$$

The above expression suggests that the effect of the payment method on price sensitivity depends on the comparison between the hassle cost and the parking price. If $h > p \times \omega$, then the effect of price on the payment amount becomes flatter as the hassle cost increases. Otherwise, if $h < p \times \omega$, then the effect of price on the payment amount becomes steeper as the hassle cost increases. Between these two cases, we consider that the former (i.e., $h > p \times \omega$) captures the payment behaviors of drivers better than the latter does (i.e., $h < p \times \omega$). Our observation is that drivers pay much more than their expected demands to reduce the risk of returning back to their cars and thus avoid receiving parking tickets. This observation suggests that the cost of underpayment h is likely to be larger than the cost of overpayment $p \times \omega$.

As we argue that the hassle cost associated with mobile payment is likely to be smaller than that associated with credit card payment, we propose the following hypothesis:

Hypothesis 3a: A decrease in the parking price leads to a larger increase in the amount of payment for those who pay with mobile applications compared with those who pay with credit cards.

Chan (2021) summarizes that consumers are generally observed to experience greater pain of payment when they pay higher prices. As various payment methods are associated with payment pain differently, the impact of price changes on the payment amount is thus anticipated to differ depending on the payment method used. Therefore, similar to our approach in earlier sections, we examine the pain of payment when comparing individuals who pay with cash versus those who use credit cards. Furthermore, when comparing cash payers to mobile payers, we include both the pain of payment and the hassle cost.

Table 2. Summary of analytical results and hypotheses.

Hypothesis	Description
H1a	Mobile payers pay less than drivers who pay with credit cards.
H1b	Cash payers pay less than drivers who pay with credit cards.
H1c(d)	Cash payers pay less (more) than mobile payers.
H2	Given the payment method, the payment amount is greater for parking spaces located in regions with lower unit parking prices.
H3a	A decrease in the parking price leads to a larger increase in the amount of payment for those who pay with mobile applications compared with those who pay with credit cards.
H3b	A decrease in the parking price leads to a larger increase in the amount of payment for those who pay with cash compared with those who pay with credit cards.
H3c(d)	A decrease in the parking price leads to a larger (smaller) increase in the amount of payment for those who pay with cash compared with those who pay with mobile applications.

The partial derivative of the critical ratio with respect to the pain of payment and price is as follows:

$$\frac{\partial^2 \frac{C_u}{C_u+C_o}}{\partial\omega\partial p} = \begin{cases} \frac{h\times(p\times\omega-h)}{(h+p\times\omega)^3} < 0 & \text{if } h > p\times\omega \text{ and } h \le \beta f, \\ \frac{h\times(p\times\omega-h)}{(h+p\times\omega)^3} \ge 0 & \text{if } h \le p\times\omega \text{ and } h \le \beta f, \\ \frac{\beta f\times(p\times\omega-\beta f)}{(\beta f+p\times\omega)^3} < 0 & \text{if } \beta f > p\times\omega \text{ and } h > \beta f, \\ \frac{\beta f\times(p\times\omega-\beta f)}{(\beta f+p\times\omega)^3} \ge 0 & \text{if } \beta f \le p\times\omega \text{ and } h > \beta f. \end{cases}$$

As discussed previously, the cost of underpayment, either the hassle cost, h, or the expected ticket price, βf, is likely to be larger than the cost of overpayment, $p\times\omega$. Therefore, it is more likely to observe the first or the third cases. Given that cash payers typically experience greater pain of payment, changes in parking price will likely have a greater impact on their payment behaviors than those who use other payment methods. Therefore, we hypothesize the following:

Hypothesis 3b: A decrease in the parking price leads to a larger increase in the amount of payment for those who pay with cash compared with those who pay with credit cards.

Hypothesis 3c(d): A decrease in the parking price leads to a larger (smaller) increase in the amount of payment for those who pay with cash compared with those who pay with mobile applications.

As discussed in the previous sections, mobile payment applications offer the convenience of remotely increasing payment amounts, which is not available with cash payments. Therefore, we argue that cash payers incur more hassle costs than mobile payers, which leads to the development of Hypothesis 3d using the analytical findings.

Before proceeding further, we summarize our hypotheses in Table 2.

4 Survey Design and Results

To understand how different payment methods impact drivers' payment amounts, we have designed an online survey that captures the decision-making processes of participants under various conditions. In this section, we first present our online survey and its methodology. Following this, we will present the results and provide valuable insights that could be helpful for municipalities on parking management systems.

4.1 Survey Design

We conducted a survey simulating a parking experience where participants made payment decisions under various conditions. We specifically focused on comparing the payment amounts under different payment methods while examining the influence of hourly parking price, which was set at $2.25 for low and $3.25 for high levels, reflecting the regression discontinuity region in our study that will be explained later.

We also examined the effect of distance from the parking spot to the destination, the reason for parking, and the length of the activity on the payment amount. Previous research has shown that one of the most important factors influencing the parking decision is the distance to the destination (Brooke et al., 2014). Following our discussion of the analytical model, we hypothesized that the differences in payment methods may be due to the hassle cost of going back to the parking location. Therefore, the actual cost of this inconvenience will vary depending on how far drivers have to walk from the parking spot to their destination. Van der Waerden et al. (2017) showed that the maximum distance car drivers are willing to walk is short in the context of work (maximum 50 m), whereas the maximum distance is more spread out for social activities. Therefore, we used 50 m as the minimum distance level to the destination. Since 400 m was specified as the typical walking distance threshold (Barton et al., 2021) in the literature, we used 400 m as the second distance level to the destination.

It has also been shown in the literature that the reason for traveling is an effective factor in parking decisions. For example, Kelly and Clinch (2006) showed that there is a widening gap in price sensitivity between business and non-business travel as proposed parking pricing scenarios increase. Qin et al. (2020) investigated how drivers choose parking and travel in areas with limited parking, and they found that parking distance and trip purpose significantly impact decision-making. In order to consider these differences, we hypothesized that different parking reasons would change the duration needs, and we used two different scenarios as reasons for parking in this study: dinner with friends and a business meeting.

Lastly, the length of the activity can have an impact on drivers' decisions about how much to pay, as it can change the level of uncertainty. Even though we expect that the parking reason might have an impact on the duration estimation, in order to control for the differences between participants, we used two lengths for the activity ranging from 35 to 45 minutes or 70 to 90 minutes.

The experiment followed a 3×2 (payment method, price; between-subjects) × 2 × 2 × 2 (distance, reason, duration; within-subjects) mixed design, with each participant responding to different scenarios. Each participant was randomly assigned to one of six between-subject conditions. Instead of full factorial design, we asked participants four within-subject questions out of eight (two distances × two reasons × two duration ranges) created using the L4 orthogonal array of Taguchi design (Taguchi and Konishi, 1987). To achieve reasonable statistical power, we recruited 342 participants from Prolific, paying for \$2 as compensation. Of these participants, 64 failed to pass the attention check and were excluded, leaving 278 participants. We provide all the details about the survey in Section EC.1 of the E-Companion.

4.2 Results

A mixed ANOVA analysis (please see Table EC.2 of the E-Companion) was conducted with payment methods and price levels as between-subjects factors; parking reason, distance from the destination, and length of the activity as within-subjects factors, and the payment duration as the dependent variable. The results showed that the main effects were significant for the payment methods ($F(2, 1103) = 7.00, p < 0.001$), the length of the activity ($F(1, 1103) = 1524.80, p < 0.001$), and the distance from the destination ($F(1, 1103) = 7.63$, $p < 0.01$).

