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Welfare Implications of Congestion Pricing: Evidence from SF*park*

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Congestion pricing offers an appealing solution to urban parking problems. Charging varying rates across time and space as a function of congestion levels may shift demand and improve allocation of limited resources. It aims to increase the accessibility of highly desired public goods to consumers who value them and to reduce traffic caused by drivers searching for available parking spaces. Using data from the City of San Francisco, both before and after the implementation of a congestion pricing parking program, we estimate the welfare implications of the policy. We use a two-stage dynamic search model to estimate consumers' search costs, distance disutilities, price sensitivities and trip valuations. We find that congestion pricing increases consumer and social welfare in congested regions but may hurt welfare in uncongested regions. Interestingly, despite the improved availability, congestion pricing may not necessarily reduce search traffic, because highly dispersed prices also induce consumers to search for more affordable spaces. In such cases, a simpler pricing policy may actually achieve higher welfare than a complex one. Lastly, compared to capacity rationing that imposes limits on parking durations, congestion pricing increases social welfare and has an ambiguous effect on consumer welfare. The insights from SF*park* offer important implications for local governments considering alternatives for managing parking and congestion, and for public sector managers to evaluate the tradeoffs between regulation vs. market-based approaches to manage public resources.

Key words: Congestion Pricing, Welfare, Dynamic Search Model, Public Sector, Traffic Management

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1. Introduction

One of the challenges in managing public goods is how to achieve an efficient allocation of the resources while keeping utilizations high. Without interventions from policy makers, individuals tend to overuse public goods ignoring the negative externalities they impose on others, leading to congestion and inefficient outcomes. This problem is commonly referred to as the tragedy of commons (Coman 1911).

This problem is present in urban parking, where the affordable price of public parking causes some users to overuse it, neglecting the impact of their behavior on others. This behavior can induce many urban transportation and other problems. As Shoup (2005) writes, "just as cattle compete in their search for scarce grass, drivers compete in their search for scarce curb parking spaces. Drivers waste time and fuel, congest traffic, and pollute the air while cruising for curb parking." Summarizing sixteen studies, Shoup (2006) found that, on average, 30 percent of urban traffic was caused by drivers cruising to search for parking rather than driving to their desired destinations.

There are two potential solutions to the commons problem. One solution is to limit an individual's usage, such as by imposing usage limits (e.g., putting limits on parking durations) or by issuing permits (commonly used in fishing, regional parks, and mining). By limiting parking time and fining noncompliant users, this policy discourages the abuse of public goods, thereby increases their accessibility to the public. Another solution modulates price to modulate demand to better match demand with limited supply. Examples include congestion pricing, which is used in traffic management and carbon emission management.

Congestion pricing has long been proposed as a solution to manage traffic congestion (Vickrey 1952). However, only recently has it been put into practice, due to the technological implementation challenges. To implement congestion pricing, cities must install technologies such as cameras or sensors to track congestion levels at frequent intervals. A few cities have experimented with different variations of congestion pricing: New York City's PARK Smart (2008), San Francisco's SF*park* (2011), and Berkeley's GoBerkeley (2012).With varying levels of pricing complexity, all programs reported increased accessibility and lower congestion (see program reports for details).[1]

Congestion pricing used in parking control works similarly to dynamic pricing used by airlines and hotels—it uses prices to shift demand and to allocate limited capacity—yet the objective is different. Whereas airlines and hotels use revenue management to maximize revenue (or profit), cities implement congestion pricing to increase availability and accessibility of public goods, and to reduce the negative externalities from overusing public resources.

Using SF*park*—the congestion pricing parking program recently implemented by the City of San Francisco—as a testbed, we wish to answer the following questions in this paper: (1) Would congestion pricing more efficiently allocate public resources, and more precisely, improve welfare via that allocation? (2) What are the caveats of implementing congestion pricing in public sectors? and (3) Which policy, imposing usage limits or congestion pricing, is more efficient in allocating limited public resources?

To answer these questions, we model a consumer's parking decision using a two-stage dynamic structural model. In the first stage, a consumer decides whether to drive and, if so, whether to

[1] PARK Smart Greenwich Village Pilot Program — Results. June 2009. New York City Department of Transportation. Pilot Project Evaluation. 2014. San Francisco Municipal Transportation Agency (SFMTA). GoBerkeley Pilot Program Results and Next Steps. December 16, 2014. Berkeley City Council.

park directly at a garage or to search for on-street parking. If a consumer decides to search, in the second stage, she will make a dynamic decision of whether to park on street, continue searching or abandon searching. We estimate consumers' search costs, distance disutilities and price sensitivities using availability and payment data made available by the SF*park* program. We use the estimates to quantify the effect of congestion pricing on consumer welfare, social welfare and search traffic.

Our model differs from most other structural search models in two ways. First, in our setting, not all consumers search. We only observe consumers' parking locations conditional on searching. To analyze what would happen with an alternative parking policy, we need to know where other consumers would park if they choose to drive. We therefore model the endogenous search decision explicitly, and we use the observations from the fixed pricing period to uncover the distribution of the underlying demand. We then use the estimated underlying demand distribution as an input when we estimate other parameters, assuming that the underlying demand distribution is constant before and after the implementation of congestion pricing for the same region, time and day.

Second, consumers in our context search on a two-dimensional map, while in most other structural search models (e.g., job search, product search), finding the next object is a realization of a random draw from the entire set of options, either with or without replacement. Searching in a two-dimensional space leads to a substantial challenge in modeling consumers' decisions and solving for the optimal search path, because a consumer's decision at every step will affect the available future options. To address this challenge, we imbed a random walk strategy with no immediate return to the dynamic search process. This allows us to capture the randomness in consumers' decisions with reasonable complexity and nuance, while avoiding the curse of dimensionality in a dynamic structural model.

We find several interesting results. First, our empirical results indicate that the effect of congestion pricing on consumer welfare may be region dependent—congestion pricing may either increase or decrease welfare depending on the characteristics of the region we study. We find that congestion pricing increased welfare in popular regions with moderate to high congestion levels. However, it actually resulted in a welfare decrease when implemented in less-congested areas. Second, while congestion pricing reduces search cost because popular blocks become more available, it induces another form of searching. An increased level of price dispersion induces more searching for better prices, particularly if consumers are price sensitive and if prices are highly dispersed geographically and updated frequently. To balance the positive availability effect and the negative price-search effect, we find that a simpler three-tier pricing policy may actually increase welfare relative to a more complex policy. Finally, we find congestion pricing leads to higher social welfare compared to a policy that imposes time limits on parking, while the effect on consumer welfare can be ambiguous.

What we learn from SF*park* offers important lessons to local governments considering alternative approaches to managing parking congestion. We document evidence that congestion pricing is indeed a viable approach to manage highly utilized public resources. It achieves higher welfare by allocating the resource to those who value it the most.

However, the implementation of congestion pricing is not without caveats. First, congestion pricing may not work as well in uncongested areas. Therefore, governments should not blindly implement congestion pricing in all regions. Rather, they should first assess the region's utilization. In under-utilized regions, the primary concern is not to redistribute demand, but to improve utilization. Therefore, a uniform pricing policy with lower rates may achieve a better welfare outcome than congestion pricing. Second, if the pricing structure gets very complex, congestion pricing may actually lead to more search traffic, not less. Therefore, a simpler policy may achieve higher welfare than a complex one.

Finally, our results contribute to a better understanding of ways to manage scarce public resources. Public sector managers often mitigate over-utilization by rationing capacity through usage limits or permits. We demonstrate that dynamic pricing can be a more efficient approach. Whereas capacity rationing usually fails to account for the heterogeneity in consumer demand, dynamic pricing allocates highly-demanded resources to those who need or value them the most. Of course, there are other implementation considerations such as feasibility, cost, and equity concerns. However, our analysis offers quantifiable results and a generalizable methodology for public sector managers to better evaluate the tradeoffs involved in making such decisions.

2. Literature Review

This paper is related to three streams of literature: (1) dynamic pricing, price discrimination and welfare analysis, (2) public sector operations management, and (3) consumer demand modeling and structural estimation. We review each stream and discuss our contributions below.

Dynamic Pricing, Price Discrimination and Welfare Analysis. First, our paper contributes to the theory and practice of dynamic pricing. In the past several decades, dynamic pricing has been successfully applied in a number of industries. American Airlines and Delta Airlines credit revenue management techniques for \$300 to \$500 million revenue gains per year (Boyd 1998). Similarly, Marriott's successful execution of revenue management has added \$150 to \$200 million in annual revenue (Marriott and Cross 2000). More recently, dynamic pricing was adopted in additional industries, such as sports, concert planning and retailing (Shapiro and Drayer 2014, Xu et al. 2016, Tereyagoglu et al. 2016, Fisher et al. 2015, Moon et al. 2017). This line of literature has focused primarily on profit/revenue maximization objectives (see Talluri and van Ryzin 2004 for an overview), with only a few recent exceptions that analyze consumer welfare under myopic vs. strategic consumers (Aflaki et al. 2016, Chen and Gallego 2016).

The ambiguous welfare effect has been a common thread in the literature on price discrimination (of which dynamic pricing is one example) for years. Starting from the seminal work by Robinson (1933), studies have found that price discrimination may or may not lead to welfare improvement, which depends on the interplay of many factors including output (Schmalensee 1981, Varian 1985), demand functions (Cowan 2007), and the presence of consumption externalities (Adachi 2005).

Few empirical analyses examine the welfare effect of price discrimination. Leslie (2004) is one of the first studies that measures the welfare effect empirically. Unlike revenue or profit, welfare is not directly observable. Therefore, it is necessary to develop structural models to explicitly capture consumers' utility functions and decision processes. Using Broadway theater as an example, Leslie (2004) finds that while price discrimination leads to a 5% increase in firm profit, its impact on consumer welfare is actually negligible. More recently, using airline data, Lazarev (2013) compares inter-temporal price discrimination to alternative pricing schemes (free resale, zero cancellation fees and third-degree price discrimination), and finds that the welfare effect is indeed ambiguous and can be moderated by the mix of business vs. leisure travelers.

We contribute to this line of literature by empirically analyzing the welfare effect of dynamic pricing through structural models. We offer insights on the conditions affecting the sign of the welfare effect in the context of a newly implemented dynamic pricing program in the public sector, where welfare is of particular interest.

Public Sector Operations Management. Recently, more research has devoted attention to public sector operations management. While a large body of research has focused on healthcare, research is also burgeoning in education, public transportation, utility, and natural resource management. Despite diverse contexts, a common theme that differentiates public versus private sector operations management is the public sector's focus on societal outcomes rather than profitability. As a result, much emphasis has been placed on quality (e.g., Kc and Terwiesch 2009), congestion and utilization (e.g., Powell et al. 2012, Jaeker and Tucker 2017), accessibility (e.g., Kim et al. 2015, Gallien et al. 2016, Kabra et al. 2015), and welfare and equity (e.g., Wang et al. 2017, Ashlagi and Shi 2016, Kok et al. 2016).

In the economics literature, since Coman (1911), the problem of the commons has become of greater concern, due to the rapid growth of world economy (see Stavins 2011 for a review and references therein). Stavins (2011) reviews and discusses two prevailing approaches used to address the commons problem: the command and control approach (setting usage limits) and the market-based approach (setting prices to internalize the externalities). Both approaches have been criticized: the command and control approach offers relatively little flexibility, ignores heterogeneity among users, and imposes additional costs to society; the market-based approach is often deemed as socially more efficient, at least from a theoretical standpoint, but it is often difficult to optimize the prices with respect to unpredictable reactions by individual decision makers facing complex price structures.

Indeed, in the transportation management literature, Bonsall et al. (2007) review multiple cases of congestion pricing used in public transportation, and attribute failures of many such programs to pricing structure complexity and consumer uncertainties about prices charged. Despite the long-standing literature on optimal pricing (e.g., Vickrey 1952, Williamson 1966, Arnott and Inci 2006), empirical analyses of consumer reaction to dynamic pricing in public transportation are relatively scarce. Two recent studies (Pierce and Shoup 2013, Ottosson et al. 2013) estimate demand elasticity to parking price changes using regression approaches. Without explicit consumer decision models and structural estimation, however, they are not able to offer insights on welfare. We find that the market-based approach indeed leads to greater social welfare compared to a command and control policy, but the effect on consumer welfare is ambiguous. Moreover, our work is related to studies of congestion in service operations, many of which analyze the role of price in controlling congestion levels in services (see Hassin and Haviv 2003 for a review and references therein).

Consumer Demand Modeling and Structural Estimation. Empirical work that incorporates consumer models is growing in operations management. Our work belongs to the increasing number of papers that use consumer choice models (Vulcano et al. 2010, Lederman et al. 2014, Kabra et al. 2015, Fisher et al. 2015), as well as models with dynamic decisions (Akşin et al. 2013, Li et al. 2014, Yu et al. 2016, Moon et al. 2017).

Our work is also closely related to literature on structural estimation of search models. This line of research estimates consumer search cost in different contexts, with (De Los Santos et al. 2012, Honka 2014, Koulayev 2014, Chen and Yao 2016) or without (Hortacsu and Syverson 2004, Hong and Shum 2006, Kim et al. 2010) observing consumers' search paths. Our work is similar to the latter in the sense that we estimate search costs and other parameters without observing search paths. However, our data is more fined-grained than theirs and the search is multi-dimensional. In particular, the fact that the search is conducted on a two-dimensional map restricts the set of available options at every step of search. Embedding a random walk with no immediate return to the dynamic search process allows us to address the challenge of dimensionality in estimation, while at the same time accounting for randomness in the consumers' search process.

3. Background on the SF*park* Program and Data Description

In this section, we introduce the SF*park* program. We then describe the data used for this study and provide summary statistics for periods before and after the implementation of the program.

3.1. The SF*park* program

The City of San Francisco implemented SF*park* in 2011 to address urban parking problems via congestion pricing. Rather than charging a constant rate at all locations and at all times, the program adjusts parking rates according to demand. One of the challenges in implementing congestion pricing is that it requires constant monitoring of parking space utilization to adequately adjust prices. SF*park* adopts several technologies, including parking sensors and smart meters, to track availability and evaluate utilization. The adoption of these technologies enabled SF*park* to implement a data-driven parking pricing strategy. It also enabled researchers to conduct detailed analysis of consumer response to congestion pricing and its welfare implications using fine-grained data that were not previously available.

The San Francisco Municipal Transportation Agency (SFMTA) pilot the program in seven parking management regions (see Figure 5), which included 6,000 metered spaces amounting to roughly a quarter of the total metered parking spaces in San Francisco. The pilot started in August 2011 and ended in June 2013. The pilot was deemed successful in reallocating demand, reducing congestion, and generating additional revenues from parking. As a result, the program was rolled out to the entire city in late 2013.

Here we provide the details of the policy and describe how SF*park* adjusts hourly parking rates dynamically based on observed occupancy rates. The program divides each paid-parking day (Monday to Saturday) into three time windows: morning (9am-12pm), noon (12pm-3pm), and afternoon (3pm-6pm). Parking is free at other times and on Sundays. For each time window, SF*park* uses the block-level average occupancy rate to determine the hourly rate for parking, where the occupancy rate is defined as the fraction of time that a block is occupied.

SF*park* started tracking the occupancy rates of the pilot areas in April 2011, four months before the official start of the program. They used occupancy data during that period to determine price adjustment rules for the pilot, which started in August 2011. Before the implementation, parking was \$2 per hour for all blocks. After the implementation, SF*park* raised the block's prices by \$0.25/hour if the occupancy rate was above 80%, lowered it by \$0.25/hour if the occupancy rate was between 60% to 80%, and lowered it by \$0.50/hour if the occupancy rate was below 60%. In addition, SF*park* also adjusted off-street parking prices (city-managed parking garages) using similar rules.[2] Finally, SF*park* set an upper- and a lower-bound for the hourly rate—the rate could not exceed \$6.00/hour or go below \$0.25/hour. As a result, parking rates vary by block, time of day, day of week, and month. Over the two-year pilot period, SF*park* made ten on-street rate

[2] Before the implementation, the garage hourly parking price ranged from \$2 to \$2.5. After the implementation, the hourly rate was raised by \$0.50 for blocks with occupancy rates above 80%, and lowered by \$0.50 for blocks with occupancy rates below 40%.

adjustments and eight off-street rate adjustments (i.e., every 8 to 12 weeks). All adjustments were announced on the program's website at least seven days before the changes went into effect.

3.2. Data

We use three datasets provided by SF*park* and choose the time period and regions for this study based on the data quality. First, parking sensor data consists of hourly block-level occupancy rates from April 2011 until June 2013. After late 2012, however, this sensor data becomes incomplete due to battery failures and sensor outages. Second, on-street meter payment data contains all parking transactions starting from the first quarter of 2011, and includes the start and end time, the payment type and the payment amount. The meter payment data is more reliable than the parking sensor data because it is not subject to battery failures. However, meter payment data is not an accurate proxy for availability, because drivers may park for longer or shorter periods than paid for or may park illegally without paying. Therefore, as long as the sensors have not experienced massive failures, the sensor data is a more accurate source for calculating occupancy rates. We therefore used the meter payment data to determine parking locations and durations, but not to infer occupancy rates. Third, off-street garage data contains usage data for publicly-owned garages. We observe transaction-level payment data in the same level of detail as the meter payment data. The garage transaction data is not subject to illegal or under/overtime parking, because payment is determined based on actual parking time.

Due to the increasing sensor failures starting in late 2012, we only use data from April 2011 to July 2012. In addition, to control for seasonality and make fair comparisons between the before and after periods, we use data from the same months in both years: April to July 2011 (the before period), and April to July in 2012 (the after period) as shown in Figure 6.[3] The SFMTA extended the parking time limit in the pilot areas from 2 to 4 hours in late April, 2011. To make fair comparisons, we exclude the days in April 2011 in which the parking time limit was only 2 hours. We also exclude consumers who parked in a garage for more than 4 hours from the main analysis. We do account for them when calculating garage occupancy rates. Among the seven piloted regions, we focus on the ones that are relatively isolated from the others: Fillmore, Marina, and Mission.[4]

Table 1 presents the before and after summary statistics of the hourly parking rates and occupancy rates for the three regions. Consistent with SF*park* guidelines, we use average occupancy rates to divide the parking blocks to high (average occupancy rates above 80%), medium (60%

[3] Even during these periods, there were some occasional meter failures. In these cases, for each block-hour under consideration, the parking sensor data marks the status of the spaces as "unknown" and indicates the duration of the failure. We exclude the "unknown" time from the calculation of occupancy rates.

[4] Fisherman's Wharf is also relatively isolated. However, since it is primarily a tourist destination where consumers might not have much knowledge of the SF*park* program, we do not include it in our study.

and 80% occupancy), and low-utilization (below 60% occupancy). Table 1 shows that after the implementation of congestion pricing, the mean parking rate increased by around 150% for high-utilization blocks, and decreased by between 40% - 70% for low-utilization blocks in Marina and Fillmore. In Mission, there were no high utilization blocks in the before period, and the parking rates in the low utilization blocks decreased slightly.[5] As expected, the average occupancy rate for low-utilization blocks increased while the average occupancy rate for high- and medium-utilization blocks decreased. This provides evidence of shifts in demand as a response to congestion pricing. Figure 7 shows how parking rates vary between blocks and how occupancy rates change in the after period via street map snapshots in Fillmore. The figure illustrates clearly that prices vary substantially by blocks—a driver could save \$2 to \$3 per hour by driving one or two additional blocks. The figure also demonstrates that the congestion levels are more evenly distributed during the after period than the before period.

4. Model

There are M_r consumers who are interested in visiting region r (i.e., Fillmore, Marina, Mission). We specify the decision process of a consumer i, whose trip destination is at block b_i^*, and is interested in parking for a duration of h_i hours. That is, block b_i^* is the ideal parking location for consumer i under conditions of unlimited availability of free parking. Although we do not observe consumers' ideal locations, we will estimate the distribution of ideal locations of the M_r consumers over the set of blocks, B_r, in region r, from the volumes and patterns of parking. To this end, let $\omega^*_{rtd}(b)$ denote the fraction of M_r consumers whose ideal location is block b during time of the day t (i.e., morning, noon, or afternoon) on day d, where $\sum_{b\in B_r} \omega^*_{rtd}(b) = 1$.[6] We allow this fraction to vary by time and day to account for variations in consumers' trip destinations. For example, a higher fraction of consumers may wish to shop at Urban Outfitters than visit the post office on a Friday afternoon compared to Tuesday morning. We will explain how we estimate $\omega^*_{rtd}(b)$ later in detail.

We assume that the ideal locations and trip durations are determined exogenously. While there may be situations when a consumer is willing to change her destination or duration based on congestion levels and parking rates, these two variables are largely determined by the purpose of the trip. For example, the destination of a consumer who plans to buy an iPhone is the Apple store, and the duration of the trip is determined by the expected time it takes to shop and purchase an iPhone. We further assume that the trip durations do not change once a customer has parked.

[5] Some parking spaces in Mission were blocked due to construction in March 2012. This induced higher occupancy rates in this area. In order to make fair comparisons, we treat these blocks as available in welfare and counter-factual analyses.

[6] Consistent SF*park*, we define morning as 9am-12pm, noon as 12pm-3pm, and afternoon as 3pm-6pm.

We model consumers' driving and parking behavior as a series of decisions. We assume that each consumer chooses among three options: (1) drive to the region and search for on-street parking, (2) drive to the region but park directly in the public garage without searching,[7] or (3) choose an outside option, which includes staying home, using other modes of transportation, or parking elsewhere.[8] A consumer will choose the option that gives her the highest expected utility.

Without loss of generality, we normalize the mean utility of the outside option to zero. Let u_{i0} denote the utility of the outside option for consumer i,

$$u_{i0} = \epsilon_{i0} \equiv V_i^{\mathrm{o}},$$

where ϵ_{i0} is an idiosyncratic shock to the outside utility of consumer i, which follows a normal distribution with mean 0 and standard deviation σ.

Consumer i obtains a mean trip value, v_{irtd}, from driving to the region relative to the outside option, irrespective of whether she parks at the garage directly or searches for on-street parking. We let the mean utility of driving to be a linear function of the duration of parking. Specifically,

$$v_{irtd} = \alpha + \beta X_{rtd} h_i,$$

where X_{rtd} contains the intercept and dummy variables indicating time of the day, day of week, and month.[9] Even though all parameters in this paper are region specific, for brevity we omit the subscript r for parameters.

A consumer who decides to drive and park directly at the garage will obtain value $v_{irtd} + \epsilon_{ig}$ from the trip, where ϵ_{ig} is an idiosyncratic shock to consumer i's utility from parking at the garage, which follows the same distribution as ϵ_{i0}. At the same time, she will incur the cost of walking to her ideal location, b_i^*, from the garage and the garage parking fee, which is based on the hourly parking rate at the garage, P_{b_g}, and the parking duration, h_i. Specifically, let u_{ig} denote the utility of parking at the garage for consumer i, then

$$u_{ig} = \alpha + \beta X_{rtd} h_i + \epsilon_{ig} - \eta_i d(b_i^*, b_g) - \theta_i P_{b_g} h_i \equiv V_i^{\mathrm{garage}},$$

[7] In most regions we study, there is one public garage operated by the city. In cases where there are multiple garages, a consumer chooses the one with the highest utility based on her destination. Since we do not have data from private garages in the corresponding regions, we include parking at a private garage as part of the outside option.

[8] We do not explicitly model the choice of a departure time (e.g., morning or afternoon, Monday or Tuesday). However, such inter-temporal shifts in demand are incorporated implicitly, to some extent, through the outside option. For instance, high prices on Tuesday afternoons result in fewer consumers driving to their destinations and more consumers choosing the outside option.

[9] We have also analyzed alternative model specifications, where v_{irtd} is a function of X_{rtd} only, a function of h_i only, or a linear additive function of X_{rtd} and h_i. None of these specifications fit our empirical observations as well.

where η_i denotes consumer i's cost of parking one block away from the destination, $d(b_i^*, b_g)$ denotes the distance from the garage to consumer i's destination, b_i^*,[10] and θ_i denotes consumer i's price sensitivity. We assume that there is always an available parking space at the garage.[11]

Finally, a consumer who chooses to drive to the region and search for on-street parking will either end up parking at a block that she finds available and affordable, or may eventually decide to abandon searching and either park at the garage or choose the outside option (e.g., give up the trip or park elsewhere). If she parks on-street, she will obtain value $v_{irtd} + \epsilon_{is}$, where ϵ_{is} is an idiosyncratic shock to consumer i's utility from on-street parking and follows the same distribution as ϵ_{i0} and ϵ_{ig}. Note that all utility shocks, ϵ_{i0}, ϵ_{ig} and ϵ_{is}, are observable to the consumer, but not to researchers. On the cost side, the consumer pays for parking, and incurs any search costs as well as a cost of walking to her destination if she parks elsewhere. We model the consumer's search for on-street parking as a dynamic search model and explain it in detail below.

4.1. Dynamic Search Model

States, Actions and Utilities We derive the general model of search under congestion pricing, where prices may vary across blocks and by time of day, day of week, and month. Fixed pricing is a special case of the general model. On the kth search, consumer i arrives at block b_k, $k = 1, 2, 3, \ldots$. There are three actions, a, that she can choose from: continue searching ($a = 0$), park at the current block if there is a spot available ($a = 1$), or stop searching for on-street parking ($a = 2$). She chooses the option that gives her the highest expected utility. The utility of each option depends on the following state variables, which are realized after consumer i arrives to the block:

- b_k: the block that the consumer arrives at on the kth search;
- P_{rtdb_k}: the hourly parking price at block b_k in region r at time t on day d;
- A_{rtdb_k}: the availability of block b_k in region r at time t on day d. A_{rtdb_k} equals one if there is at least one parking spot available and zero otherwise;
- ϵ_{irtdb_k}: the shock to the cost of searching observed by consumer i at block b_k in region r at time t on day d.

Consumer i's utility from choosing an action a at block b_k is given by $u_i(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k}; a)$. We specify the utility from each action below.

[10] The distance between two blocks is calculated as the minimum number of blocks that one has to walk from one block to the other. We assume all blocks have same length.

[11] Based on garage payment data, these garages are never full and the maximum occupancy rates are 75%, 72%, and 38% for Marina, Fillmore and Mission, respectively.

- If consumer i decides to stop searching for on-street parking ($a = 2$), she faces two options. She can either park at the garage or choose the outside option (e.g., give up the trip completely, park at a private garage, etc.), and would choose the option that maximizes her utility.[12]

$$u_i(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k}; 2) = \max\left(V_i^{\text{garage}}, V_i^{\text{o}}\right) \equiv V_i^{\text{garage|o}}.$$

- If consumer i decides to park on-street ($a = 1$), then when the block is available, $A_{rtdb_k} = 1$, she gets the utility:

$$u_i(b_k, P_{rtdb_k}, 1, \epsilon_{irtdb_k}; 1) = v_{irtd} + \epsilon_{is} - \eta_i d(b_i^*, b_k) - \theta_i P_{rtdb_k} h_i \equiv V_i^{\text{park}}(b_k, P_{rtdb_k}).$$

If there is no parking spot available in the block, $A_{rtdb_k} = 0$, she cannot park there. In that case, we denote her utility from parking by negative infinity.

$$u_i(b_k, P_{rtdb_k}, 0, \epsilon_{irtdb_k}; 0) = -\infty.$$

- If consumer i decides to continue searching, $a = 0$, she gets the expected utility:

$$\begin{aligned}
&u_i(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k}; 0) \\
&= -s_i \epsilon_{irtdb_k} + E\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{rtdb_{k+1}}; a) | (b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{rtdb_k})\big], \\
&\equiv -s_i \epsilon_{irtdb_k} + V_i^{\text{search}}(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k}),
\end{aligned}$$

where s_i is consumer i's per block search cost and ϵ_{irtdb_k} is the shock to search cost s_i. That is, we assume that the actual cost incurred by continuing to search, $s_i \epsilon_{irtdb_k}$, depends on both the per block search cost, s_i, which is known to the consumer before searching, and a search cost shock ϵ_{irtdb_k}, which is only realized after arriving at block b_k. The shocks, ϵ_{irtdb_k}, are i.i.d across consumers, regions, time, day and blocks, and follow a standard log normal distribution, i.e., $log(\epsilon_{irtdb_k})$ follows the standard normal distribution.[13] The lognormal distribution guarantees that the overall search cost $s_i \epsilon_{irtdb_k}$ is non-negative (i.e., a customer will not give up an available parking spot because she suddenly "enjoys" searching). The expectation term in the above equation is the expected value

[12] We assume that the set of outside options available after the search starts is the same as that in the first stage. Ideally, we would allow them to be different, as after the search starts, some outside options would be less appealing. For example, while a consumer may choose the private garage or give up the trip completely, she might not choose to drive back home and get a cab. However, since we cannot empirically distinguish between customers who choose the outside option in the first stage versus those who do so in the second stage, we assume that the two are the same. Alternatively, it is possible to assume that once the search starts, the outside options are no longer available. Our conclusions are robust to this alternative specification.

[13] As we shall discuss in the estimation section, s_i also follows a lognormal distribution, i.e., $\log s_i \sim N(\mu_s, \sigma_s)$. Therefore, $s_i \epsilon_{irtdb_k}$ is also lognormally distributed. Note that without observing individual search paths, it is impossible to separately estimate the variances of s_i and ϵ_{irtdb_k}. We therefore standardize the distribution of ϵ_{irtdb_k} to a standard lognormal distribution.

of continuing to search once arriving at block b_k. The expectation is taken with respect to the conditional distribution of state variables $(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{irtdb_{k+1}})$ given the current state variables $(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k})$. If a consumer continues to search, she will follow a random walk strategy (with no immediate return) and will arrive at one of the adjacent blocks randomly.

Ideally, we would have liked to model shocks specific to searching each of the adjacent blocks as modulated by the relative costs, such as from having to wait to turn left, proceeding straight with the flow of the traffic, or quickly turning right on a red light. Although intellectually appealing, including block-specific shocks would introduce three unobserved state variables (most blocks have three adjacent blocks at each end) which increases the estimation complexity substantially. Without much loss of generality, we introduce one shock to the search cost, which captures, for example, the general traffic condition that makes a consumer more or less willing to continue searching. To introduce randomness in the block to search next, we further assume that if the consumer continues searching, she will choose one of the adjacent blocks randomly. This allows for idiosyncratic shocks that affect a consumer's stopping decision without over-complicating the model and the estimation, while at the same time incorporating randomness in search paths. Although the random walk assumption abstracts away from some decisions (e.g., which block to drive to based on different beliefs about the expected utility of each adjacent block), it does offer reasonable levels of complexity and nuance. Given the many transient random factors at play (traffic, blockage, road condition, traffic lights, emotions, etc.) and limited deliberation time in traffic, a random walk may actually be a more realistic model of consumer behavior. In sum, the model incorporates randomness in both the decision to continue searching (through the idiosyncratic shock to search cost) and in the search paths (from the random walk).

Evolution of States and Consumer Beliefs As discussed previously, the evolution of the state variable b_k follows a random walk with no immediate return. That is, a consumer has equal probabilities to transition from the current block to any of the adjacent blocks. For simplicity of illustration, we slightly abuse notation by ignoring the direction of driving (i.e., which block a consumers searches next), but we simulate driving directions in our estimation via Simulated Methods of Moments. At the initial block, the direction of driving is randomly generated, and the remaining blocks are generated from a random walk with no immediate return. Denote B_{rb_k} as the set of adjacent blocks accessible from the current block b_k, and $|B_{rb_k}|$ as the number of the adjacent blocks. The joint evolution of state variables P_{rtdb_k} and A_{rtdb_k} depends on the region, time and day, and the location of the current block. For the evolution of the search cost shock, recall that ϵ_{irtdb_k} is i.i.d. across consumers, regions, times, days, and blocks. We also assume that it is independent from P_{rtdb_k} and A_{rtdb_k}. Under these assumptions, when a consumer decides to continue searching (i.e., $a=0$), the transition probability is:

$$
\begin{aligned}
&Pr\big(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{rtdb_{k+1}}; 0|b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k}\big)\\
&= \begin{cases} \frac{1}{|B_{rb_k}|} f^{P,A}_{rtdb}\big(P_{rtdb_{k+1}}, A_{rtdb_{k+1}}|b_k, P_{rtdb_k}, A_{rtdb_k}\big) f^{\epsilon}(\epsilon_{irtdb_{k+1}}), & \text{if } b \in B_{rb_k} \\ 0, & \text{otherwise,} \end{cases}
\end{aligned}
$$

where $f^{P,A}_{rtdb}$ and f^{ϵ} are the density functions of the state variables.