Specifically, post hoc Tukey tests revealed that participants assigned to mobile payment condition ($M = 79.18, SD = 25.59$) pay for ∼4 minutes less than cash ($M = 82.94, SD = 26.60; t = 3.21, p < 0.01$, Cohen's $d = 0.14$) and around 4.5 minutes less compared to those assigned to credit cards ($M = 83.58, SD = 26.57; t = 3.44, p < 0.01$, Cohen's $d = 0.17$). While the average payment under the cash method was lower than that under credit cards, we did not find a significant difference between cash and credit payment methods ($M = 0.64, SD = 1.25; t = 0.35, p = 0.94$, Cohen's $d = 0.02$). This finding demonstrates that drivers perceive both payment methods as equal due to their associated hassle costs. Likewise, the hourly parking price ($F(1, 1103) = 0.59, p = 0.44$) and its interaction with payment method ($F(2, 1103) = 2.17, p = 0.11$) were not significant. We consider these findings as indicative of a disconnect between price perception and actual payment behavior, as there is no physical outflow of money in the survey environment. We will estimate the effect of price and its interaction with payment methods on the payment amount using real-life transaction data in the following section.

Furthermore, post hoc Tukey tests showed that participants spent more when the parking spot was far from the destination ($M = 83.35, SD = 26.33; t = 2.76, p < 0.01$, Cohen's $d = 0.11$) compared to when it was close ($M = 80.53, SD = 26.25$). This finding is likely because they prioritize the convenience of a longer parking time over the hassle of a long walk. This behavior represents the trade-off between the cost of parking and the perceived effort or time saved from reducing the distance walked.

We also observed that the coefficient of the variable representing duration was 39.9, closely matching the 40-minute average difference between the time intervals. This result shows that there is a direct and proportional relationship, where each minute increase in the expected parking time needs leads to a nearly equivalent increase in the duration. Given that this variable effectively captured the time requirement estimation, the analysis of our survey data showed that parking reason ($F(1, 1103) = 1.10, p = 0.30$) did not play a significant role in the payment amounts of the participants. Although it was originally hypothesized that the parking reason might change the duration needed, it is observed that the given duration interval actually did the heavy lifting.

5 Empirical Analysis

Our survey data provided insight into the impact of consumer behavior and preferences on parking payment, particularly payment methods. However, survey findings highlight the gap between price perception and actual payment behavior. In this section, we will estimate the effect of price and its interaction with payment methods using real-life transaction data. After introducing the data we use, our empirical model is presented to explore the effects of parking price and its interaction with payment methods on the payment amount. Lastly, we present the results of the empirical analysis.

5.1 Data Description

Our empirical analysis leverages extensive data collected from our partner organization, which operates public parking stations in one of the most densely populated cities in North America. In this municipality, drivers are required to pay a parking fee for a certain period after parking their vehicle, rather than paying for the actual duration of time their vehicle remains parked in the lot until they return to retrieve it. Drivers can use street parking meters/kiosks located near their parking spaces, or mobile parking payment applications. The transaction data obtained from these payment instruments span

Figure 4. Regression discontinuity design (RDD) region on a map.

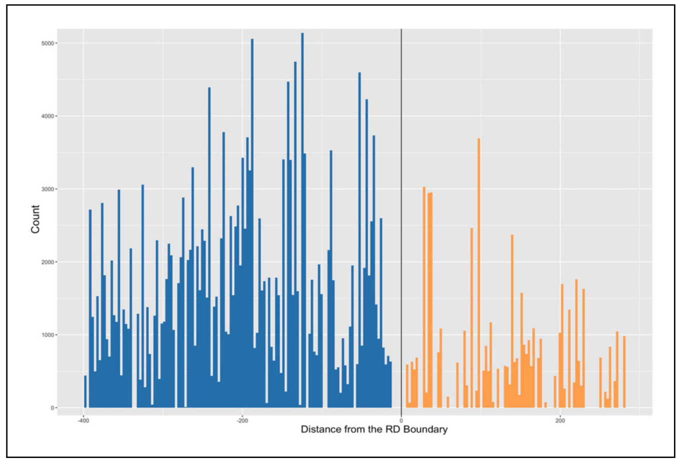

Figure 5. Number of observations in both regions.

different periods before and after COVID-19 and include the payment amount, parking spot name, start date and time of parking, and the payment method (i.e., cash, credit card, and mobile).

We analyzed the transaction data in detail and observed price discontinuity in some of the street segments. The discontinuity region is shown in Figure 4, in which the hourly parking price is $1 higher ($3.25 vs. $2.25) in the blue region (darker) than in the orange region (light). Calvo et al. (2019) clarifies that a sharp RDD is suitable when there is perfect compliance meaning all subjects above the specified threshold receive treatment and those below do not. Therefore, we test the hypotheses on this city region without having to control for other factors, thanks to the sharp RDD, which allows us to evaluate the treatment impact of the price change. The validity of a sharp RDD relies on the quasi-random assignment of individuals to the treatment or control group near the cutoff point (Lee and Lemieux, 2010). We will discuss the validity of the RDD in detail in Section EC.2.4 of the E-Companion. However, we can gain preliminary insights by visually examining our assignment variable. Figure 5 displays the number of observations in both regions on the y-axis and the distance from the price change boundary on the x-axis. The absence of any peaks on either side of the boundary (distance = 0) indicates that the RDD is nearly as good as a random setting.

As a dataset not carefully screened for analysis can lead to misleading findings, we preprocessed the data rather than directly using the raw data in the empirical phase. First, paid parking starts later in the afternoons on Sunday and commuting patterns differ from other days. To have consistency across days, we excluded Sundays from the dataset, accounting for 7.8% of the transactions in the discontinuity region. Second, in our transaction data, the start/end time of paid street parking may change depending on the location. To obtain standardized data regarding the time of the day, we filtered the transaction data to cover time intervals from 9 a.m. to 6 p.m., which constituted a removal of an additional 0.2% of the data. Third, we screened for erroneous transactions with payment amounts for <5 minutes and removed them from further analysis. Similarly, we excluded transactions exceeding a duration of 171 minutes based on the interquartile range (IQR) criterion used for detecting outliers. Under this criterion, any values below the first quartile (Q1) minus 1.5 times the IQR or above the third quartile (Q3) plus 1.5 times the IQR are considered outliers. Here, 171 minutes corresponds to Q3 plus 1.5 times the IQR of payment amounts obtained from the parking spaces in the blue (dark) region where the unit parking price is $1 higher than the orange (light) region. As shown in the box plot of payment amounts presented in Section EC.2.1 of the E-Companion, observations exceeding this mentioned upper limit are significantly longer in duration in the orange (light) region than in the blue (dark) region. By imposing this upper duration limit, we aimed to balance the data, ensuring both regions were analyzed under similar conditions and preventing our results from being biased by these outlier transactions. Collectively, these two steps resulted in the removal of 9.1% of the data. Finally, we removed transactions from parking spaces located more than 400 m away from the boundary, as the literature indicates that the typical walking distance threshold is 400 m (Barton et al., 2021), resulting in a further reduction of 17%. It is worth mentioning that there were no observations in the orange (light) region beyond this distance. Although the preprocessing steps resulted in a 31.4% reduction in the original dataset, they were carefully implemented to improve data quality while maintaining the representativeness of the dataset. To ensure a comprehensive analysis, we also conducted a repeat analysis including the entire dataset, detailed in Section EC.2.3.2, Table EC.6 of the E-Companion.

Table 3 provides a summary of the data used in our analysis, including those of the months for which data were collected, the total number of transactions, and the use of mobile applications for payment in each month. In 2019, the month of December saw a decrease in the number of street parking transactions, as expected during the holiday season, even without

Table 3. Summary of payment transaction data in the regression discontinuity region after data preprocessing.

Year	2019		2020	
Month	No. of transactions	Mobile, %	No. of transactions	Mobile, %
April	69,870	65	7,989	77
May	70,678	66	16,580	75
December	59,606	71	37,728	78

accounting for the colder winter months. Although there was an increase in the number of transactions in December 2020 compared to April and May 2020, the number of transactions did not reach the same levels as those in the previous year. The transaction data also revealed that traditional payment methods, which can act as potential vectors for virus transmission, were less preferable to drivers even more during the pandemic.

After preprocessing our data, we conducted a descriptive analysis of the effect of the interaction of price and payment method on payment amount in the region of regression discontinuity. Figures 6 and 7 use local sample means with evenly and quantile spaced bins, as suggested by Calonico et al. (2015), to show the relationship between payment method, price, and payment amount. The quantile spaced bin approach considers the sparsity of the data by ensuring that each bin has a roughly equal number of observations. In contrast, the evenly spaced bin approach uses intervals of equal width to group the data points into categories. Both figures show that a decrease in price leads to an increase in payment amounts. Additionally, if we compare the payment amounts in the two regions according to payment methods, we see that these changes are not uniform across payment methods. This suggests that the impact of price adjustments may differ depending on the payment method used, as we discussed in the hypothesis development section. To empirically support the findings indicated by the visual analysis, we present the details of our empirical work in the next subsection.

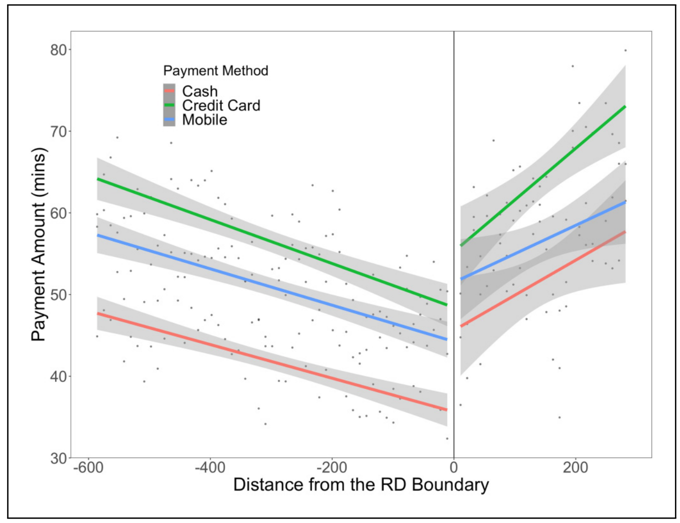

Figure 6. Regression discontinuity design on payment amount-evenly spaced bins.

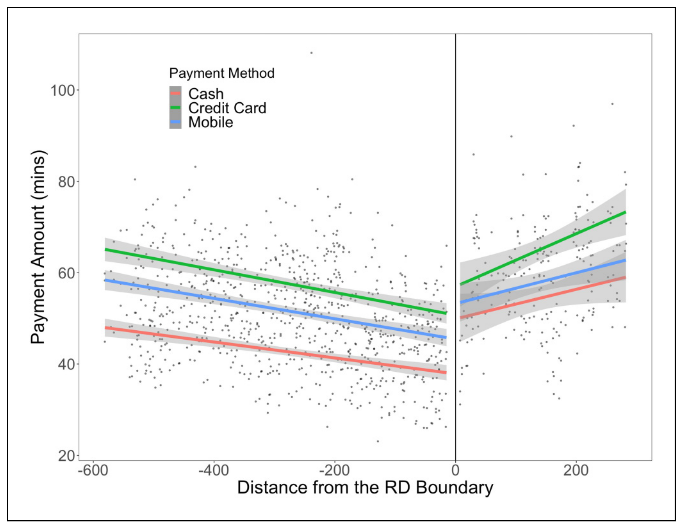

Figure 7. Regression discontinuity design on payment amount-quantile spaced bins.

5.2 *Empirical Models and Findings*

This subsection provides our empirical model and main findings about the effect of parking pricing and its interaction with payment methods on the payment amount. Consistent with our analytical model, we define our dependent variable Q_{ij}^{t} as the payment amount of the jth transaction for parking space i at the timestamp t. The original transaction data report the payment amount in dollars, but we convert the available payment amount into minutes using the hourly parking price of each parking space.

As discussed in the hypothesis development section, the analytical model has two critical parameters: payment method and parking price. The effect of the parking price will be observed using an independent variable called *treated*. Given that the RDD mechanism introduced a shock in parking price but not in the payment methods, we use the payment method as a moderator in our analysis. We observe the main effect of the payment method through the survey we conducted. In our analysis, we use credit card payment as the base payment method to observe the relative effects of mobile and cash payments in comparison. Table 4 presents the descriptions of the variables used in our study, while Table 5 shows their means and variances.

To test our hypotheses regarding the effects arising from the price and its interaction with payment methods, we construct

Table 4. Description of variables.

Variable	Definition
Q_{ij}^t	Payment amount (in minutes) of *j*th transaction for parking space *i* at timestamp *t*
$treated_i$	Binary variable indicating if the transaction is obtained from less costly parking space *i* (=1)
$cash_{ij}^t$	Binary variable indicating if *j*th transaction of parking space *i* is made via cash at timestamp *t* (=1)
$mobile_{ij}^t$	Binary variable indicating if *j*th transaction of parking space *i* is made via mobile app at timestamp *t* (=1)
$dist_i$	Distance of parking space *i* from the RD boundary

Table 5. Summary statistics of variables.

Variable	Mean	Std. Dev.	Min	Max
Q_{ij}^t	50.184	35.733	5.133	170.933
$treated_i$	0.164	0.370	0	1
$cash_{ij}^t$	0.198	0.399	0	1
$mobile_{ij}^t$	0.695	0.461	0	1
$dist_i$	235.311	147.047	7.100	400.000

the regression discontinuity model given by equation (2):

$$\begin{aligned} log(Q_{ij}^t) = \beta_0 &+ \beta_1 treated_i + \beta_2 cash_{ij}^t + \beta_3 mobile_{ij}^t + \beta_4 dist_i \\ &+ \beta_5 treated_i \times cash_{ij}^t \\ &+ \beta_6 treated_i \times mobile_{ij}^t + \beta_7 treated_i \times dist_i \\ &+ \beta_8 cash_{ij}^t \times dist_i + \beta_9 mobile_{ij}^t \times dist_i \\ &+ \beta_{10} treated_i \times cash_{ij}^t \times dist_i + \beta_{11} treated_i \\ &\times mobile_{ij}^t \times dist_i + \sigma_h + \gamma_d + \eta_m + \theta_y + \epsilon_{ij}^t, \qquad (2) \end{aligned}$$

where σ_h, γ_d, η_m, and θ_y are the time of day, day of the week, month, and year fixed effects, respectively.