Next, we discuss consumer beliefs. We assume that consumers have rational expectations about the distributions of price, availability and search cost shock. A fully rational consumer would need to possess an extreme level of sophistication: not only would she form rational expectations of the availability, price and search cost shock at each specific block, she would also form rational expectations of the spatial correlations of these state variables, and would therefore update her belief about the distribution of these state variables at a future block based on the observed states of all previous blocks visited. Such assumption not only introduces a substantial computational burden to the estimation of a dynamic model with multiple state variables, but it is also too complex from a consumer's perspective.

Instead, we simplify beliefs and decisions by assuming that consumers' belief of P_{rtdb_k} and A_{rtdb_k} are i.i.d. across block b_k. Under this assumption, consumers still have different expectations about the price and availability in different hours of a day, on different days, and in different regions. However, within a region and at a given time t and day d, all blocks will appear *ex-ante* the same. To explain, taking availability as an example, the assumption implies that a consumer forms an expectation that all blocks have the same probability to be available and that this expectation is rational. That is, this probability equals the observed average probability of a block being available across all blocks in the region at time t on day d. Specifically, let ϕ_{rtdb} denote the probability of block b being available (i.e., at least one spot in the block is available) in region r at time t on day d, and $\tilde{\phi}_{rtdb}$ denotes consumers' belief of availability. We have $\tilde{\phi}_{rtdb} = \frac{\sum_{b\in B_r} \phi_{rtdb}}{|B_r|} \equiv \phi_{rtd}$. Note that whether a consumer finds a block available is based on the real-time availability of the block, rather than the average availability. In other words, consumers' beliefs are correct on average, but not for a specific snapshot. We further assume that consumers do not update their beliefs after observing the states of the current block.[14] Under such assumptions, the expected value for a customer who continues to search can be written as:

$$V_i^{\text{search}}(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k})$$

[14] As noted previously, it is possible to consider a model where consumers update their beliefs at every step. However, such a model requires that consumers know the spatial conditional probability functions of the states at one block given those observed at other blocks. This would make a consumer's decision extremely complex and introduce significant computational challenges to the estimation. Even though our model does not allow updating, we do conduct sensitivity analyses where consumers have different beliefs across blocks according to their popularity levels.

$$
\begin{aligned}
&= E\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{rtdb_{k+1}}; a)|(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{rtdb_k})\big] \\
&= E\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{rtdb_{k+1}}; a)|b_k\big] \\
&\equiv V_i^{\text{search}}(b_k).
\end{aligned}
$$

That is, the expected value of searching, $V_i^{\text{search}}(b_k)$, is a function of the current block b_k, and it varies across consumers due to differences in parameters and ideal locations. Note that the second equality above follows from the fact that consumers do not update their beliefs of price and availability, and that the search shocks ϵ_{rtdb_k} are i.i.d across blocks.

Although consumers may not have complete knowledge of the states of every individual block, it may be too restrictive to assume that consumers' price and availability beliefs are identical for all blocks. We analyze an alternative partial-knowledge model where we group blocks into three levels (high, medium, and low) according to their popularity before the implementation of congestion pricing.[15] Thus, we assume that consumers knew the prior popularity level of a block, and form respective conditional rational expectations of all state variables. For example, the probabilities of finding a block with high, medium and low popularity available are $\phi_{rtd}^H, \phi_{rtd}^M, \phi_{rtd}^L$, respectively, and each probability equals to the average availability probability of all blocks of the particular type. Note that under this assumption, consumers will no longer follow the random walk strategy. Rather, they will choose the next block knowing each adjacent block's popularity level. In other words, a consumer will follow an optimal search path defined by where to start and which block to drive to next if she continues searching. We present the details of the consumer decision process in Appendix D.3.

Optimal Decision Rule The optimal decision rule, $a_i^*(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k})$, of consumer i can be characterized as follows:

- If the current block is available, i.e., $A_{rtdb_k} = 1$, a consumer can choose from three potential actions: continue searching ($a = 0$), park at the current location ($a = 1$), or abandon on-street parking ($a = 2$). A consumer will choose the action that gives her the highest utility:

$$
a_i^*(b_k, P_{rtdb_k}, 1, \epsilon_{irtdb_k}) = \begin{cases} 0, & \text{if } -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k) > \max\left(V_i^{\text{garage}|\text{o}}, V_i^{\text{park}}(b_k, P_{rtdb_k})\right) \\ 1, & \text{if } V_i^{\text{park}}(b_k, P_{rtdb_k}) \geq \max\left(V_i^{\text{garage}|\text{o}}, -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k)\right) \\ 2, & \text{otherwise.} \end{cases}
$$

[15] Empirically, we determine whether a block has a high, medium, or low popularity based on SF*park*'s definition. High popularity blocks are those with an average occupancy rate of 80% or higher before implementation. Medium popularity blocks are those with average occupancy rates of between 60% and 80%. Low popularity blocks are those with average occupancy rates of 60% or lower.

- If the current block is unavailable, i.e., $A_{rtdb_k}=0$, a consumer has two options to choose from: continue searching ($a=0$) and stop searching ($a=2$).

$$a_i^*(b_k, P_{rtdb_k}, 0, \epsilon_{irtdb_k}) = \begin{cases} 0, & \text{if } -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k) > V_i^{\text{garage|o}} \\ 2, & \text{otherwise.} \end{cases}$$

Let $u_i^*(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k})$ denote the maximum utility a consumer can get after arriving at block b_k, i.e.,

$$u_i^*(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k}) = \max_{a=\{0,1,2\}} u_i(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k}; a).$$

- When the block is available, i.e., $A_{rtdb_k}=1$,

$$\begin{aligned}
&u_i^*(b_k, P_{rtdb_k}, 1, \epsilon_{irtdb_k}) \\
&= \begin{cases} -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k), & \text{if } -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k) > \max\left(V_i^{\text{garage|o}}, V_i^{\text{park}}(b_k, P_{rtdb_k})\right), \\ V_i^{\text{park}}(b_k, P_{rtdb_k}), & \text{if } V_i^{\text{park}}(b_k, P_{rtdb_k}) \geq \max\left(V_i^{\text{garage|o}}, -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k)\right), \\ V_i^{\text{garage|o}}, & \text{otherwise.} \end{cases} \\
&= \begin{cases} -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k), & \text{if } \epsilon_{irtdb_k} < \frac{V_i^{\text{search}}(b_k) - V_i^{\text{garage|o}}}{s_i}, P_{rtdb_k} \geq \frac{s_i\epsilon_{irtdb_k} - V_i^{\text{search}}(b_k) + v_{rtd} + \epsilon_{irtd} - \eta_i d(b_i^*, b_k)}{\theta_i h_i}, \\ V_i^{\text{park}}(b_k, P_{rtdb_k}), & \text{if } P_{rtdb_k} < \frac{v_{rtd} + \epsilon_{irtd} - \eta_i d(b_i^*, b_k) - V_i^{\text{garage|o}}}{\theta_i h_i}, \epsilon_{irtdb_k} > \frac{V_i^{\text{search}}(b_k) - V_i^{\text{park}}(b_k, P_{rtdb_k})}{s_i}, \\ V_i^{\text{garage|o}}, & \text{otherwise.} \end{cases}
\end{aligned}$$

- If the block is unavailable, i.e., $A_{rtdb_k}=0$,

$$\begin{aligned}
&u_i^*(b_k, P_{rtdb_k}, 0, \epsilon_{irtdb_k}) \\
&= \begin{cases} -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k), & \text{if } -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k) > V_i^{\text{garage|o}}, \\ V_i^{\text{garage|o}}, & \text{otherwise,} \end{cases} \\
&= \begin{cases} -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k), & \text{if } \epsilon_{irtdb_k} < \frac{V_i^{\text{search}}(b_k) - V_i^{\text{garage|o}}}{s_i}, \\ V_i^{\text{garage|o}}, & \text{otherwise.} \end{cases}
\end{aligned}$$

$V_i^{\text{search}}(b_k)$ can be calculated recursively (see Appendix A).

4.2. Choice of Driving

Next, we return to the discussion of the consumer's initial decision. Recall that in the first stage, consumer i chooses among three options: (1) drive to the region and search for on-street parking, (2) drive to the region but park directly at a public garage without searching, and (3) choose the outside option. We have previously specified the utility of the latter two options. We now derive the expected utility of the first option. Denote the expected utility of a consumer i who decides to drive and search for on-street parking by u_{is}. Then,

$$u_{is} = \max_{b_1 \in B_r} E_{(P_{rtdb_1}, A_{rtdb_1}, \epsilon_{irtdb_1})} u_i^*(b_1, P_{rtdb_1}, A_{rtdb_1}, \epsilon_{irtdb_1}),$$

where b_1 is the block from which a consumer starts to search, i.e., $k = 1$. Note that consumer i chooses an initial block b_1 from the set of blocks in the region, B_r, to maximize the expected utility-to-go. The expectation is taken over the state variables $(P_{rtdb_1}, A_{rtdb_1}, \epsilon_{irtdb_1})$, because they are unknown at the time she makes the decision—consumer i only observes the realizations of these random variables after she arrives at block b_1.

In the first stage, consumer i chooses the option that brings her the highest expected utility among u_{is}, u_{ig}, and u_{i0}, where

$$
\begin{aligned}
u_{is} &= \max_{b_1 \in B_r} E_{(P_{rtdb_1}, A_{rtdb_1}, \epsilon_{irtdb_1})} u_i^*(b_1, P_{rtdb_1}, A_{rtdb_1}, \epsilon_{irtdb_1}), \\
u_{ig} &= v_{irtd} + \epsilon_{ig} - \eta_i d(b_i^*, b_g) - \theta_i P_{b_g} h_i, \\
u_{i0} &= \epsilon_{i0}.
\end{aligned}
$$

Under the assumption of identical and rational beliefs across blocks, it is easy to see that consumer i's best starting location is her ideal location b_i^*, because all blocks are *ex-ante* the same except for their distances to the ideal location. Under the assumption of stratified beliefs across blocks, however, consumers may not always choose their ideal locations to start their search. For example, a consumer may want to start from a less congested block located far from her ideal location, if she has a high search cost and a low distance disutility cost.

5. Identification and Estimation

Whether consumer i drives to the destination and where she eventually parks are determined by her ideal location b_i^*, trip valuation parameters α and β, search cost s_i, distance disutility η_i, price sensitivity θ_i, and her utility and search cost shocks. Therefore, the primitives of the model that we wish to estimate are: ideal location distribution $\omega_{rtd}^*(b)$, trip valuation parameters α and β, the *joint* distribution of (s_i, η_i, θ_i) and the standard deviation σ of the utility shocks. All parameters are region specific. Observe that we cannot identify the ideal location distribution and the consumer attributes jointly. To see this, imagine that we observe a uniform distribution of final parking locations under congestion pricing. That could be because consumers' ideal locations are largely evenly distributed, or because consumers are very price sensitive and therefore reallocate themselves accordingly. Therefore, to be able to separately estimate the ideal location distribution and the consumer attributes, we exploit observations of final parking locations both before and after the implementation of congestion pricing. In particular, we highlight that consumers' driving and parking decisions observed under fixed pricing are pivotal to the separate identification of the ideal location distribution and the consumer attributes. We discuss the identification and estimation of the ideal location distribution and the consumer attributes in detail.

5.1. Identification and Estimation of Ideal Location Distribution

5.1.1. Identification As mentioned above, consumers' decision under fixed pricing enables us to identify the ideal location distribution. In particular, under fixed pricing, a consumer will always park if the block she arrives at is available—prices are fixed, so continuing to search does not provide any benefit, but involves costs, leading to lower expected utility. This is in contrast to the congestion pricing case in which a customer may decide to forego an available spot if the block is too expensive.

Now imagine a hypothetical situation in which there are no capacity constraints at any block (or, equivalently, that the constraints are never binding). Without capacity constraints, consumers will always park at their ideal locations, making the consumer's observed parking location precisely her ideal location. Under the realistic situation of binding capacity constraints, however, lack of space at the ideal location may force consumers to park in adjacent blocks or in a garage. That is, in the presence of capacity constraints, the observed demand at a block could include consumers whose ideal location is at that block as well as an overflow of consumers arriving from adjacent blocks that are full. This allows us to generate moment conditions that equate the model-predicted demand to the observed demand at each block.

Note, however, that this discussion only establishes the association of ideal and final parking locations for those consumers who choose to drive. Our objective, however, is not to estimate the ideal location distribution *conditional* on driving. To properly evaluate welfare changes and to conduct counterfactual analyses, we need to estimate the *unconditional* ideal location distribution of all M_r consumers in the market. To do so, we need to establish the conditions under which a consumer chooses to drive and conditional on driving, whether she searches on-street or parks directly in the garage. The fraction of consumers who drive depends on the expected congestion level of a day—everything else equal, a consumer has a lower incentive to drive on a congested day. Also, the fraction of consumers who search on-street is a function of the distance between the ideal location and the garage—on a congested day, a consumer whose ideal location is closer to the garage is more likely to go to the garage directly, compared to other consumers. If we knew these fractions, we could rewrite the aforementioned moment conditions in terms of the unconditional ideal locations. Instead, we estimate these fractions non-parametrically using reduced-form polynomial functions.

Once we estimate the ideal location distribution using the data from the before period, we use it as an input in the after period. Therefore, in the after period, we only need to estimate the consumer related parameters: trip valuation parameters, consumer attributes and the standard deviation of the utility shocks. Note that for this method to work, we assume that while the number of consumers who choose to drive may change, the *unconditional* ideal location distributions in the pre- and post-periods are the same for the same region, time and day. That is, the *relative* popularity of an Apple store is the same on Monday mornings in April in both 2011 and 2012. Though this assumption may not be perfect, it is reasonable, given that we have carefully chosen the same study periods to mitigate the impact of seasonality, and we also distinguish morning, noon, and afternoon, day of week and month in calculating these ideal location distributions. We also conduct sensitivity analyses around the ideal locations by introducing varying levels of noises to make sure that the results are robust to estimation errors in the ideal location distribution. Refer to Appendix D.2 for details.

5.1.2. Estimation With the intuition in mind, we now describe the details of the estimation.

- **Ideal Location Demand**

  Recall that there are M_r consumers in the market, among which $M_r\omega^*_{rtd}(b)$ consumers have an ideal location of block b. Only a fraction of them will decide to drive and search for on-street parking. This fraction depends on the relative utility of the outside option versus that of driving and searching on-street. The fraction of consumers who choose to search for on-street parking over the outside option is a function of the expected congestion level. Everything else equal, the more congested the region is during time t on day d, the less likely it is that a consumer will choose to search for on-street parking. This fraction also depends on the relative utility of parking directly at the garage versus that of driving and searching on-street. The fraction of consumers who choose to search for on-street parking over directly parking at garage is a function of the distance between the garage and the ideal location. The further away the garage is from the ideal location, the fewer consumers will choose to park directly at the garage. In sum, the fraction of consumers who drive and search for on-street parking, π, is then a function of the expected availability, ϕ_{rtd}, and the distance between the garage and the ideal location b, $d(b, b_g)$.

- **Underlying Demand**

  Let $q^*_{rtd}(b)$ denote the underlying demand. The demand equals to the number of consumers for which the ideal location is b and who decide to drive and search for on-street parking. We then have:

$$q^*_{rtd}(b) = M_r \cdot \omega^*_{rtd}(b) \cdot \underbrace{\pi(\phi_{rtd}, d(b, b_g))}_{\substack{\text{Fraction that drives} \\ \text{and searches on-street}}} . \quad (1)$$

- **Actual Demand**

  The actual demand for a block, denoted as $q_{rtd}(b)$, can then be written as the sum of $q^*_{rtd}(b)$ and the overflow demand. The overflow demand comprises the consumers who are not able to find a parking spot at any nearby block. Let $q_{rtd}^{\text{overflow}}(b',b)$ denote the overflow demand from block b' to block b. We then have:

$$q_{rtd}(b) = q^{*}_{rtd}(b) + \sum_{b' \in B_{rb}} q_{rtd}^{\text{overflow}}(b',b), \tag{2}$$

- **Overflow Demand**

  It is worthwhile to emphasize that the overflow demand from b' to b includes not only consumers whose ideal location is at adjacent blocks b', but also b''s overflow demand originating from other blocks. Therefore, the overflow demand is defined *recursively* as a function of the actual demand of adjacent blocks:

$$q_{rtd}^{\text{overflow}}(b',b) = q_{rtd}(b') \cdot \underbrace{(1-\phi_{rtdb'})}_{\substack{\text{Fraction that}\\ \text{cannot park at } b'}} \cdot \underbrace{\rho(\phi_{rtd}, d(b',b_g))}_{\substack{\text{Fraction that}\\ \text{continues searching}}} \cdot \frac{1}{|B_{rb'}|}, \tag{3}$$

  where ρ denotes the fraction of consumers who will continue searching. Similarly to π, the fraction ρ is also a function of the expected availability, ϕ_{rtd}, and the distance of the garage to the block under consideration, $d(b',b_g)$.[16] Recall that $\phi_{rtdb'}$ is the availability of the specific block b', while ϕ_{rtd} is consumers' belief of the availability of any block.

- **Observed Demand**

$$q^{\text{obs}}_{rtd}(b) = q_{rtd}(b) \cdot \phi_{rtdb}. \tag{4}$$

Equations (1) to (4) can be simplified to one equation involving only the observed demand:

$$\begin{aligned} \frac{q^{\text{obs}}_{rtd}(b)}{\phi_{rtdb}} &= M_{rtd} \cdot \omega^{*}_{rtd}(b) \cdot \pi(\phi_{rtd}, d(b,b_g)) \\ &\quad + \sum_{b' \in B_{rb}} q^{\text{obs}}_{rtd}(b') \cdot \frac{1-\phi_{rtdb'}}{\phi_{rtdb'}} \cdot \rho(\phi_{rtd}, d(b',b_g)) \cdot \frac{1}{|B_{rb'}|}. \end{aligned} \tag{5}$$

Note that the above equation should hold for all blocks in the region, i.e., $\forall b \in B_r$. We observe both $q^{\text{obs}}_{rtd}(b)$ and ϕ_{rtdb} from data. We need to estimate the ideal location distribution $\omega^{*}_{rtd}(b)$ for all $b \in B_r$, and the functions $\pi(\cdot)$ and $\rho(\cdot)$. We choose a flexible form to approximate $\pi(\cdot)$ and $\rho(\cdot)$. Specifically, we use the following second-order approximation:

$$\pi(\phi_{rtd}, d(b,b_g)) \approx \gamma_0 + \gamma_1\phi_{rtd} + \gamma_2 d(b,b_g) + \gamma_3\phi_{rtd} d(b,b_g) + \gamma_4\phi_{rtd}^2 + \gamma_5 d(b,b_g)^2,$$
$$\rho(\phi_{rtd}, d(b,b_g)) \approx \delta_0 + \delta_1\phi_{rtd} + \delta_2 d(b,b_g) + \delta_3\phi_{rtd} d(b,b_g) + \delta_4\phi_{rtd}^2 + \delta_5 d(b,b_g)^2.$$

[16] This is an approximation. More precisely, the fraction of consumers who continue searching depends on the difference between the distance between the ideal location and the current block versus the distance between the ideal location and the garage. Given a particular ideal location distribution, we approximate the fraction using a function of distance between the garage and the current location and the expected availability. Based on geographical locations of all blocks in each region, we calculate that the proxy has high correlations with the original variable, i.e., 0.95 to 0.96.

We then estimate $\omega^*_{rtd}(b)$, γ and δ based on the moment conditions specified in Equation (5) using observations from region r, time t and day d. To illustrate that these parameters can be identified, suppose that there are N_t hours in time window t, and N_d days in month m, then we have $N_t \times N_d \times |B_r|$ observations to estimate $|B_r| - 1 + 12$ parameters. For example, if there are 3 hours on a Monday morning, 4 Mondays in May, and 25 blocks in a region, we then have $3 \times 4 \times 25 = 300$ observations to estimate $25 - 1 + 12 = 36$ parameters.[17] Note that these polynomial functions are used to estimate the unconditional distribution of ideal locations. The estimated coefficients in π and ρ are not used in the estimation of consumer attributes (e.g., search costs, disutility costs, and price sensitivities), or in any counterfactual analysis. Rather, we derive the consumer equilibrium decisions based on the model previously described.

Estimation of Availability. Recall that the availability of a block, ϕ_{rtdb}, is defined as the probability of finding an available parking spot at block b in region r at time t on day d. Note that even though we observe the utilization of a block (i.e., occupancy rate), φ_{rtdb}, from meter sensor data, we do not directly observe the availability ϕ_{rtdb}. We derive availability ϕ_{rtdb} from observed utilization by modeling the block as an $M/G/s_{rb}/0$ loss system. To explain, s_{rb} is the number of servers, i.e., the number of parking spaces at block b. The number 0 indicates that it is a loss system (the maximum length of the queue is zero), implying that consumers who find that the block is full do not wait. Suppose the arrival rate to block b at time t on day d is λ_{rtdb} and that the service rate is μ_{rtdb}. We assume that the arrival rate follows a Poisson process but that the time spent parking can follow any distribution. According to the Erlang loss formula, the probability that a consumer can successfully park, i.e., she is not "lost", is:

$$\phi_{rtdb} = 1 - \frac{\left(\frac{\lambda_{rtdb}}{\mu_{rtdb}}\right)^{s_{rb}}}{s_{rb}!} \Bigg/ \sum_{k=0}^{s_{rb}} \frac{\left(\frac{\lambda_{rtdb}}{\mu_{rtdb}}\right)^{k}}{k!} \tag{6}$$

Since only a fraction, ϕ_{rtdb}, of arriving consumers can be served, the utilization of the system is:

$$\varphi_{rtdb} = \frac{\phi_{rtdb}\lambda_{rtdb}}{s_{rb}\mu_{rtdb}} \tag{7}$$

Rearrange and substitute Equation (6) back into Equation (7), then we can obtain ϕ_{rtdb} by solving:

$$\phi_{rtdb} = 1 - \frac{\left(\frac{\varphi_{rtdb}s_{rb}}{\phi_{rtdb}}\right)^{s_{rb}}}{s_{rb}!} \Bigg/ \sum_{k=0}^{s_{rb}} \frac{\left(\frac{\varphi_{rtdb}s_{rb}}{\phi_{rtdb}}\right)^{k}}{k!} \tag{8}$$

[17] It is possible to do such calculations for all regions and verify that the parameters are identified for all regions. Note that although the system of equations is identified, the day-of-week effect places restrictions on the number of observations we can use to recover the ideal location distribution. To avoid overfitting, we have also tried an alternative model where we incorporate a weekday versus weekend effect instead of the effect of each day separately. The results are consistent. We do not include the demand at the garage as a moment condition because including it would require another function to be estimated non-parametrically.

Discussion. Finally, we discuss a potential limitation of this estimation of the ideal location distribution, and how we address it. We make the assumption that because consumers always prefer to park at their ideal location under the condition of equal prices in all blocks, they will always check that ideal location first before searching further. However, some consumers may anticipate congestion at the ideal location and park opportunistically on the way to the ideal location or deliberately drive to a less congested area and park there. This possibility may induce errors in the estimated ideal location distribution. Moreover, the polynomial approximation of π and ρ functions may also introduce estimation errors.

To ensure that our conclusions are not driven by such error sources, we conduct sensitivity analyses to test the robustness of the results. Specifically, we conduct two sets of robustness tests. In the first set of tests, we conduct sensitivity analyses around the ideal location distribution. We introduce varying levels of noisy perturbations to the estimated ideal location distribution, and re-estimate our model to see if the results are consistent under a different ideal location distribution. The details are presented in Appendix D.2. In the second set of robustness tests, under various ideal location distributions, we now allow consumers to start searching from locations other than their ideal locations, based on the expected congestion levels of different blocks. We re-estimate the model and re-calculate the welfare changes, and we find that the results are robust.

5.2. Identification and Estimation of Consumer Attributes

Now that we have exploited longitudinal variations in parking locations under fixed pricing to estimate the ideal location distribution, we can separately identify consumer attributes exploiting parking patterns under congestion pricing (assuming that the underlying ideal location distribution does not change given the same region, time and day). The three key consumer attributes of interest are: search cost, distance disutility, and price sensitivity. In this section, we first illustrate the intuition behind the identification of these key parameters and then explain the estimation procedures of these and other parameters in the model.

5.2.1. Identification In this subsection, we discuss the intuition behind the identification. First, we would like to address a common question regarding identification of dynamic search models: is it possible to identify search costs and other relevant parameters without observing individuals' search paths? The answer to this question is yes. Indeed, there are studies that estimate search related parameters in dynamic models without observing the actual search paths. For example, Hortacsu and Syverson (2004) model how investors search over funds with varying attributes, and estimate heterogeneous search costs using market share data and price data only. Hong and Shum (2006) develop a method to uncover heterogeneous search costs using price data alone, using equilibrium conditions from sequential and non-sequential search models. Kim et al. (2010) estimate consumer search costs in online retailing using view-rank data. As Hortacsu and Syverson (2004) say, these papers demonstrate "how aggregate data can be used to identify and estimate search costs separately from product differentiation, with particular attention to minimizing the impact of functional form restrictions." Other papers exploit the additional variations provided by search paths to estimate search costs. For example, De Los Santos et al. (2012), Koulayev (2014) and Chen and Yao (2016) all use consumer click stream data to estimate search costs.

Similar to Hortacsu and Syverson (2004), Hong and Shum (2006), and Kim et al. (2010), we do not directly observe consumers' search paths. However, our data is actually finer-grained than theirs, because we observe each decision maker's final decision, not just aggregate market shares and prices. We now explain which variations in our data drive the identification of each parameter.

Separation of Price Sensitivity from Search Cost and Distance Disutility. Price sensitivity (i.e., the distribution of θ_i) is identified through variations in parking locations when prices vary. For illustration purposes, consider the simple case in Figure 1, where there is only one block b and one garage g in the region. In this case, block b is the ideal location for all consumers, but some will have to park at the garage on a congested day. What differentiates on-street versus off-street parking is the parking fee and the distance disutility. Although the distance disutility is unchanged before and after the implementation of congestion pricing, the parking fee changes. When the on-street price increases following the implementation of congestion pricing, more consumers park at the garage and fewer park on street, and vice versa. The extent to which price changes can induce the reallocation of parking between on- and off-street identifies price sensitivity (relative to distance disutility). Specifically, in Figure 1, consumers are more price-sensitive in Scenario 2 than in Scenario 1, as more consumers reallocate in Scenario 2.

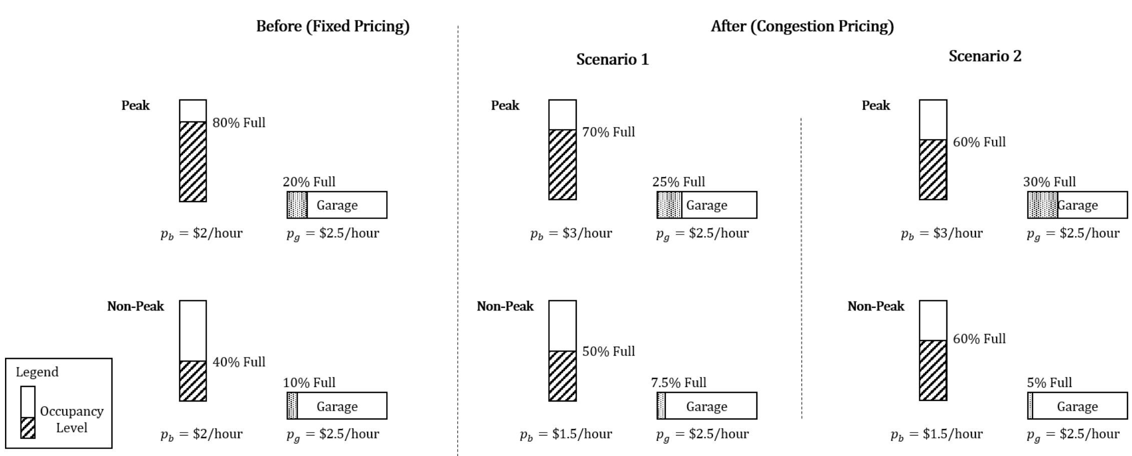

Figure 1 Identification Illustration: Separate Price Sensitivity from Distance Disutility

Though a rather simplified case, what Figure 1 illustrates is that price sensitivity can be identified from the redistribution of demand caused by congestion pricing. The same logic applies to a more general case with multiple blocks in the region. For example, as Figure 2 demonstrates, the redistribution of demand from the popular block b_1 to other less popular blocks b_2, b_3, as well as to the garage allow us to identify price sensitivity relative to search cost and distance disutility. A higher price sensitivity relative to the other two parameters suggests that more consumers would continue searching and park further away from the popular block seeking a lower parking price. Consequently, this leads to a larger scale of reallocation of observed parking demand (i.e., Scenario 2 instead of Scenario 1).

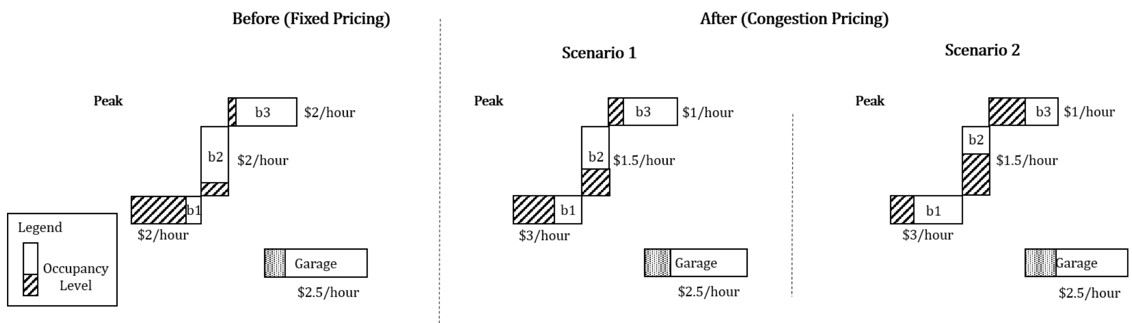

Figure 2 **Identification Illustration: Separate Price Sensitivity from Search Cost and Distance Disutility**

Separation of Search Cost from Distance Disutility. There are two sources of variation that separate search cost and distance disutility. The first is the extent to which parking demand shifts to the garage rather than to nearby, less congested blocks. By choosing to park at the garage, a consumer avoids additional search cost but usually incurs a greater walking distance to her destination. By choosing to continue searching, a consumer will incur the search cost but may reduce the walking distance if she finds a parking space nearby. Therefore, by observing that parking demand shifts to the garage rather than to nearby less congested blocks, one can infer that consumers are relatively more sensitive to the inconvenience induced by searching than walking. Figure 3 illustrates the argument. In Scenario 2, more consumers shift their demand to the garage, which is located farther away from the popular block b_1, in response to a price increase at b_1, than to the nearby less congested block b_2. Thus, consumers in Scenario 2 have a relatively higher search cost and a lower distance disutility.

The second source of variation that separates search cost from distance disutility comes from the fact that the incremental changes in search cost and respective incremental changes in walking distance as the driver searches for parking do not correlate perfectly. If a consumer chooses to continue searching, the total number of blocks searched always increases by one regardless of

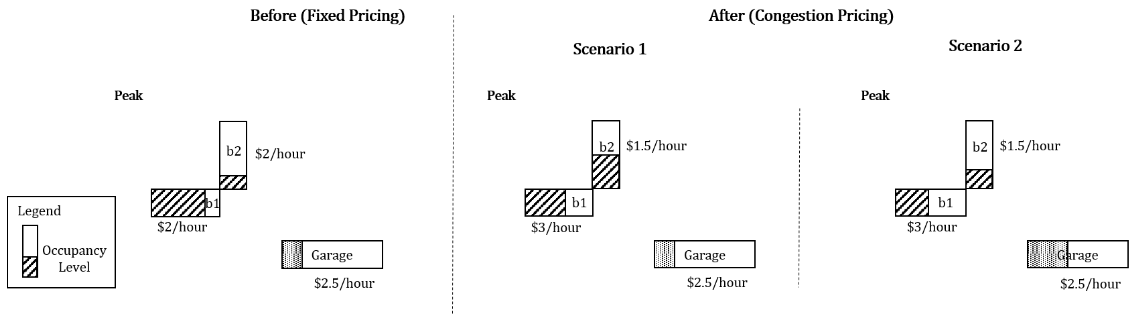

Figure 3 **Identification Illustration: Separate Search Cost and Distance Disutility**

which nearby block she visits next. But the walking distance from the next searched block to the destination may increase or decrease depending on which way she turns (see Figure 4).[18]

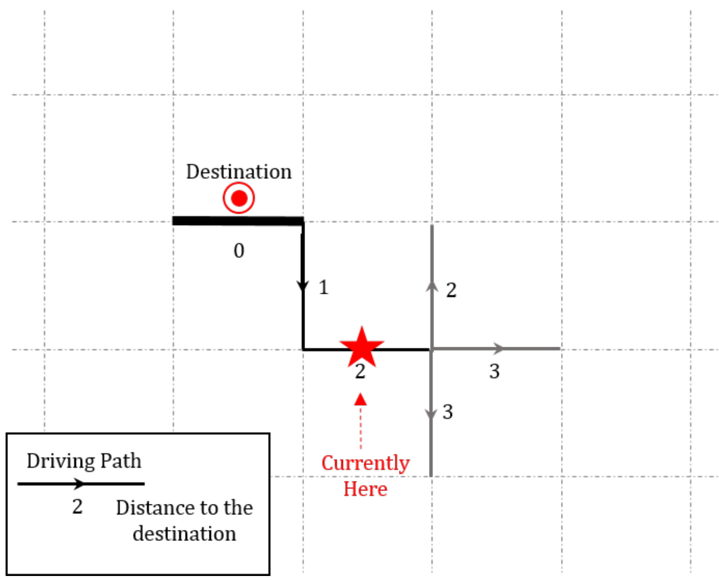

Figure 4 **Identification Illustration: Separate Search Cost and Distance Disutility**

Note that this seemingly subtle variation comes from the fact that the search is conducted on a two-dimensional space. If instead the search were conducted on a unidimensional line, then the number of blocks searched would perfectly correlate with the distance from the ideal location, when the consumer either moved toward or away from the ideal location. In this case, it would be more difficult to determine whether a redistribution of demand is caused by aversion to search or by aversion to walking.