This study uses survival analysis to estimate drivers' parking durations. An accelerated failure time model is fitted with four alternative parametrization techniques—log-normal, log-logistic, Weibull, and exponential. We use the results from the log-normal distribution setting, which assumes a dependent variable following a log-normal distribution in equation (2), as it has the minimum Akaike's information criterion. We provide the details of the survival analysis in Section EC.2.2 of the E-Companion. Note that the exponential of the coefficients (i.e., $\hat{c} = \exp(\hat{\beta}_1)$) will give us the marginal effect of a unit change in the independent variable. This means that if the multiplier $\hat{c}$ is greater (less) than one, the survival time, in our case payment amount Q^*, will become higher (lower) with a change in the variable of interest.

Table 6 shows the estimates for our coefficients of interest in which credit card payment is considered the base payment method. The initial model (column (1)) includes only the binary treatment variable. The subsequent model (column (2)) incorporates the distance from the RDD boundary and an interaction term with the treatment. The final model (column (3)) further adds payment method dummies and their interactions with both treatment and distance from the RDD boundary. Having obtained empirical support for the effect of payment methods on payment amounts from our online survey, we test the effect of price by comparing the payment amounts from the same payment method from regions with higher and lower unit prices, $treated = 0$ and $treated = 1$, under column (1), or at the boundary ($dist = 0$) under column (2) and column (3). In all three cases, we observe that decreasing the unit parking price by \$1 significantly increases the payment amounts. The coefficient estimates indicate that the treatment's impact increases the payment amount by an average of 16% (exp(0.1509)). Our moderation analysis reveals that, compared to credit card payment, the positive impact of the treatment is most pronounced under the cash payment method, with an increase of 37% ($\beta_{treated:cash} = 0.1452, p < 0.001$), and second most under the mobile payment method, with an increase of 26% ($\beta_{treated:mobile} = 0.0618, p < 0.05$). Therefore, we conclude that credit card payers are less affected by the unit reduction in the parking fee, as stated in H3a and H3b. Finally, the results of our analysis provide support for H3c, showing that the change in cash payments is more than the change in mobile payments.

Table 7 provides a snapshot of our analytical results and their empirical support. The results of our research reveal that payment method and price indeed have effects on the payment amount, as descriptively demonstrated in Figures 6 and 7. The findings have actionable insights into the use of payment methods and pricing policies in urban parking management. First, a difference across payment methods indicates that mobile payments facilitate shorter parking. This will, therefore, improve the turnover rate of parking spaces and decrease the overall search time for available parking. Second, findings underline the fact that the parking behavior of a driver is not solely influenced by price or payment method but rather by the interaction of both. Consequently, any analysis of the impact of a policy change must inherently take both factors into consideration. For example, price sensitivity in parking durations is likely higher in neighborhoods frequently visited by younger demographics, such as university districts, compared to business regions like financial districts or plazas. This is because younger visitors are more inclined to use mobile payment methods, whereas business districts attract a profile that predominantly uses credit cards. Given that drivers with low price sensitivity are less responsive to price changes, municipalities could increase parking prices in business districts without significantly reducing demand. In contrast, in areas like university districts, where the demographic consists of younger drivers

Table 6. Survival analysis results with staggered specifications.

	Dependent variable: Payment amount		
	(1)	(2)	(3)
(Intercept)	3.5570***	3.4429***	3.5952***
	(0.0115)	(0.0131)	(0.0166)
treated	0.1509***	0.2379***	0.1712***
	(0.0127)	(0.0183)	(0.0302)
distance		0.0006***	0.0005***
		(0.0000)	(0.0000)
treated:distance		−0.0004***	0.0003
		(0.0001)	(0.0002)
cash			−0.3432***
			(0.0143)
mobile			−0.1223***
			(0.0092)
treated:cash			0.1452***
			(0.0281)
treated:mobile			0.0618*
			(0.0267)
distance:cash			0.0001
			(0.0000)
distance:mobile			0.0001**
			(0.0000)
treated:distance:cash			−0.0008***
			(0.0002)
treated:distance:mobile			−0.0007***
			(0.0002)
Log(scale)	−0.3061***	−0.3088***	−0.3177***
	(0.0075)	(0.0073)	(0.0071)
Fixed-effects			
Time of day	Yes	Yes	Yes
Day	Yes	Yes	Yes
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	262,451	262,451	262,451
R^2	0.035	0.040	0.057
LR	–	1403.747***	4716.390***

Clustered (time of day) standard-errors in parentheses.
Notes: *p<0.05; **p<0.01; ***p<0.001.

who are more inclined to use mobile payment methods, raising parking prices could be more challenging due to higher price sensitivity. In Section 6, we conduct a simulation study to support these inferences with numerical evidence.

We provide additional support to our main findings by conducting OLS regression analysis as a robustness check, with the detailed outcomes displayed in Section EC.2.3.1, Table EC.3 of the E-Companion. We also applied moderation analysis with propensity score weighting and subsample analysis with and without propensity score weighting as a robustness test. We provide the details of these analyses in Sections EC.2.3.2 and EC.2.3.3 of the E-Companion, respectively. Our findings from these approaches are highly consistent with the results presented here. The validity of our RDD mechanism has been shown in Section EC.2.4 of the E-Companion. Furthermore, as we mentioned previously, our dataset includes observations from the months before and during COVID-19, as well as from the spring and winter months. To provide more focused and effective results, we use subsample analysis to evaluate how COVID-19 and seasonality affect our findings. We present these results as a further robustness analysis in Section EC.4 of the E-Companion.

6 Impact of Policy Changes

In the previous two sections, we estimated the impact of parking fees and payment methods on the amount of payment. In this section, combining these results with a discrete event simulation study, we measure the impact of parking fees and payment methods on key metrics such as street parking occupancy levels and driver search times—a critical aspect influencing urban life quality.

We conduct the simulation study in multiple steps. First, recall that in Section 5, we measure the impact of price changes only in the vicinity of the RDD boundary. To expand our simulation beyond regression discontinuity, we now use the propensity score matching (PSM) approach. This method involves matching treatment streets (those included in the RDD study) with control streets (other streets within the city) based on street-specific features. Utilizing the optimal full matching method available in the *Matchit* (Ho et al., 2011) CRAN package, we estimated the following specification:

$$\begin{aligned} data.matched = matchit(&treatment_i \sim \beta_1 Rest_i \\ &+ \beta_2 Buss_i + \beta_3 Garages_i \\ &+ \beta_4 capacity_i + \beta_5 hourlyPrice_i, \\ &method = \text{“}full\text{”}), \end{aligned} \tag{3}$$

where the variable $treatment_i$ is set to 1 if the street i is from the discontinuity region and 0 if it is any other street from the city. The explanatory variables in equation (3) stand for the number of business and professional services, *Buss*, the number of restaurants operating, *Rest*, and the number of outside parking opportunities, *Garages*, within 400 m proximity of the street segment to which parking space i belongs. This data is not directly available in the transaction records. Details on how we obtained it can be found in Section EC.2.3.2 of the E-Companion. In addition to these three independent variables, we also use hourly parking price and the capacity of the street in which the parking space is located. In Section EC.3.1 of the E-Companion, we present a detailed explanation of the PSM method, along with the summary statistics of the variables in Table EC.12 of the E-Companion.

This methodical pairing aimed to construct a counterfactual scenario through which each street is analyzed as if it were influenced by the conditions at the boundary, thus extending the RDD analysis beyond its limitations. Namely, by leveraging the observed impact of parking price changes in treatment

Table 7. Summary of empirical results.

Hypothesis	Description	Conclusion
H1a	Mobile payers pay less than drivers who pay with credit cards.	Supported
H1b	Cash payers pay less than drivers who pay with credit cards.	Not supported
H1c(d)	Cash payers pay less (more) than mobile payers.	Not supported (supported)
H2	Given the payment method, the payment amount is greater for parking spaces located in regions with lower unit parking prices.	Supported
H3a	A decrease in the parking price leads to a larger increase in the amount of payment for those who pay with mobile applications compared with those who pay with credit cards.	Supported
H3b	A decrease in the parking price leads to a larger increase in the amount of payment for those who pay with cash compared with those who pay with credit cards.	Supported
H3c(d)	A decrease in the parking price leads to a larger (smaller) increase in the amount of payment for those who pay with cash compared with those who pay with mobile applications.	Supported (not supported)

streets that closely resemble control streets, we then estimate the impact of these price changes in the control streets. Finally, we adjust the base payment amounts in our simulation study using the multipliers derived from the RDD. This enables us to extrapolate our findings to make reliable out-of-sample predictions about the impacts of changes in pricing structures and payment methods on the payment amount.

After estimating the impact of price changes and payment methods for all the streets, we develop a discrete event simulation model to investigate the impacts of two different policy changes separately: (i) changes in pricing policy and (ii) implementation of a mobile application, on street parking occupancy and search time. The flow of the simulation is explained at the beginning of Section EC.3.3.1 of the E-Companion using the flowchart given in Figure EC.9 of the E-Companion. We use the same structure for all our simulation studies.

6.1 The Impact of Different Pricing Schemes

In this subsection, we present findings from two simulation studies designed to examine parking behavior under different pricing policies. The first study implements a constant pricing policy where the hourly parking rate remains uniform across all durations. In our second simulation study, we introduce a progressive pricing policy where the hourly parking rate changes progressively based on the total duration of parking. These simulations help to show how pricing policies influence driver decisions.

6.1.1 Constant Pricing Policy. The first objective of our simulation study is to examine the effect of a constant pricing scheme on street parking occupancy and search time. We increase and decrease the parking prices by \$1 for each street and observe the corresponding changes in these variables. As observed in the empirical analysis, the reaction to the change in price varies depending on the preferred payment method. In our simulation study, we consistently recognize the intertwined impact of parking price and payment method using the findings from our survey and the estimators we obtained from the RDD. Throughout the simulation, we use 10 street sets totaling 91 streets over a period of 6 days and under three pricing scenarios: decreased price, original price, and increased price. This analysis includes a total of 1,638 observations (91 streets × 6 days × 3 scenarios). Table EC.13 of the E-Companion shows the details of each street set with the maximum and minimum capacity among neighboring streets in each set.

We present the regression results derived from an analysis of our simulation outputs in Table 8. Results of the regression analysis show that if the price increases by \$1, the occupancy decreases significantly by 1.6% on average, and, consequently, the search time will decrease by 1.2 minutes. On the other hand, if the price decreases by the same amount, the average occupancy increases significantly by 2% with an increase in search time by 2.1 minutes. These numerical results align with the logical reasoning behind the observed behavior. As seen in our empirical study, lower parking prices encourage drivers to park longer as the cost is less restrictive. This extended parking duration means each parking space is used for longer, reducing the number of times a spot becomes accessible to new drivers. As parking spaces become less frequently available due to longer stays, new or potential drivers face longer search times.

A key finding across all evaluated streets is that the effect of decreasing the price is greater than the effect of increasing the price for both performance measures. As shown in Figure EC.10 of the E-Companion, a decrease in price by \$1 can extend search times by up to 3.5 minutes. Conversely, Figure EC.11 of the E-Companion illustrates that an equivalent price increase results in a maximum reduction of search time by only 1.9 minutes. Similarly, Figures EC.12 and EC.13 of the E-Companion show that the occupancy might increase by up to 9.4% when the price decreases by \$1, whereas a price increase leads to a maximum occupancy reduction of only 3.8%.

Additionally, the results show that pricing policy has the highest impact in areas with medium occupancy rates, indicating the existence of a "sweet spot" where the impact peaks before diminishing. Medium occupancy streets are the most responsive to pricing strategies since there is enough demand

Table 8. Regression results on the effect of constant pricing policy.

	Dependent variable:	
	Search time (1)	Occupancy (2)
Decreased price	2.140^{***}	2.045^{***}
	(0.146)	(0.268)
Increased price	-1.196^{***}	-1.550^{***}
	(0.146)	(0.268)
Constant	26.418^{***}	90.125^{***}
	(0.591)	(1.083)
Fixed-effect		
Day	Yes	Yes
Street	Yes	Yes
Observations	1,638	1,638
R^2	0.876	0.911

Notes: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

to be sensitive to price changes and enough space to accommodate increased usage when prices are decreased. This leads to more pronounced changes in both search times and occupancy rates.

We also created different simulation scenarios to evaluate the robustness of our results by changing the parameters of the simulation study, such as the number of times drivers return to their intended parking street, the time spent between consecutive blocks, search distance, and the amount of deviation from the payment amount. The results of the robustness check presented in Section EC.3.3.1 of the E-Companion show that although the magnitudes of the results we discuss here are different, the direction of the change in occupancy and search time does not change depending on the simulation parameters.

Overall, our simulation with a constant pricing policy offers insightful information that can guide the development of more effective and customer-centric parking policies. It is evident that cities may establish more specialized parking policies that fulfill the demands of residents and visitors by considering factors such as pricing. For example, the results of our analysis suggest that lowering the parking price instead of increasing it can have a greater impact on occupancy rates and search time. Moreover, we observed that even though the effect is in the same direction for all streets, the size of the change in occupancy or search time varies according to the streets. These insights can help policymakers and parking managers make more informed decisions and develop effective strategies to improve search times and parking occupancy rates.

6.1.2 Progressive Pricing Policy. Given that drivers respond differently to price changes, municipalities might consider implementing progressive pricing policies to benefit from these differences. To observe the effect of progressive pricing, we mainly simulate two different scenarios, (i) decreased price during the first 60 minutes of parking then increased price for the part of the payment exceeding 60 minutes ("low-then-high pricing") and (ii) increased price during the first 60 minutes of parking then decreased price for the part of the payment exceeding 60 minutes ("high-then-low pricing"). The former might encourage drivers to use parking spaces for shorter duration and consequently increase the turnover of parking spots. However, the latter makes parking for longer duration economically sensible, potentially reducing drivers' risk of getting parking tickets for those who need longer stays. We compare the same set of streets over a period of 6 days, but this time, we do so under two pricing scenarios: progressive pricing and the corresponding constant pricing. Our analysis in this part includes a total of 1,092 observations (91 streets × 6 days × 2 scenarios).