[18] In this figure, a consumer may turn left, right, or continue straight from the current block. If she turns left, she is equally as far from her ideal location as she is now; while if she turns right or continues straight, she will be one block farther from her ideal location. That is, the expected increase in distance if she continues searching is $(\frac{1}{3}\times 2+\frac{1}{3}\times 3+\frac{1}{3}\times 3)-2=\frac{2}{3}$, while the expected increase in the number of blocks searched is exactly 1.

5.2.2. Estimation Given the ideal location distribution, the remaining parameters to be estimated include: 1) the joint distribution of consumers' search cost, distance disutility, and price sensitivity, i.e., the joint distribution of (s_i, η_i, θ_i), 2) trip valuation parameters α and β, and 3) the standard deviation of the utility shocks, σ. We assume that the joint distribution of (s_i, η_i, θ_i) follows a multivariate lognormal distribution $lnN(\mu_{s,\eta,\theta}, W_{s,\eta,\theta})$, where μ is the mean and W is the variance-covariance matrix of the corresponding normal distribution. By estimating the joint distribution, we allow a consumer's search cost, distance disutility and price sensitivity to be correlated, and we estimate the correlations empirically. Let $\Theta = (\mu_{s,\eta,\theta}, W_{s,\eta,\theta}, \alpha, \beta, \sigma)$. Observe that because the scale of utility is irrelevant to choices, not all parameters can be identified. We choose to normalize μ_θ to 1, to conveniently measure welfare in dollar values later.

To estimate Θ, we use Simulated Method of Moments (SMM). SMM is conceptually identical to the more commonly used Generalized Method of Moments (GMM), except that with SMM the moments are calculated using model-based simulations rather than calculated directly from the model. Researchers use SMM instead of GMM in cases where it is difficult (or impossible) to derive moment conditions from the model directly. For example, in our setting it is impossible to derive an explicit analytical form for the equilibrium. Therefore, we solve it numerically with simulations. Specifically, given an admissible set of parameters Θ, we simulate the driving decision and parking location for every consumer in the market. We then calculate the number of people who park at each block and at the garage, as well as their total parking duration, and match these to the corresponding moments observed in the data. Clearly, the moments calculated from the simulation depend on the parameter Θ. If the model is correctly specified with Θ equal to its true value, then the simulated moments will be the same as what we observe in the data. That is, one can estimate Θ by minimizing the distance between the simulated moments and the observed moments. In particular, we define the following notations:

- $q^{\text{obs}}_{rtd}(b), q^{\text{sim}}_{rtd}(b;\Theta)$: the number of consumers who park at block b at time t and day d in the observed data and the simulated data, respectively.
- $Q^{\text{obs}}_{rtd}(b), Q^{\text{sim}}_{rtd}(b;\Theta)$: the total parking minutes at block b at time t and day d in the observed data and the simulated data, respectively.
- $q^{\text{obs}}_{rtdg}, q^{\text{sim}}_{rtdg}(\Theta)$: the number of consumers who park at the garage at time t and day d in the observed data and the simulated data, respectively.
- $Q^{\text{obs}}_{rtdg}, Q^{\text{sim}}_{rtdg}(\Theta)$: the total parking minutes at the garage at time t and day d in the observed data and the simulated data, respectively.

The following moment conditions equalize the simulated moments to the observed moments:

$$m(\Theta) = E\begin{bmatrix} q^{\text{obs}}_{rtd}(b) - q^{\text{sim}}_{rtd}(b;\Theta), \forall b,t,d \\ Q^{\text{obs}}_{rtd}(b) - Q^{\text{sim}}_{rtd}(b;\Theta), \forall b,t,d \\ q^{\text{obs}}_{rtdg} - q^{\text{sim}}_{rtdg}(\Theta), \forall t,d \\ Q^{\text{obs}}_{rtdg} - Q^{\text{sim}}_{rtdg}(\Theta), \forall t,d \end{bmatrix} = 0 \tag{9}$$

Solve for the parameters $\hat{\Theta}$ that minimize the distance between the above $(|B|+1)\times 2$ moment conditions and the zero vector. Note that we match the simulated moments with the observed moments in both the before (fixed pricing) and after (congestion pricing) periods. Appendix B presents the details of how to calculate $q^{\text{sim}}_{rtd}(b;\Theta), Q^{\text{sim}}_{rtd}(b;\Theta), q^{\text{sim}}_{rtdg}(\Theta), Q^{\text{sim}}_{rtdg}(\Theta)$.

6. Estimation Results, Welfare Analysis, and Robustness Tests

In this section, we report the estimated availability, ideal location distributions and model parameters. Based on the estimates, we then calculate welfare changes from before and after the implementation of congestion pricing. Lastly, we discuss the robustness tests to ensure that our results are driven by data variations rather than by specific modeling assumptions.

6.1. Estimation Results

Availability. We calculate the real-time availability for each hour and each block in our sample periods using the occupancy data reported by the parking sensors. Recall that we calculate availability based on the occupancy rates and the number of spaces in each block as shown in Equation (8). Table 2 summarizes the availability estimates for high-, medium-, and low-utilization blocks in each region during both before and after periods. We find that they exhibit similar patterns as the occupancy rates shown in Table 1.

Ideal Location Demand. We estimate an ideal location distribution for each time window (i.e., morning, noon, afternoon) on each day of week (Monday to Saturday) for each month (May to July) based on data observed for each corresponding time period, respectively, before the implementation of congestion pricing.[19] That is, for each region, we estimate a total of $3\times 6\times 3 = 54$ ideal location distributions. We report the summary statistics of these estimates in Table 3 and the detailed estimates in Appendix C. In particular, we obtain an average R-square of 0.84, 0.73, and 0.60 for Marina, Fillmore, and Mission, respectively.

Parameter Estimates. With the estimates of the ideal location distributions, assuming the population's ideal location distributions are the same for the respective time periods before and after the implementation of congestion pricing, we can estimate the remaining model parameters (see Table 4). Recall that the log scaled mean price sensitivity is normalized to one. Therefore, we estimate the standard deviation of price sensitivity, the mean and standard deviation of the per-block search cost, and the distance disutility. We also estimate the correlation matrix of price sensitivity, search cost and distance disutility. Lastly, we estimate 11 parameters that affect trip valuation.

[19] While we also observe data from the last week of April, due to the small number of observations, we bundle the observations in April together with May.

To interpret the magnitudes, we convert the estimates of search cost, distance disutility and average trip valuation into dollar values. In Marina, for example, we estimate that it costs consumers approximately \$0.39 to \$2.82 to search an additional block and \$1.10 to \$4.58 to park one block away from their destination, and that a trip is worth between -\$1.61 and \$7.89 to consumers (all measured by first and third quartiles). The estimated parameter ranges are similar across all regions.[20]

We also examine the estimated correlations between search cost, distance disutility and price sensitivity. As expected, less price sensitive consumers also value their time more (we find negative correlations between price sensitivity and search costs, and between price sensitivity and distance disutility). Moreover, customers who dislike search also dislike parking farther away from their destinations (there is a positive correlation between search cost and distance disutility).

Based on the estimated model, we calculate the average price elasticity (i.e., percentage change in a block's occupancy rate as a result of one percent change in its price) to be -0.88, -0.94 and -0.64 for Marina, Fillmore and Mission, respectively. The estimates are of the same magnitude as those reported in Pierce and Shoup (2013) and Ottosson et al. (2013), i.e., from -0.8 to -0.4. Finally, to evaluate the model fit, we compare predicted and observed moments (i.e., number of drivers and parking minutes) for each block (as in Hendel and Nevo 2006). Figure 13 demonstrates a close moment fit by blocks. We also calculate the amount of variation in the observed moments that can be explained by the model. At the hourly level, the model explains an average of 62% to 86% of the variations in the data.[21]

6.2. Welfare and Search Externality

Welfare. Using the model estimates, we quantify the effect of congestion pricing on both consumer and social welfare. Denote the actual utility that consumer i obtains by u_i^{actl} . Also let b_i^{actl} denote the actual parking location for consumer i,

$$b_i^{\text{actl}} = \begin{cases} b, & \text{if consumer } i \text{ parks at block } b \text{ eventually, } b \in B_r; \\ b_g, & \text{if consumer } i \text{ parks at the garage eventually;} \\ o, & \text{if consumer } i \text{ chooses the outside option eventually;} \end{cases}$$

[20] These interquartile ranges are for the entire population, which explain why some trip valuations are negative (lower than the value of the outside option). For those consumers who choose to drive, the interquartile ranges for trip valuations are between \$2.04 and \$12.45, \$1.70 and \$10.88, and \$0.84 and \$5.25 in Marina, Fillmore and Mission, respectively.

[21] We also conduct an in-sample and out-of-sample analysis by randomly selecting two-thirds of time and day in each region to be used for the in-sample analysis and the remaining one third for out-of-sample analysis. The in-sample R-squares are 79.3%, 87.4%, 62.8% for Marina, Fillmore and Mission, respectively, while the out-of-sample R-squares are 71.9%, 87.9%, and 62.0% for each region, respectively.

Let N_i denote the actual number of searches that consumer i has made. We have,

$$u_i^{\text{actl}} = \begin{cases} v_{irtd} + \epsilon_{is} - N_i\big(\sum_{k=1}^{N_i} s_i \epsilon_{irtdb_k}\big) - \eta_i d(b_i^*, b_i^{\text{actl}}) - \theta_i P_{rtdb_i^{\text{actl}}} h_i, & \text{if } b_i^{\text{actl}} = b, b \in B_r; \\ u_{ig} - N_i\big(\sum_{k=1}^{N_i} s_i \epsilon_{irtdb_k}\big), & \text{if } b_i^{\text{actl}} = b_g; \\ u_{i0} - N_i\big(\sum_{k=1}^{N_i} s_i \epsilon_{irtdb_k}\big), & \text{if } b_i^{\text{actl}} = \text{o}. \end{cases}$$

We can then calculate consumer welfare, CW, and social welfare, SW, as follows:

$$CW = \sum_{i=1}^{M_r} \frac{1}{\theta_i} u_i^{\text{actl}},$$

$$SW = CW + \sum_{i=1}^{M_r} P_{rtdb_i^{actl}} h_i.$$

Following the literature (see Meijer and Rouwendal 2006 and references therein), we divide utility by price sensitivity θ_i such that welfare is expressed in dollar values. In calculating social welfare, we treat parking payment as a transfer of income from consumers to the government, which is then distributed back to the local community in various ways.[22]

The upper panel of Table 5 shows the total consumer and social welfare changes and the breakdown to the different elements that go into the calculation. Consumer welfare increases by \$4.30 and \$11.66 per a hundred consumers (or 5.6% and 14.6% of total payment) in Marina and Fillmore, respectively, following the implementation of congestion pricing. However, consumer welfare decreases by \$5.06 per a hundred consumers (or 7.1% of total payment) in Mission. We observe the same directional changes in social welfare.

Where do the welfare improvements originate from in Marina and Fillmore? In both regions, following the implementation of congestion pricing, consumers incur lower search costs and lower distance disutility. At the same time, more consumers find it attractive to drive to the destination and hence the total trip valuation is higher. The gains from the reduced search costs and distance disutility and the increased total trip valuation lead to higher social welfare. They also offset the higher parking payments, leading to higher consumer welfare. The opposite occurs in the Mission district. Following congestion pricing, both search costs and distance disutility increase, and the total trip valuation decreases as the number of consumers who drive decreases. The overall effect is that both social and consumer welfare decrease. The inconsistent welfare implications in different regions highlight the critical tradeoff between utilization and congestion. From the perspective of resource utilization, social planners would like to attract as many consumers as possible and keep utilizations high. However, high utilization also generates congestion, which reduces the utility that

[22] Due to lack of relevant data, this calculation of social welfare does not capture the potential indirect effects that the program may have on society, such as changes in city traffic, pollution, and economics of local businesses.

each consumer obtains from accessing the resource. We will examine why congestion pricing may lead to lower welfare and which pricing policies may increase welfare in Mission in Section 7.1.

Search Externality. Even though we do not have data to measure the societal impact of congestion pricing on other aspects such as local businesses, city traffic and pollution precisely, we are able to examine its effect on search traffic, which we measure by the total number of blocks searched. Surprisingly, despite the fact that congestion pricing leads to lower total search costs in Marina and Fillmore, the changes in search traffic are negligible (see the lower panel of Table 5) (i.e., the total number of blocks searched does not change but the total search costs are lower, because more consumers with lower search costs choose to search). Why does the total search traffic increase despite having better availability following the implementation of congestion pricing? We find that even though congestion pricing reduces the search for availability, it introduces another type of search—the search for better prices, especially when prices are highly dispersed geographically. In Marina and Fillmore, the price-based search exactly offsets the reduction in availability-based search, leading to the same level of search traffic as before the implementation of congestion pricing, while in the Mission, the total search traffic actually increases.

6.3. Robustness Tests

We conduct multiple robustness tests to ensure that our results are not driven by specific modeling assumptions. In particular, we evaluate the robustness of our results along the following dimensions: **(1) Market size.** To ensure that our results are not sensitive to the choice of market size, we perform the analyses for multiple market sizes. The details and results are presented in Appendix D.1. **(2) Ideal location distribution.** As discussed in Section 5.1.2, the ideal location distribution may contain estimation errors. To test robustness to such errors, we simulate different levels of estimation errors through random perturbation, and then re-estimate the model parameters and re-calculate the welfare changes. The details and results are presented in Appendix D.2. **(3) Consumers' beliefs.** Rather than assuming that consumers' beliefs regarding availability and price are identical across blocks at a given time and day in a region, we allow consumers to form heterogeneous beliefs across blocks. That is, we assume that consumers distinguish between high-, medium- and low-popularity blocks, and that they form separate beliefs for each type of block. Under such beliefs, the estimated ideal location distribution is no longer accurate. We therefore simulate ideal location distributions with different levels of estimation errors, and then re-estimate the model parameters and re-calculate welfare changes under these consumer beliefs. The details and results are presented in Appendix D.3. **(4) Parking duration distribution.** Due to the irregularities observed in the distribution of parking durations (details explained in Appendix B), we draw parking durations from the observed empirical distribution. Note, however, that the observed distribution is censored, so that the underlying distribution can be different. To see whether censoring may affect our conclusions, we simulate different distributions of parking durations based on different censoring levels and introduce additional noises. We re-estimate the model and re-calculate consumer and social welfare. Details and results are presented in Appendix D.4.

As shown in Figures 9 to 12, our conclusions regarding welfare and search traffic changes are very robust to all these alternative modeling assumptions.

7. Counterfactual Analyses

We conduct three sets of counterfactual analyses. First, we examine which alternative pricing policies may lead to welfare improvement for uncongested regions such as Mission. Second, we examine simpler pricing structures to balance availability-based and price-based searching. Third, we compare congestion pricing to a policy that puts a limit on parking duration, and evaluate which policy is more efficient in allocating public parking resources.

7.1. Congestion Pricing in Uncongested Regions

Recall that the congestion pricing policy implemented by SF*park* lowered consumer and social welfare in Mission. A critical difference between Mission and the other two regions is that Mission was not very congested even before the implementation. Before the SF*park* program was implemented, the average occupancy rate in Mission was 63%, as opposed to 75% and 72% in Marina and Fillmore. Table 1 shows all blocks had occupancy rates below 80% during the before period, i.e., April to July in 2011.[23] We also find that occupancy rates are less dispersed geographically in Mission as compared to the other regions implying that the primary goal for Mission is not to reallocate demand across blocks, but to increase utilization. We therefore hypothesize that lower parking rates may increase welfare in Mission, by increasing the fraction of consumers who drive to the destination.

Specifically, we consider two counterfactuals with lower prices: (1) uniform pricing, where each block is priced equally at a rate which is \$0.50 lower than the average price charged during the after period; (2) congestion pricing, in which each block is priced \$0.50 lower compared to the corresponding price during the after period for that block. We solve the new equilibrium following procedures presented in Appendix E, with results shown in Table 6. We find that lowering parking prices increases consumer and social welfare in both cases. Much of the gain can be attributed to higher fractions of consumers driving to the destination, i.e., 54% as opposed to 50%. Even though consumers incur slightly higher search costs or park farther away, the social gain from the increased total trip valuation more than offsets losses in search costs and distance utility. Moreover, welfare

[23] There were blocks with occupancy rates slightly above 80% in other months that year, which led to subsequent price increases.

differences between the two counterfactuals are negligible, confirming our intuition that when the region is underutilized, demand reallocation is secondary to the benefit gained from increased utilization. Although the counterfactuals do not necessarily point to the optimal pricing levels in Mission, they illustrate that it is important to ascertain whether congestion is a real concern in the region. If not, then alternative policies aimed at increasing utilization may lead to more desirable outcomes.

7.2. Balance Availability-Based and Price-Based Searching

Recall that even though congestion pricing leads to higher consumer and social welfare in Marina and Fillmore, it does not necessarily reduce search traffic. The reason is that although there is less search for availability, consumers may also search for better prices, especially if prices are highly dispersed and updated dynamically. To balance between better availability management and a simpler price structure, we examine a pricing policy with only three price levels, each corresponding to the high, medium, and low-utilization blocks, respectively. Given there are only three price levels, we assume that consumers have perfect knowledge about each block's price. To allow for a fair comparison, we set each of the three price levels to equal the average price observed for high, medium and low-utilization blocks, respectively. We keep the rate constant for the entire study period regardless of the time of the day and day of week.

We solve for the equilibrium under the three-tier pricing policy. Note that given perfect knowledge of prices, consumers may not start from the ideal locations and may choose at which block to continue searching, instead of following a random walk strategy. The results, presented in Table 7, suggest that the simpler pricing policy achieves higher social and consumer welfare in all three regions, compared to the more complex pricing policy currently in place. Much of this gain can be attributed to lower search costs and lower payments.[24] Moreover, the simpler pricing policy reduces total search traffic by 30.7% and 7.4% in Marina and Fillmore, respectively, which is equivalent to reductions of 9.2% and 2.2% in total traffic, assuming that search traffic represents roughly 30% of all city traffic (Shoup 2006).

[24] An alternative is to eliminate price search by providing full price information. In fact, the city has made price information available through multiple channels. Unfortunately, consumers did not seem to be aware of or use such information. Based on a survey conducted following the program, 81.8% of the 1584 respondents who parked on street answered that they were unaware of the ways to get information to help them park. Even among those who responded that they knew how to get this information, 83.6% responded that they either never or only rarely accessed the information that were available on multiple channels, including 511.org phone and website, SF*park* APP and website and other. Therefore, we focus our counterfactual analysis on the simpler pricing policy rather than on the complex pricing policy with complete price transparency. However, to get a sense of the relative welfare gains, we have also analyzed the full information complex policy and found that the simpler pricing policy achieves at least 50% of the welfare gains that can be achieved by the complex policy with full price information. Details available from the authors.

7.3. Usage Limits versus Congestion Pricing

The regulation approach (e.g., usage limits or permits) and the market-based approach (e.g., price-based approach) are the two most commonly used approaches in managing public resources. In city parking, most local governments impose parking duration limits to regulate the usage of public parking spaces, but some have recently used congestion pricing to match demand with limited supply. For example, the City of San Francisco previously imposed 2-hour parking limits on most blocks, but relaxed the limit to 4 hours when it decided to pilot the new congestion pricing program in April 2011, (the start of the before period). To compare the two approaches, we examine the counterfactual of uniform pricing with 2-hour parking limit. In this case, if a consumer wants to park for more than the 2-hour limit, she has three options: she could either compromise and park for up to 2 hours on street, park at the garage for the entire time demanded, or choose the outside option.[25] The results are presented in Table 8.

We find that social welfare is higher for all regions under congestion pricing compared to imposing time limits. The results have an intuitive explanation. To maximize social welfare, a social planner would allocate the parking spaces to consumers who value them the most. Congestion pricing aims at doing exactly that—by charging different prices based on congestion levels, it gives the more desired spots to customers who value them most (customers with higher trip valuation and lower search costs, distance disutility and price sensitivity). The prices themselves are only a transfer, so they do not affect social welfare calculations. In contrast, imposing limits on parking durations makes consumers who want to park longer particularly worse off, because they are forced to park for shorter time or seek alternative options. This is especially problematic if consumers' valuations for the trip are positively correlated with the length of the trip, implying that drivers who value the trip more will likely be hurt the most. Therefore, congestion pricing leads to a more efficient allocation compared to time limits, and we would expect social welfare to be higher with congestion pricing compared to time limits.

The comparison of consumer welfare is less intuitive, because the prices charged affect consumer welfare. There is a tradeoff from the perspective of consumer welfare: although congestion pricing can allocate demand more efficiently, it usually does so by charging higher average prices; with the time limit policy, prices are fixed, so it does not extract additional rents from consumers, but this comes at the expense of a better allocation. Which effect dominates depends on many factors such as the time limits imposed, the levels and spread of prices, and market and consumer characteristics. Therefore, the overall effect on consumer welfare is ambiguous, as Table 8 illustrates.

[25] Potentially, a customer can add more time after parking for 2 hours. However, "feeding the meter" (i.e., extending the time beyond the legal limit) is illegal and may result in a citation, and is both inconvenient and costly for consumers.

It is worthwhile to note that prices charged by SF*park*, as well as the time limits imposed, are likely not the optimal ones. Still, the intuition described above likely holds. We expect that optimal congestion pricing would lead to a more efficient allocation and result in a higher social welfare compared to the optimal time limit.

8. Conclusion

Congestion pricing is often considered an effective tool to match supply with demand. Using data from SF*park*, we find evidence that congestion pricing helps to increase parking availability in congested areas, reduces search costs, and allows consumers to park closer to their destinations when they need to. These benefits outweigh the increased payments and lead to an overall increase in consumer and social welfare.

Interestingly, we also find that congestion pricing can sometimes reduce consumer and social welfare. This often happens in areas with relatively low congestion levels, where improving the overall utilization by setting a proper price level is often more important than reallocating demand by charging variable prices. Therefore, city governments should not apply congestion pricing blindly. Rather, they should diagnose and address the primary concern of each region accordingly.

Our results also show that cities that consider implementing congestion pricing policies should avoid setting unnecessarily complicated pricing rules. Even though congestion pricing is intended to reduce search and traffic, it may introduce another type of search. If prices are dispersed geographically, consumers may choose to bypass available but expensive parking spots in hopes of finding lower priced ones. Therefore, even though a more sophisticated pricing policy may result in better availability across all blocks, it may not necessarily lead to reduced search and traffic overall. To achieve the best welfare outcome, it is important to balance the desired availability targets with the complexity of the pricing policy.

More generally, our learnings from SF*park* also offer important lessons to other public sectors. Both regulation-based and market-based approaches have been used in many public sectors, but there remains a constant debate between them. We provide evidence that the market-based congestion pricing approach generates higher social welfare than the regulation-based usage limit approach. This is because congestion pricing tends to allocate resources to consumers who value them the most, while usage limits may hurt these consumers more. Although policy decisions are often multi-faceted and it is difficult to account for and measure all possible factors, our analysis offers a generalizable methodology and quantifiable results that public sector managers can use to better evaluate the tradeoffs involved.

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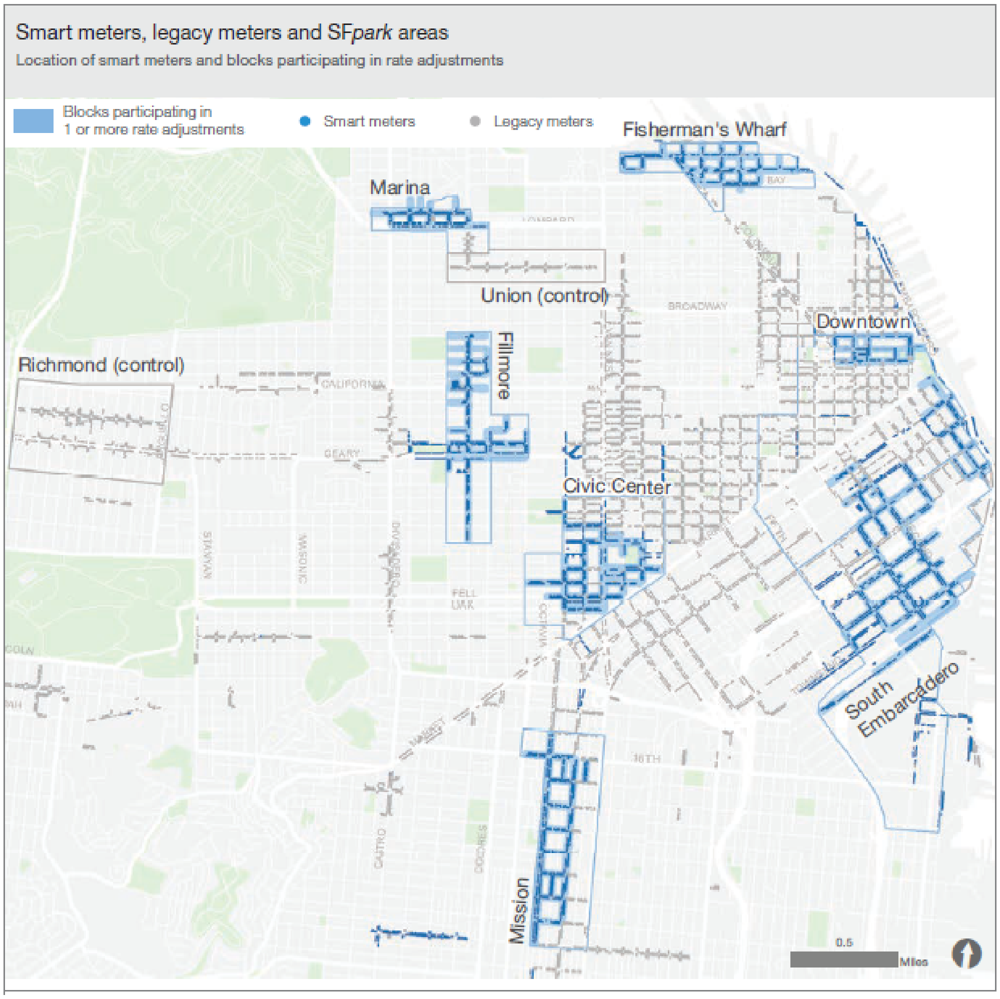


Source: SFpark Pilot Project Report. June, 2014.

Figure 5 **Smart Meters, Legacy Meters and SFpark Areas**

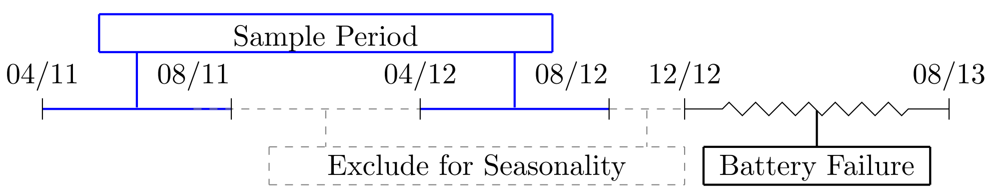
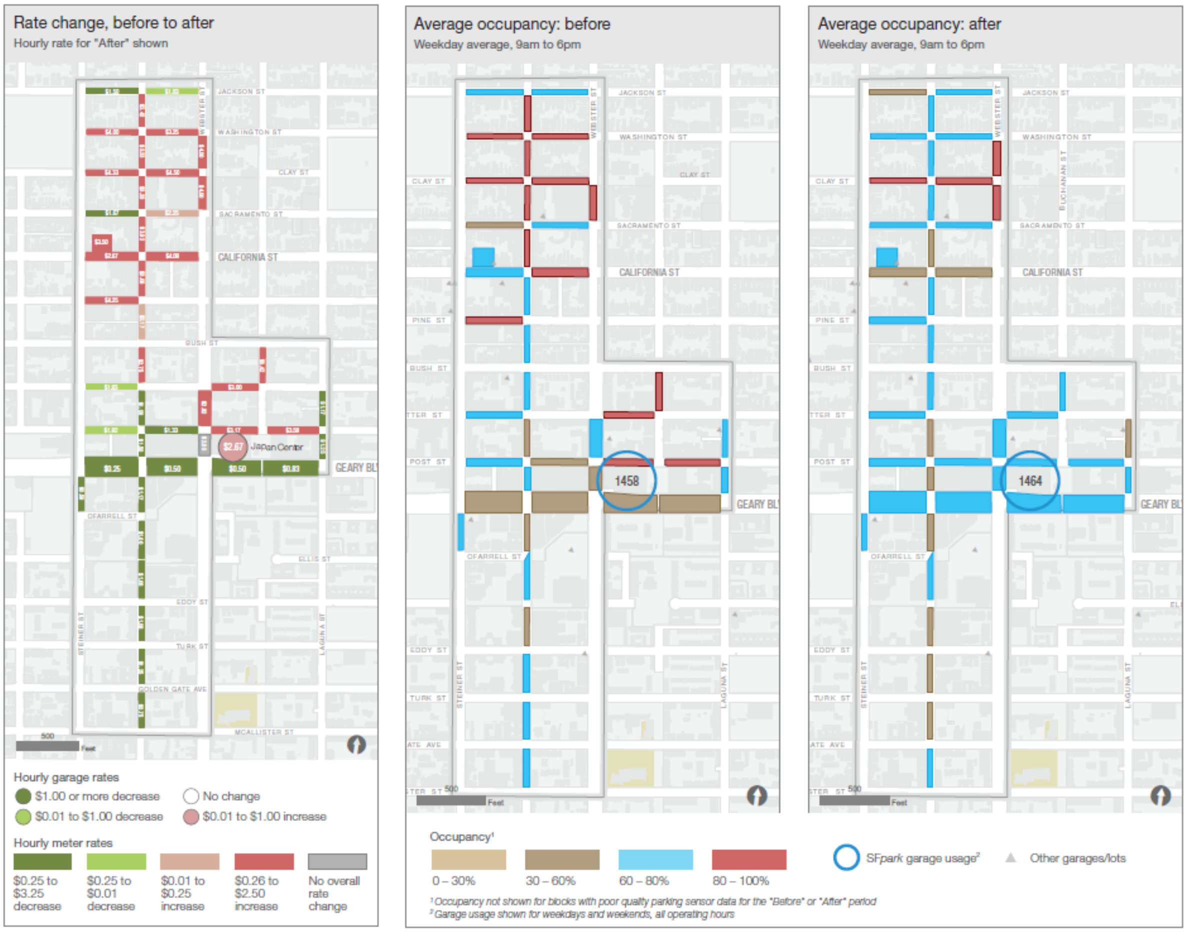


Figure 6 **Timeline**



Source: SFpark Pilot Project Evaluation. June, 2014

Figure 7 Snapshots of Fillmore

Table 1 Summary Statistics

	Marina					Fillmore					Mission				
	Total	High	Mid	Low	Garage	Total	High	Mid	Low	Garage	Total	High	Mid	Low	Garage
Rate - before	2.00	2.00	2.00	2.00	2.50	2.00	2.00	2.00	2.00	2.00	2.00	-	2.00	2.00	2.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Rate - after	2.36	3.24	2.51	1.00	1.72	2.23	3.21	2.02	1.41	2.22	2.29	-	2.46	1.97	2.00
	(0.85)	(0.45)	(0.75)	(0.77)	(0.40)	(0.93)	(0.38)	(0.83)	(0.57)	(0.41)	(0.74)		(0.74)	(0.78)	(0.41)
Occupancy - before	0.75	0.83	0.75	0.56	0.13	0.72	0.85	0.69	0.56	0.26	0.63	-	0.65	0.56	0.12
	(0.16)	(0.11)	(0.14)	(0.16)	(0.06)	(0.19)	(0.14)	(0.16)	(0.18)	(0.13)	(0.18)		(0.17)	(0.19)	(0.06)
Occupancy - after	0.74	0.81	0.74	0.57	0.19	0.70	0.81	0.67	0.58	0.23	0.69	-	0.70	0.64	0.12
	(0.16)	(0.12)	(0.14)	(0.16)	(0.08)	(0.19)	(0.17)	(0.17)	(0.20)	(0.14)	(0.18)		(0.17)	(0.17)	(0.05)
Number of Blocks	19	6	10	3	1	45	13	25	7	1	25	0	6	19	2
Number of Spaces	319	95	162	62	205	714	93	483	138	920	261	0	173	88	448

* Standard deviations are in parentheses. High, medium and low utilization blocks are defined using average occupancy rate greater than 80%, between 60% and 80%, and below 60%, respectively. When calculating the occupancy rate, we excluded non-operational hours for parking spaces when applicable, for example, peak-time tow away zones. "Before" refers to our sample period before congestion pricing: April to July in year 2011, "after" refers to our sample period after congestion pricing: April to July in year 2012.