Table 9 shows the changes in occupancy and search time arising from the different pricing policies. Our simulation study shows that the low-then-high pricing policy decreases the search time for drivers by one minute while decreasing the average occupancy of streets by 0.6%. This result is expected as low-then-high pricing motivates drivers to opt for shorter parking duration compared to constant low pricing. Consequently, shorter parking duration leads to parking spots becoming available more frequently compared to the constant pricing policy. As parking spots are occupied for a shorter duration with the low-then-high pricing, there would be more available parking spots on average. As a result, as discussed by Pierce and Shoup (2013), even having one or two spaces available on every block would decrease cruising. Conversely, with the high-then-low pricing, drivers tend to increase their payments to benefit from lower prices if they want to reduce their risks of underpayment. Our results highlight that this policy significantly increases the occupancy by 1.3% on average, with an increase in the search time by 1.4 minutes.

As observed under the constant pricing policy, changes in occupancy and search time are more pronounced in areas with medium occupancy rates. Figures EC.14 and EC.15 of the E-Companion show that the change in occupancy rate in areas with medium occupancy can decrease up to 2% with a 1.5-minute reduction in search time by a low-then-high pricing policy. However, in high occupancy areas, although parking durations have been shortened, the spaces are being filled with new drivers quickly. That means the change in occupancy rate is lower due to high demand. On the other hand, by implementing a high-then-low pricing strategy, we can expect an increase of up to 5.5% in average occupancy rates.

These findings suggest that a municipality should have different pricing strategies appropriate to the different parts of the city to benefit from the differences between data-driven policy rules and constant pricing. For example, constant pricing is straightforward to implement and manage compared to progressive pricing models. Constant pricing is, therefore, appropriate in specific scenarios where its simplicity and predictability are advantageous. This is especially true in areas with moderate activity and residential neighborhoods where parking demand is stable but not excessive. That approach

Table 9. Regression results on the effect of progressive pricing policy.

	Dependent variable:			
	Low-then-high		*High-then-low*	
	Search time (1)	Occupancy (2)	Search time (3)	Occupancy (4)
New pricing	-1.089^{***}	-0.555^{*}	1.416^{***}	1.316^{***}
	(0.144)	(0.233)	(0.143)	(0.270)
Constant	27.979^{***}	91.315^{***}	24.528^{***}	89.102^{***}
	(0.710)	(1.146)	(0.704)	(1.331)
Fixed-effect				
Day	Yes	Yes	Yes	Yes
Street	Yes	Yes	Yes	Yes
Observations	1,092	1,092	1,092	1,092
R^2	0.869	0.922	0.885	0.920

Notes: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

keeps a stable turnover of parking spaces and manageable search times, ensuring a balanced supply and demand. In high-demand, busy areas such as downtown business districts, entertainment and dining regions, and tourist attraction centers, a low-then-high pricing policy works better. This would encourage high turnover by motivating drivers to initially park for shorter periods to ensure that parking spaces are frequently available and minimize cruising for parking. On the contrary, high-then-low pricing would be beneficial in areas where municipalities want to discourage short-term parking to prioritize availability for those who plan to park for longer periods. Park-and-ride and airport parking are good examples of this situation. Similarly, for suburban shopping malls, using high-then-low pricing might capture revenue from shoppers who only make a quick visit and make it more attractive for shoppers who plan to spend a long time. By using different pricing policies, municipalities can ensure more efficient use of parking resources, improve occupancy rates, and reduce search times.

6.2 The Impact of Implementing a Mobile App for Street Parking

Although mobile payment adoption is of great practical significance, academic research on its implications and consequences remains limited to date (Xu et al., 2024). In this subsection, we examine the benefits of implementing a mobile payment option regarding search times and occupancy. Specifically, we conducted two distinct simulations to evaluate the impact of mobile payment options on street parking under a constant pricing policy. The first scenario operated with only cash and credit card payment options, while the second scenario exclusively incorporated mobile payments. In the former simulation, we distributed mobile arrivals proportionally as if they would pay by cash or credit card, mimicking the distribution of cash and credit card users as observed in real payment data. Similarly, in the latter simulation, we converted all cash and credit card arrivals to mobile payments. The corresponding payment conversions used the differences we obtained from our online survey results. By comparing the average search times and occupancy rates of these two scenarios, we aim to determine the potential benefits of implementing mobile payment options for street parking. To rigorously do so, our study applies the t-test separately for each street, where the null hypothesis states that mobile applications do not affect search time and occupancy. We provided the details of the simulation and the analysis in Section EC.3.3.3 of the E-Companion.

As we observed previously with the constant and progressive pricing policies, the findings show that the effect of introducing mobile applications is not the same for every street (please see Figures EC.20 and EC.21 of the E-Companion). These figures also show the existence of a "sweet spot" after which the benefits from mobile implementation start diminishing. Our results show that in certain street groups with medium occupancy, the implementation of mobile applications can actually lead to a decrease in occupancy by up to 3.9%. On the other hand, if a municipality starts using mobile applications in busy areas where the demand is high and the streets are already crowded, the reduction in occupancy rates can be as low as 0.3%. In these areas where there is high demand for parking, the introduction of mobile applications to shorten parking duration has allowed new drivers to quickly fill empty parking spots. As a result, there are usually no significant differences in search time. When we further investigated the streets with significant changes in occupancy and search time, we observed that introducing mobile applications can reduce search time by up to 1 minute without requiring any additional changes. While it may seem like a small improvement, a 1-minute reduction in search time saves significant time on daily parking activities, reducing driver stress and contributing to smoother traffic flow and lower emissions. Additionally, not only streets with medium occupancy range, we noticed that the occupancy rate could drop by up to 2.6% in certain streets near busy areas. This reduction would help improve the balance between streets and eventually reduce cruising. Overall, the introduction of mobile applications contributes to driver satisfaction by ensuring that fewer drivers leave the system without parking and that the search times for parking drivers are reduced.

These findings have several managerial implications. Considering the experience of drivers, municipalities can make street parking more convenient, efficient, and hassle-free by implementing mobile payment alternatives. The observed reductions in search times, coupled with decreased occupancy rates, suggest that high-demand urban centers should be prioritized for mobile payment implementation. These areas will greatly benefit from the improvements offered by mobile payments and are the most useful in improving parking turnover. That being said, the strategy for implementing mobile payments should account for the adoption rates of the app. Given that younger demographics are more inclined to quickly adopt new technology, municipalities should first introduce the app in areas popular with these younger groups. This phased approach allows municipalities to leverage early adopters to spot and address any issues, ensuring a smoother and more effective expansion as the app reaches a broader audience.

In conclusion, implementing mobile payment options for street parking could significantly benefit drivers and cities. By reducing search times and occupancy rates, cities can improve the overall efficiency of urban mobility.

7 Conclusion

This study examined the impact of payment options and price adjustments in on-street parking and their interaction with payment amounts, search times on average, and occupancy levels. First, we constructed an online survey to demonstrate the differences between drivers' payment behaviors depending on the payment method they use. According to the survey results, drivers, on average, spent less when using mobile applications as opposed to using credit cards or cash, whereas there is no significant difference between credit cards and cash payers. In this respect, the findings of our study on the behavioral effects of cash and credit card payments are consistent with recent literature indicating that the difference between the two payment methods is diminishing. However, our research differed from the literature by revealing a situation where mobile payers pay less. Additionally, we conducted an empirical analysis using parking transaction data from one of the most densely populated cities in North America. Our findings indicated that a \$1 decrease in the hourly parking fee increases the total payment amount by an average of 16%. The positive impact of the price reduction was most significant when using the cash payment method, with an increase of 37%, and second most significant with the mobile payment method, with an increase of 26%.