Table 2 Summary of Availability Estimates

	Marina					Fillmore					Mission				
	Total	High	Mid	Low	Garage	Total	High	Mid	Low	Garage	Total	High	Mid	Low	Garage
Availability - before	0.79 (0.27)	0.51 (0.32)	0.90 (0.13)	0.90 (0.18)	1.00 (0.00)	0.78 (0.25)	0.64 (0.31)	0.82 (0.19)	0.97 (0.07)	1.00 (0.00)	0.97 (0.06)	-	0.97 (0.06)	0.99 (0.05)	1.00 (0.00)
Availability - after	0.81 (0.26)	0.60 (0.33)	0.91 (0.14)	0.85 (0.23)	1.00 (0.00)	0.80 (0.25)	0.67 (0.32)	0.84 (0.18)	0.96 (0.06)	1.00 (0.00)	0.95 (0.12)	-	0.93 (0.11)	0.98 (0.74)	1.00 (0.00)

* Standard deviations are in parentheses. High, medium and low utilization blocks are defined using average occupancy rate greater than 80%, between 60% and 80%, and below 60%, respectively. “Before” refers to our sample period before congestion pricing: April to July in year 2011, “after” refers to our sample period after congestion pricing: April to July in year 2012.

Table 3 Summary of Ideal Location Distribution Estimates

	Marina	Fillmore	Mission
Mean (%)	5.21	2.19	4.00
Min (%)	1.09	0.19	1.49
Max (%)	14.81	7.19	7.95
# of Distribution Estimated	54	54	54
Average R-Sq	0.84	0.73	0.60

Table 4 Model Estimates

	Marina	**Fillmore**	**Mission**
Search cost (log-scaled) mean	0.05 (0.02)	0.12 (0.09)	0.14 (0.02)
Search cost (log-scaled) sd	0.15 (0.05)	0.20 (0.15)	0.38 (0.29)
Distance disutility (log-scaled) mean	0.81 (0.45)	0.50 (0.11)	0.48 (0.11)
Distance disutility (log-scaled) sd	0.21 (0.16)	0.16 (0.06)	0.25 (0.14)
Price sensitivity (log scaled) mean		Normalized to 1	
Price sensitivity (log-scaled) sd	0.63 (0.41)	0.58 (0.17)	0.46 (0.06)
Error terms sd	6.83 (2.61)	5.70 (2.18)	3.94 (1.23)
Search cost×distance disutility corr	0.02 (0.22)	0.22 (0.46)	0.19 (0.14)
Search cost×price sensitivity corr	-0.30 (0.52)	-0.37 (0.32)	-0.19 (0.05)
Distance disutility× price sensitivity corr	-0.27 (0.19)	-0.35 (0.18)	-0.16 (0.23)
Search cost dollar value*	[$0.39, $2.82]	[$0.39, $3.33]	[$0.46, $2.87]
Distance disutility dollar value	[$1.10, $4.58]	[$0.73, $3.76]	[$0.92, $2.81]
Trip valuation dollar value	[-$1.61, $7.89]	[-$1.23, $6.82]	[$0.59, $3.72]

	Marina	**Fillmore**	**Mission**
Trip valuation - α	0.02 (0.24)	0.01 (0.25)	0.00 (0.16)
Trip valuation - intercept	4.44 (0.68)	3.10 (0.92)	1.69 (0.14)
Trip valuation - May		Baseline	
Trip valuation - June	-0.05 (0.29)	0.24 (0.12)	0.15 (0.44)
Trip valuation - July	0.04 (0.25)	0.17 (0.40)	0.23 (0.36)
Trip valuation - Monday		Baseline	
Trip valuation - Tuesday	0.04 (0.06)	0.20 (0.24)	-0.17 (0.23)
Trip valuation - Wednesday	0.12 (0.14)	0.12 (0.26)	0.18 (0.23)
Trip valuation - Thursday	0.12 (0.12)	0.16 (0.26)	0.10 (0.24)
Trip valuation - Friday	0.07 (0.11)	0.19 (0.19)	-0.19 (0.23)
Trip valuation - Saturday	0.03 (0.12)	-0.16 (0.11)	0.04 (0.22)
Trip valuation - morning		Baseline	
Trip valuation - noon	0.42 (0.21)	0.34 (0.14)	0.86 (0.41)
Trip valuation - afternoon	0.02 (0.03)	0.57 (0.38)	0.68 (0.05)

* The dollar value interval displays the first and the third quartiles of the distribution over commuters.

Table 5 Welfare and Search Externality

Panel A: Welfare Calculations						
	Marina		**Fillmore**		**Mission**	
	Before	*After*	*Before*	*After*	*Before*	*After*
Search Cost	34.76	29.74	54.39	42.28	4.77	6.50
Distance Disutility	40.49	30.42	37.46	30.34	4.03	6.17
Payment	76.65	93.3	80.06	90.52	71.57	71.61
Trip Valuation	677.57	683.43	590.29	593.20	287.52	286.37
Consumer Welfare Change	**4.30**		**11.66**		**-5.06**	
Social Welfare Change	**20.95**		**22.12**		**-5.02**	
Panel B: Summary Statistics of Consumer Actions and Search Traffic						
Go with the Car (%)	49.97	52.53	49.99	51.52	50.21	49.71
Park at Garage (%)	2.33	2.51	12.49	13.10	2.44	2.54
Search on Availability (%)	16.76	14.96	15.87	13.95	1.75	1.72
Search on Price(%)	0.00	2.05	0.00	2.14	0.00	0.36
# of Searches	20.85	20.90	21.47	21.62	1.89	2.28

* Consumer welfare is normalized to dollar value at the size of a hundred commuters. Results are based on 50 rounds of simulations.

Table 6 Welfare and Search Externality with Lowering Prices Uniformly by $0.5

Panel A: Welfare Calculations				
	Before (Uniform Pricing)	After (SFpark Pricing)	Counterfactual I (Uniform pricing $0.5 lower)	Counterfactual II (SFpark Pricing $0.5 lower)
Search Cost	4.77	6.5	6.67	6.82
Distance Disutility	4.03	6.17	4.94	5.04
Payment	71.57	71.61	61.19	61.16
Trip Valuation	287.52	286.37	293.98	293.88
Consumer Welfare Change		-5.06	14.03	13.71
Social Welfare Change		-5.02	3.65	3.30
Panel B: Summary Statistics of Consumer Actions and Search Traffic				
Go with the Car (%)	50.21	49.71	54.19	54.22
Park at Garage (%)	1.75	1.72	2.00	2.15
Search Availability (%)	0.00	0.36	2.30	2.23
Search Price (%)	1.89	2.28	0.00	0.06
Total # of Searches	2.44	2.54	2.67	2.71

* Consumer welfare is normalized to dollar value at the size of a hundred commuters. Results are based on 50 rounds of simulations.

Table 7 Welfare and Search Externality with Three-Tier Pricing

Panel A: Welfare Calculations									
	Marina			Fillmore			Mission		
	Before (Uniform Pricing)	After (SFpark Pricing)	Counterfactual (3-Tier Pricing)	Before (Uniform Pricing)	After (SFpark Pricing)	Counterfactual (3-Tier Pricing)	Before (Uniform Pricing)	After (SFpark Pricing)	Counterfactual (3-Tier Pricing)
Search Cost	34.76	29.74	26	54.39	42.28	40.27	4.77	6.5	4.75
Distance Disutility	40.49	30.42	33.27	37.46	30.34	32.8	4.03	6.17	5.09
Payment	76.65	93.3	78.51	80.06	90.52	81.48	71.57	71.61	73.2
Trip Valuation	677.57	683.43	682.92	590.29	593.18	594.45	287.52	286.37	286.84
Consumer Welfare Change		4.30	19.47		11.66	21.52		-5.06	-3.35
Social Welfare Change		20.95	21.33		22.12	22.94		-5.02	-1.72
Panel B: Summary Statistics of Consumer Actions and Search Traffic									
Go with the Car (%)	49.97	52.53	51.72	49.99	51.52	51.59	50.21	49.71	49.83
Park at Garage (%)	2.33	2.51	2.56	12.49	13.10	13.55	2.44	2.54	2.43
Search Availability (%)	16.76	14.96	12.56	15.87	13.95	11.96	1.75	1.72	1.73
Search Price (%)	0.00	2.05	0.00	0.00	2.14	0.00	0.00	0.36	0.00
Total # of Searches	20.85	20.90	14.44	21.47	21.62	19.89	1.89	2.28	1.87

* Consumer welfare is normalized to dollar value at the size of a hundred commuters. Results are based on 50 rounds of simulations.

Table 8 Welfare and Search Externality with 2-hour Usage Limit

Panel A: Welfare Calculations

	Marina			Fillmore			Mission		
	Before (Uniform Pricing)	After (SFpark Pricing)	Counterfactual (2-hour limit+ uniform pricing)	Before (Uniform Pricing)	After (SFpark Pricing)	Counterfactual (2-hour limit+ uniform pricing)	Before (Uniform Pricing)	After (SFpark Pricing)	Counterfactual (2-hour limit+ uniform pricing)
Search Cost	34.76	29.74	28.53	54.39	42.28	45.93	4.77	6.5	4.73
Distance Disutility	40.49	30.42	34.04	37.46	30.34	32.94	4.03	6.17	5.64
Payment	76.65	93.3	72.04	80.06	90.52	76.62	71.57	71.61	66.93
Trip Valuation	677.57	683.43	667.01	590.29	593.18	582.11	287.52	286.37	279.64
Consumer Welfare Change		4.30	6.73		11.66	8.24		-5.06	-4.81
Social Welfare Change		20.95	2.12		22.12	4.80		-5.02	-9.45

Panel B: Summary Statistics of Consumer Actions and Search Traffic

	Marina Before	Marina After	Marina Counterfactual	Fillmore Before	Fillmore After	Fillmore Counterfactual	Mission Before	Mission After	Mission Counterfactual
Go with the Car (%)	49.97	52.53	51.51	49.99	51.52	50.47	50.21	49.71	50.15
Park at Garage (%)	2.33	2.51	2.77	12.49	13.10	13.75	2.44	2.54	2.54
Search Availability (%)	16.76	14.96	14.17	15.87	13.95	13.18	1.75	1.72	1.74
Search Price (%)	0.00	2.05	0.00	0.00	2.14	0.00	0.00	0.36	0.00
Total # of Searches	20.85	20.90	16.64	21.47	21.62	16.63	1.89	2.28	1.90

* Consumer welfare is normalized to dollar value at the size of a hundred commuters. Results are based on 50 rounds of simulations.

Appendix A: Calculation of The Value of Continued Search

In this section, we show how $V_i^{\text{search}}(b_k)$ can be calculated recursively. Under the assumption that consumer beliefs of (P_{rtdb_k}, A_{rtdb_k}) are i.i.d. across blocks, we can write the expected value of a consumer from continuing to search:

$$
\begin{aligned}
V_i^{\text{search}}(b_k) &= E\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{irtdb_{k+1}}; a)|(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k})\big] \\
&= E\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{irtdb_{k+1}}; a)|b_k\big] \\
&= E\Big[E_{(P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{irtdb_{k+1}})}\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{irtdb_{k+1}}; a)|(b_{k+1}, b_k)\big]\Big] \\
&= \frac{1}{|B_{rb_k}|}\sum_{b_{k+1}\in B_{rb_k}}\Big[\iiint\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{irtdb_{k+1}}; a) \\
&\quad \cdot f_{rtd}^{P,A}(P_{rtdb_{k+1}}, A_{rtdb_{k+1}}) f_{rtd}^{\epsilon}(\epsilon_{irtdb_{k+1}}) dP_{rtdb_{k+1}} dA_{rtdb_{k+1}} d\epsilon_{irtdb_{k+1}}\Big] \\
&= \frac{1}{|B_{rb_k}|}\sum_{b_{k+1}\in B_{rb_k}}\Big[\phi_{rtd}\iint \max_{a=\{0,1,2\}} u_i(b_{k+1}, P, 1, \epsilon; a) f_{rtd}^{P|A}(P|A=1) f_{rtd}^{\epsilon}(\epsilon) dP d\epsilon \\
&\quad + (1-\phi_{rtd})\iint \max_{a=\{0,1,2\}} u_i(b_{k+1}, P, 0, \epsilon; a) f_{rtd}^{P|A}(P|A=0) f_{rtd}^{\epsilon}(\epsilon) dP d\epsilon\Big]
\end{aligned} \tag{10}
$$

The first double integral in the brackets represents the expected value-to-go if the next block is available, i.e., $A_{rtdb_{k+1}} = 1$. The second double integral in the brackets represents the expected value-to-go if the next block is unavailable, i.e., $A_{rtdb_{k+1}} = 0$. The function $f_{rtd}^{P|A}$ denotes the density function of price conditional on availability. We expand these two double integrals further:

$$
\begin{aligned}
&\iint \max_{a=\{0,1,2\}} u_i(b_{k+1}, P, 1, \epsilon; a) f_{rtd}^{P|A}(P|A=1) f_{rtd}^{\epsilon}(\epsilon) dP d\epsilon \\
= &\int_{\epsilon \le \frac{V_i^{\text{search}}(b_{k+1}) - V_i^{\text{garage|o}}}{s_i}} \Big(-s_i\epsilon + V_i^{\text{search}}(b_{k+1})\Big) \\
&\cdot \bar{F}_{rtd}^{P|A}\left(\frac{s_i\epsilon - V_i^{\text{search}}(b_{k+1}) + v_{rtd} + \epsilon_{irtd} - \eta_i d(b_i^*, b_{k+1})}{\theta_i h_i}|A=1\right) f_{rtd}^{\epsilon}(\epsilon) d\epsilon \\
+ &\int_{P \le \frac{v_{rtd} + \epsilon_{irtd} - \eta_i d(b_i^*, b_{k+1}) - V_i^{\text{garage|o}}}{\theta_i h_i}} V_i^{\text{park}}(b_{k+1}, P) \bar{F}_{rtd}^{\epsilon}\left(\frac{V_i^{\text{search}}(b_{k+1}) - V_i^{\text{park}}(b_{k+1}, P)}{s_i}\right) f_{rtd}^{P|A}(P|A=1) dP \\
+ &\, V_i^{\text{garage|o}} \bar{F}_{rtd}^{P|A}\left(\frac{v_{rtd} + \epsilon_{irtd} - \eta_i d(b_i^*, b_{k+1}) - V_i^{\text{garage|o}}}{\theta_i h_i}|A=1\right) \bar{F}_{rtd}^{\epsilon}\left(\frac{V_i^{\text{search}}(b_{k+1}) - V_i^{\text{garage|o}}}{s_i}\right),
\end{aligned} \tag{11}
$$

where $F_{rtd}^{\epsilon}(\epsilon)$ is the CDF of ϵ, $F_{rtd}^{P|A}(P|A)$ is the conditional CDF of P, $\bar{F}_{rtd}^{\epsilon}(\epsilon) = 1 - F_{rtd}^{\epsilon}(\epsilon)$ and $\bar{F}_{rtd}^{P|A}(P|A) = 1 - F_{rtd}^{P|A}(P|A)$. And

$$
\begin{aligned}
&\iint \max_{a=\{0,1,2\}} u_i(b, P, 0, \epsilon; a) f_{rtd}^{P|A}(P_{rtdb_{k+1}}|A=0) f_{rtd}^{\epsilon}(\epsilon) dP d\epsilon \\
= &\int_{\epsilon < \frac{V_i^{\text{search}}(b_{k+1}) - V_i^{\text{garage|o}}}{s_i}} \Big(-s_i\epsilon + V_i^{\text{search}}(b_{k+1})\Big) f_{rtd}^{\epsilon}(\epsilon) d\epsilon \\
+ &\, V_i^{\text{garage|o}} \bar{F}_{rtd}^{\epsilon}\left(\frac{V_i^{\text{search}}(b_{k+1}) - V_i^{\text{garage|o}}}{s_i}\right)
\end{aligned} \tag{12}
$$

In sum, we see that the value $V_i^{\text{search}}(b_k)$ is a function of the expected values to continue searching from the adjacent blocks, $V_i^{\text{search}}(b_{k+1})$, the expected value of parking at the adjacent blocks, $V_i^{\text{park}}(b_{k+1}, P)$, and the values to stop searching $V_i^{\text{garage}|\text{o}}$.[26] Note that Equations (10), (11), and (12) are derived under the assumption that consumer beliefs are identical across blocks. For the version of the model in which we assume that consumers can distinguish between high-, medium- and low-popularity blocks, we re-derive these calculations. The derivations and results of the alternative model are shown in Appendix D.3.