Second, we simulated street parking to show that a driver's parking behavior is not solely dictated by price or payment method individually, but rather by the interaction between these two factors, which in turn affects occupancy and search time. Simulation results showed that lowering the price reduces parking availability and, therefore, increases search times. However, increased parking prices exhibited asymmetric effects on search time and occupancy levels compared to price reduction policies. Therefore, our study provides valuable insights for future research on performance-based pricing, which typically assumes symmetrical impacts on both sides. Third, in the simulation study, we introduced a progressive pricing policy, which better reflects the interaction between price and payment methods compared to a constant policy. This policy exposes drivers to varying marginal prices depending on how long they stay parked. Our simulation study revealed that the progressively increasing policy has a positive impact on both operational metrics. Lastly, we also tested the effect of mobile payment adoption, combined with pricing strategies, on parking occupancy and search times. The results showed that adopting mobile payment reduces search time and occupancy levels. Overall, the simulation results complement the empirical findings on payment behavior and provide prescriptive insights into the effects of payment methods and pricing changes on parking performance measures.

Our results provide actionable managerial insights for municipalities aiming to optimize parking management through targeted policies. First, our empirical findings indicate that credit card users are less sensitive to price changes compared to mobile payment users. This suggests that municipalities can tailor their pricing strategies based on the demographic composition of different neighborhoods. For example, drivers in business districts are more likely to use credit cards for parking payments, making it feasible to increase prices in these areas without significantly reducing demand. In contrast, raising parking prices could be more challenging due to higher price sensitivity in areas like university districts, where the demographic consists of younger drivers who are more inclined to use mobile payment methods. Second, our results recommend applying different pricing policies based on the demand patterns of specific areas. A constant pricing policy is ideal for residential neighborhoods with stable and predictable parking demand, as it helps maintain consistent occupancy and reduces search times. Conversely, in high-demand areas such as shopping districts and tourist attractions, a low-then-high pricing strategy can promote quicker turnover, ensuring that parking spaces remain available. Additionally, for locations like park-and-ride facilities or airports, a high-then-low pricing model is beneficial as it discourages short-term parking and prioritizes availability for long-term users. Finally, our findings advocate for a phased approach to implementing mobile payment systems. Instead of launching the system citywide, municipalities should initially focus on high-demand urban centers where mobile payments can have the greatest impact on parking turnover. Furthermore, beginning the rollout in districts with younger populations, who are more likely to adopt new technologies, can help identify and address potential challenges early on. This phased approach allows municipalities to fine-tune the system before expanding it more broadly, ensuring a smoother and more effective citywide adoption.

While our study provided valuable insights, some limitations that future research can address need to be noted. First, given data limitations, our analysis was limited to the consequences of a $1 change in parking prices. The effects of various price changes can be explored in more detail, and more thorough simulation studies on pricing can be performed. This is especially important because, although there is a growing literature on pricing focusing specifically on sharing economy models such as ride-sharing (Bimpikis et al., 2019; Ma et al., 2020), such use for parking spaces is not yet widespread. Second, our study assumed that if there is no available parking space on the intended parking streets, drivers will randomly search for available parking spaces by visiting the neighboring streets. While this assumption was appropriate for our purposes, there might be different search strategies commonly used by drivers. Lastly, we did not address the potential revenue implications of pricing policies or implementing mobile payment options. Instead, this study focused on the direct impact of policy changes on search times and occupancy rates. Future research could explore revenue aspects for a more comprehensive analysis. These limitations suggest avenues for future research to expand on our findings and provide a more complete understanding of the impact of parking pricing policies.

Acknowledgments

The authors express their gratitude to the department editor (Nitin Joglekar), the anonymous senior editor, and the referees for their invaluable suggestions, which significantly enhanced the quality of this manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Wei Qi acknowledges the support from the National Natural Science Foundation of China [Grants 72242106 and 72188101] and the Natural Sciences and Engineering Research Council of Canada [Grant RGPIN-2019-04769]. The first author is supported by funding provided by the Fonds de recherche du Québec – Société et culture (FRQSC). The works of Mehmet Gumus were supported in part by research grants from the Natural Sciences and Engineering Research Council of Canada [Grant 217601 NSERC RGPIN-2019-06091]; and the Institute for Data Valorization [IVADO G254088].

ORCID iDs

Sena Onen Oz https://orcid.org/0009-0002-6758-2538
Mehmet Gumus https://orcid.org/0000-0003-3814-896X
Wei Qi https://orcid.org/0000-0003-3948-835X

Supplemental Material

Supplemental materials for this article are available online (doi: 10.1177/10591478251344226).

References

Alemi F, Rodier C and Drake C (2018) Cruising and on-street parking pricing: A difference-in-difference analysis of measured parking search time and distance in San Francisco. *Transportation Research Part A: Policy and Practice* 111: 187–198.

Arnott R and Rowse J (2013) Curbside parking time limits. *Transportation Research Part A: Policy and Practice* 55: 89–110.

Barton H, Grant M and Guise R (2021) *Shaping Neighbourhoods: For Local Health and Global Sustainability*. New York, NY: Routledge.

Benjaafar S and Shen X (2023) Pricing in on-demand and one-way vehicle-sharing networks. *Operations Research* 71(5): 1596–1609.

Bimpikis K, Candogan O and Saban D (2019) Spatial pricing in ride-sharing networks. *Operations Research* 67(3): 744–769.

Boden J, Maier E and Wilken R (2020) The effect of credit card versus mobile payment on convenience and consumers' willingness to pay. *Journal of Retailing and Consumer Services* 52: 101910.

Brooke S, Ison S and Quddus M (2014) On-street parking search: Review and future research direction. *Transportation Research Record* 2469(1): 65–75.

Calonico S, Cattaneo MD and Titiunik R (2015) Optimal data-driven regression discontinuity plots. *Journal of the American Statistical Association* 110(512): 1753–1769.

Calvo E, Cui R and Serpa JC (2019) Oversight and efficiency in public projects: A regression discontinuity analysis. *Management Science* 65(12): 5651–5675.

Castro F and Frazelle AE (2024) Getting out of your own way: Introducing autonomous vehicles on a ride-hailing platform. *Production and Operations Management* 33(10): 2014–2030.

Chan EY (2021) The consumer in physical pain: Implications for the pain-of-paying and pricing. *Journal of the Association for Consumer Research* 6(1): 10–20.

Chatman DG and Manville M (2014) Theory versus implementation in congestion-priced parking: An evaluation of SFpark, 2011–2012. *Research in Transportation Economics* 44: 52–60.

Falk T, Kunz WH, Schepers JJL, et al. (2016) How mobile payment influences the overall store price image. *Journal of Business Research* 69(7): 2417–2423.

Hampshire RC and Shoup D (2018) What share of traffic is cruising for parking? *Journal of Transport Economics and Policy (JTEP)* 52(3): 184–201.

He Q-C, Nie T, Yang Y, et al. (2021) Beyond repositioning: Crowdsourcing and geo-fencing for shared-mobility systems. *Production and Operations Management* 30(10): 3448–3466.

He Q, Ma W, Vatsa P, et al. (2024) Impact of mobile payment adoption on household expenditures and subjective well-being. *Review of Development Economics* 28(1): 264–285.

Ho C-Y, Kim N, Rong Y, et al. (2022) Promoting mobile payment with price incentives. *Management Science* 68(10): 7614–7630.

Ho D, Imai K, King G, et al. (2011) MatchIt: Nonparametric preprocessing for parametric causal inference. *Journal of Statistical Software* 42(8): 1–28.

Jin F, Cheng Y, Li X, et al. (2024) Connecting the last mile: The impact of dockless bike-sharing on public transportation. *Production and Operations Management* 0(0).

Jin Z, Wang Y, Lim YF, et al. (2023) Vehicle rebalancing in a shared micromobility system with rider crowdsourcing. *Manufacturing & Service Operations Management* 25(4): 1394–1415.

Kelly JA and Clinch JP (2006) Influence of varied parking tariffs on parking occupancy levels by trip purpose. *Transport Policy* 13(6): 487–495.

Lee DS and Lemieux T (2010) Regression discontinuity designs in economics. *Journal of Economic Literature* 48(2): 281–355.

Li Z, Liang C, Hong Y, et al. (2022) How do on-demand ridesharing services affect traffic congestion? The moderating role of urban compactness. *Production and Operations Management* 31(1): 239–258.

Lie C, Hunt M, Peters HL, et al. (2010) The "negative" credit card effect: Credit cards as spending-limiting stimuli in New Zealand. *The Psychological Record* 60(3): 399–411.

Liu Y and Dewitte S (2021) A replication study of the credit card effect on spending behavior and an extension to mobile payments. *Journal of Retailing and Consumer Services* 60: 102472.

Liu Y, Luo J and Zhang L (2021) The effects of mobile payment on consumer behavior. *Journal of Consumer Behaviour* 20(3): 512–520.

Ma J, Xu M, Meng Q, et al. (2020) Ridesharing user equilibrium problem under od-based surge pricing strategy. *Transportation Research Part B: Methodological* 134: 1–24.

Mak H-Y (2022) Enabling smarter cities with operations management. *Manufacturing & Service Operations Management* 24(1): 24–39.

Millard-Ball A, Weinberger R and Hampshire R (2013) Comment on Pierce and Shoup: Evaluating the impacts of performance-based parking. *Journal of the American Planning Association* 79(4): 330–336.

Millard-Ball A, Weinberger RR and Hampshire RC (2014) Is the curb 80% full or 20% empty? Assessing the impacts of San Francisco's parking pricing experiment. *Transportation Research Part A: Policy and Practice* 63: 76–92.

Milosavljević N and 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, Kong H, Wang H, et al. (2021) Impact of pricing policy change on on-street parking demand and user satisfaction: A case study in Nanning, China. *Transportation Research Part A: Policy and Practice* 148: 445–469.

Moore A and Taylor M (2011) Time to cut up those debit cards? Effect of payment mode on willingness to spend. *Journal of Consumer Policy* 34(4): 415–422.

Naumov S and Keith D (2023) Optimizing the economic and environmental benefits of ride-hailing and pooling. *Production and Operations Management* 32(3): 904–929.

Ostermeijer F, Koster H, Nunes L, et al. (2022) Citywide parking policy and traffic: Evidence from Amsterdam. *Journal of Urban Economics* 128: 103418.

Ottosson DB, Chen C, Wang T, et al. (2013) The sensitivity of on-street parking demand in response to price changes: A case study in Seattle, WA. *Transport Policy* 25: 222–232.

Pierce G and Shoup D (2013) Getting the prices right: An evaluation of pricing parking by demand in San Francisco. *Journal of the American Planning Association* 79(1): 67–81.

Prelec D and Loewenstein G (1998) The red and the black: Mental accounting of savings and debt. *Marketing Science* 17(1): 4–28.

Prelec D and Simester D (2001) Always leave home without it: A further investigation of the credit-card effect on willingness to pay. *Marketing Letters* 12(1): 5–12.

Pu Z, Li Z, Ash J, et al. (2017) Evaluation of spatial heterogeneity in the sensitivity of on-street parking occupancy to price change. *Transportation Research Part C: Emerging Technologies* 77: 67–79.

Qi W, Sha M and Li S (2022) When shared autonomous electric vehicles meet microgrids: Citywide energy-mobility orchestration. *Manufacturing & Service Operations Management* 24(5): 2389–2406.

Qin H, Yang X, Wu Y-J, et al. (2020) Analysis of parking cruising behaviour and parking location choice. *Transportation Planning and Technology* 43(7): 717–734.

Rodríguez A, Cordera R, Alonso B, et al. (2022) Microsimulation parking choice and search model to assess dynamic pricing scenarios. *Transportation Research Part A: Policy and Practice* 156: 253–269.

Shoup D (2018) *Parking and the City*. New York, NY: Routledge.

Siddiq A and Taylor TA (2022) Ride-hailing platforms: Competition and autonomous vehicles. *Manufacturing & Service Operations Management* 24(3): 1511–1528.

Soman D (2001) Effects of payment mechanism on spending behavior: The role of rehearsal and immediacy of payments. *Journal of Consumer Research* 27(4): 460–474.

Soman D (2003) The effect of payment transparency on consumption: Quasi-experiments from the field. *Marketing Letters* 14(3): 173–183.

Taguchi G and Konishi S (1987) *Orthogonal Arrays and Linear Graphs: Tools for Quality Engineering*. Livonia, MI: American Supplier Institute.

Thomas M, Desai KK and Seenivasan S (2011) How credit card payments increase unhealthy food purchases: Visceral regulation of vices. *Journal of Consumer Research* 38(1): 126–139.

United Nations, Department of Economic, Population Division Social Affairs (2019) *World Urbanization Prospects: The 2018 Revision (ST/ESA/SER.A/420)*. New York: United Nations.

Van der Waerden P, Timmermans H and Bruin-Verhoeven M (2017) Car drivers' characteristics and the maximum walking distance between parking facility and final destination. *Journal of Transport and Land Use* 10(1): 1–11.

Wang H, Li R, Wang XC, et al. (2020) Effect of on-street parking pricing policies on parking characteristics: A case study of Nanning. *Transportation Research Part A: Policy and Practice* 137: 65–78.

Xu Y, Ghose A and Xiao B (2024) Mobile payment adoption: An empirical investigation of alipay. *Information Systems Research* 35(2): 807–828.

Yang W, Vatsa P, Ma W, et al. (2023) Does mobile payment adoption really increase online shopping expenditure in china: A gender-differential analysis. *Economic Analysis and Policy* 77: 99–110.

Yu H, Huang M and Yue X (2024) Sharing the shared rides: Multi-party carpooling supported strategy-proof double auctions. *Production and Operations Management* 33(7): 1569–1590.

Zellermayer O (1996) *The Pain of Paying*. Pittsburgh, PA: Carnegie Mellon University.

Zhou X, Lv M, Ji Y, et al. (2023) Pricing curb parking: Differentiated parking fees or cash rewards? *Transport Policy* 142: 46–58.

How to cite this article

Onen Oz S, Gumus M and Qi W (2025) Coins, Cards, or Apps: Impact of Payment Methods on Street Parking Occupancy and Search Times. *Production and Operations Management* 34(11): 3647–3666.