Appendix B: Simulated Methods of Moments Estimation Procedure

In this section, we provide the detailed steps of implementing Simulated Methods of Moments Estimation.

- **Step 1: Solve the Model**

  Given a set of parameters Θ and simulated shocks, we solve for the decision of each consumer: whether she drives, and if so, where she parks.

  1. For each consumer i in region r at time t on day d, draw the ideal location b_i^* from the ideal location distribution $\omega_{rtd}^*(b), b \in B_r$. Draw a search cost, distance disutility and price sensitivity (s_i, η_i, θ_i) from the multivariate lognormal distribution $lnN(\mu_{s,\eta,\theta}, W_{s,\eta,\theta})$. Finally, we need a draw of parking duration h_i. Observe from Figure 14 that the distribution of parking duration does not fit common distributions such as normal, lognormal or extreme value. Rather, there are often spikes at 30-minute, 1-hour, 2-hour, 3-hour, and 4-hour marks. Therefore, estimating the distribution of parking duration assuming it follows certain distribution is problematic. Instead, we draw parking durations from the empirical distribution and conduct sensitivity analyses around it. The details are discussed in Appendix D.4.
  2. Simulate the random utility shocks $\epsilon_{i0}, \epsilon_{ig}, \epsilon_{is}$ from i.i.d normal distributions with mean 0 and standard deviation σ. Also simulate a sequence of search cost shocks $\epsilon_{irtdb_k}, k = 1, 2, 3, ...$ from the standard log normal distribution.
  3. Calculate the utility of the outside option, u_{i0}, the utility of parking at the garage, u_{ig}, and the utility of driving and starting searching on street, u_{is}. While it is straightforward to calculate the first two utilities, to calculate u_{is}, we first need to solve the dynamic search model. We explain the details below.
  4. At each step of the dynamic search, the consumer can choose whether to park at the current block, continue to search or abandon searching. Given the ideal location, the parameters, and the simulated shocks, it is straightforward to calculate the utility from parking at the current block and from giving up search. However, to calculate the expected utility from continuing to search, $V_i^{\text{search}}(b_k)$, we need to solve Equation (10) recursively. Observe from Equations (10), (11) and (12), that $V_i^{\text{search}}(b_k)$ is a function of the expected utility from continuing to search at each of the nearby blocks, $V_i^{\text{search}}(b_{k+1})$, where $b_{k+1} \in B_{b_{rk}}$. That is, it is possible to solve for the fixed point of the vector $V_i^{\text{search}}(b)$ using the system of $|B_r|$ equations. Note that ϕ_{rtd} and the conditional

[26] When a customer arrives at a boundary of a region, we allow her to drive outside the boundary, in which case we will no longer observe her in the data. We approximate the value of driving outside the boundary based on the utility obtained from parking at a block at $2 per hour (i.e., parking price at legacy meters). We also assume that the distance of a block located outside the boundary to the ideal location is (at least) one block larger compared to the distance between the boundary and ideal locations.

distribution $f_{rtd}^{P|A}$ are calculated based on observations in the data under the rational expectation assumption. In the counterfactual analyses, however, we calculate new equilibrium distributions following the procedure outlined in Appendix E. Once we calculate the utility from continuing to search, we solve for the optimal decision at each step according to the optimal decision rule. Finally, we calculate the expected utility of a consumer who chooses to drive and start searching on street, u_{is}.

5. Determine whether a consumer decides to drive and, if so, whether she starts searching on street or parks at the garage directly.
6. Repeat these steps for all M_r consumers in the region at time t on day d.
7. Repeat these steps for all times and days in all regions.

- **Step 2: Calculate Simulated Moments** Based on the simulation, for each region, time and day, calculate 1) the number of consumers who choose to drive and end up parking at each block, 2) the number of consumers who choose to drive and end up parking at the garage, 3) the total minutes parked at each block, and 4) the total minutes parked at the garage.
- **Step 3: Match Simulated Moments to Observed Moments** Solve the moment conditions in Equation (9) to obtain the parameter estimates $\hat{\Theta}$.

Appendix C: Ideal Location Estimation

Figure 8 shows the detailed estimates of the ideal location distributions. Recall that we estimate the ideal location distribution for each region, time window (i.e., morning, noon, afternoon), day of week (i.e., Monday to Saturday) and month separately. Since the estimates are very similar across months, for brevity, we report the average of the estimates across months. In addition, we shows the estimates of the parameters in the approximation functions π and ρ in Table 9.

Appendix D: Robustness Tests

We evaluate the robustness of our model along the following dimensions:

D.1. Market Size

In the baseline model, we set the market size to be twice the average number of drivers in the before period, which yields a market size of 700 in Marina, 1135 in Fillmore and 1420 in Mission. We perform the sensitivity analysis by choosing different levels of market size, which are 1.5, 2.5 and 3.0 times the average number of drivers in the before period. This choice rule yields market sizes of 525, 875 and 1050 for Marina, 850, 1420 and 1700 for Fillmore, and 1065, 1775 and 2130 for Mission. Results in Figure 9 shows that changes in consumer welfare, social welfare and search traffic are robust to the choice of market size.

D.2. Ideal Location Estimation Errors

To make sure that our results are robust to estimation errors in ideal location distributions, we introduce several levels of noise to the existing ideal location distribution estimates, and we re-estimate consumer attributes and re-calculate welfare and search traffic. We follow the perturbation procedure below to introduce different levels of noises. Let $\hat{\omega}_{rtd}(b), b = 1, 2, ..., |B_r - 1|$ denote the vector of estimated ideal location distribution for region r at time t on day d, and $\omega'_{rtd}(b), b=1,2,...,|B_r-1|$ denote the new ideal location distribution after perturbation.

$$\omega'_{rtd}(b)=\max\left(\hat{\omega}_{rtd}(b)+\tau\varepsilon_{rtd}(b),0\right), b=1,2,...,|B_r-1|,$$

where $\varepsilon_{rtd}(b)$ is a random draw from a standard normal distribution, and τ is a scaling factor. Specifically, we set $\tau=1\%,3\%,5\%$ to vary the level of noises introduced. Note that the maximum is taken to ensure that the fraction of consumers whose ideal location is at a specific block is non-negative. Lastly, we also make sure that the new ideal location distribution vector thus obtained satisfies $\sum_{b=1}^{|B_r-1|}\omega'_{rtd}(b)\leq 1, \forall r,t,d$. If not, we redraw the error vector $\varepsilon_{rtd}(b), b=1,2,...,|B_r-1|$. To get a sense of how much noise we introduce through this perturbation procedure, we calculate the noise to signal ratio defined as $\frac{\sum_b|\tau\varepsilon_{rtd}(b)|}{\sum_b\hat{\omega}_{rtd}(b)}$, which ranges from 0.15–0.78 for Marina, 0.36–1.78 for Fillmore, and 0.20–0.98 for Mission.

The results in Figure 10 demonstrate that our conclusions regarding changes in consumer welfare, social welfare and search traffic remain unchanged.

D.3. Consumer Beliefs

We now allow consumers to form different beliefs of price and availability for high-, medium- and low-popularity blocks, $\{P^H_{rtd},A^H_{rtd}\},\{P^M_{rtd},A^M_{rtd}\},\{P^L_{rtd},A^L_{rtd}\}$. We also assume that consumers know which block is high-, medium-, and low-popularity block. Under such assumptions, consumers' decisions differ from those derived under identical beliefs in two ways. First, consumers may choose to start their search from a block that is not their destination given their knowledge of all blocks' popularity. Second, consumers will derive an optimal search path instead of following a random walk strategy at the intersection: they choose where to go next based on which block yields the highest expected utility. We now derive the transition probability and the optimal decision rule under such assumptions.

Let $b^*_{k+1}(b_k,P_{rtdb_k},A_{rtdb_k},\epsilon_{irtdb_k})$ denote the block that consumer i will visit if she chooses to continue searching after block b_k. Let $U_b=\{H,M,L\}$ denote the popularity level of block b. We can now write down the transition probability:

$$\begin{aligned}&Pr\left(b_{k+1},P_{rtdb_{k+1}},A_{rtdb_{k+1}},\epsilon_{rtdb_{k+1}};0|b_k,P_{rtdb_k},A_{rtdb_k},\epsilon_{irtdb_k}\right)\\
&=\begin{cases}f_{rtdb}^{P,A|U_{b_{k+1}}}\left(P_{rtdb_{k+1}},A_{rtdb_{k+1}}|b_k,P_{rtdb_k},A_{rtdb_k}\right)f^{\epsilon}(\epsilon_{irtdb_{k+1}}), & \text{if } b_{k+1}=b^*_{k+1}(b_k,P_{rtdb_k},A_{rtdb_k},\epsilon_{irtdb_k}),\\ 0, & \text{otherwise,}\end{cases}\end{aligned}$$

where $f_{rtdb}^{P,A|U}$ is the joint density function of P,A for block type U. Under the assumptions that consumers form rational expectations for each block type and that consumers do not update their beliefs, the value of continued search can be simplified as:

$$\begin{aligned}&V_i^{\text{search}}(b_k,P_{rtdb_k},A_{rtdb_k},\epsilon_{irtdb_k})\\
&=E\Big[\max_{a=\{0,1,2\},b_{k+1}\in B_{rb_k}}u_i(b_{k+1},P_{rtdb_{k+1}},A_{rtdb_{k+1}},\epsilon_{rtdb_{k+1}};a)|(b_k,P_{rtdb_k},A_{rtdb_k},\epsilon_{rtdb_k})\Big]\\
&=\max_{b_{k+1}\in B_{rb_k}}E\Big[\max_{a=\{0,1,2\}}u_i(b_{k+1},P_{rtdb_{k+1}},A_{rtdb_{k+1}},\epsilon_{rtdb_{k+1}};a)|(b_{k+1},b_k,P_{rtdb_k},A_{rtdb_k},\epsilon_{rtdb_k})\Big]\\
&=\max_{b_{k+1}\in B_{rb_k}}E\Big[\max_{a=\{0,1,2\}}u_i(b_{k+1},P_{rtdb_{k+1}},A_{rtdb_{k+1}},\epsilon_{rtdb_{k+1}};a)|(b_{k+1},b_k)\Big]\\
&\equiv\max_{b_{k+1}\in B_{rb_k}}V_i^{\text{search}}(b_{k+1},b_k)\\
&\equiv V_i^{\text{search}}(b_k). \qquad (13)\end{aligned}$$

Optimal Decision Rule. Note that the optimal decision rule now concerns two decisions; (1) whether to park, continue searching or stop searching, and (2) which block to search next if the search continues. For consumer i, the optimal decision rule $\{a_i^*(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k}), b_{k+1}^*(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k})\}$ can be characterized as follows.

If consumer i decides to continue searching, she will drive to block $b_{k+1}^*(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k})$ such that:

$$\begin{aligned}
& b_{k+1}^*(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k}) \\
= & \arg\max_{b_{k+1}\in B_{rb_k}} E\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{rtdb_{k+1}}; a)|(b_{k+1}, b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{rtdb_k})\big] \\
= & \arg\max_{b_{k+1}\in B_{rb_k}} E\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{rtdb_{k+1}}; a)|(b_{k+1}, b_k)\big] \\
= & \arg\max_{b_{k+1}\in B_{rb_k}} E\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{rtdb_{k+1}}; a)|b_k\big]
\end{aligned}$$

The optimal decision $a_i^*(b_k, P_{rtdb_k}, A_{rtdb_k})$ can be characterized similarly as before:

- When the current block is available, i.e., $A_{rtdb_k} = 1$, a consumer will choose the action that gives her the highest utility:

$$\begin{aligned}
& a_i^*(b_k, P_{rtdb_k}, 1, \epsilon_{irtdb_k}) \\
= & \begin{cases} 0, & \text{if } -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k) > \max\big(V_i^{\text{garage}|\text{o}}, V_i^{\text{park}}(b_k, P_{rtdb_k})\big) \\ 1, & \text{if } V_i^{\text{park}}(b_k, P_{rtdb_k}) \geq \max\big(V_i^{\text{garage}|\text{o}}, -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k)\big) \\ 2, & \text{otherwise.} \end{cases}
\end{aligned}$$

- When the current block is unavailable, i.e., $A_{rtdb_k} = 0$,

$$a_i^*(b_k, P_{rtdb_k}, 0, \epsilon_{irtdb_k}) = \begin{cases} 0, & \text{if } -s_i\epsilon_{irtdb_k} + V_i^{\text{search}}(b_k) > V_i^{\text{garage}|\text{o}} \\ 2, & \text{otherwise.} \end{cases}$$

Note that $V_i^{\text{search}}(b_k)$ is defined by Equation (13). We now show how it can be calculated recursively.

$$\begin{aligned}
V_i^{\text{search}}(b_k) = & \max_{b_{k+1}\in B_{rb_k}} E\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{rtdb_{k+1}}; a)|(b_{k+1}, b_k)\big] \\
= & \max_{b_{k+1}\in B_{rb_k}} \Big[\iiint \big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtd}^{U_{b_{k+1}}}, A_{rtd}^{U_{b_{k+1}}}, \epsilon_{irtdb_{k+1}}; a) \\
& \cdot f_{rtd}^{P,A|U_{b_{k+1}}}(P_{rtd}^{U_{b_{k+1}}}, A_{rtd}^{U_{b_{k+1}}}) f_{rtd}^{\epsilon}(\epsilon_{irtdb_{k+1}}) dP_{rtd}^{U_{b_{k+1}}} dA_{rtd}^{U_{b_{k+1}}} d\epsilon_{irtdb_{k+1}}\Big] \\
= & \max_{b_{k+1}\in B_{rb_k}} \Big[\phi_{rtd}^{U_{b_{k+1}}} \iint \max_{a=\{0,1,2\}} u_i(b_{k+1}, P, 1, \epsilon; a) f_{rtd}^{P|A,U_{b_{k+1}}}(P|A^{U_{b_{k+1}}} = 1) f_{rtd}^{\epsilon}(\epsilon) dP d\epsilon \\
& + (1 - \phi_{rtd}^{U_{b_{k+1}}}) \iint \max_{a=\{0,1,2\}} u_i(b_{k+1}, P, 0, \epsilon; a) f_{rtd}^{P|A,U_{b_{k+1}}}(P|A^{U_{b_{k+1}}} = 0) f_{rtd}^{\epsilon}(\epsilon) dP d\epsilon\Big], \qquad (14)
\end{aligned}$$

where ϕ_{rtd}^U denotes consumers' belief of availability for blocks of type $U, U = \{H, M, L\}$. Under the rational expectation assumption, we have $\phi_{rtd}^U = \frac{\sum_{b\in B_r^U} \phi_{rtdb}}{|B_r^U|}$, where $B_r^U, U = \{H, M, L\}$ denote the set of high-, medium, and low-popularity blocks in region r.

We can further expand the first double integral in Equation (14) as follows:

$$\begin{aligned}
& \iint \max_{a=\{0,1,2\}} u_i(b_{k+1}, P^{U_{b_{k+1}}}, 1, \epsilon; a) f_{rtd}^{P|A,U_{b_{k+1}}}(P|A^{U_{b_{k+1}}} = 1) f_{rtd}^{\epsilon}(\epsilon) dP d\epsilon \\
= & \int_{\epsilon \leq \frac{V_i^{\text{search}}(b_{k+1}) - V_i^{\text{garage}|\text{o}}}{s_i}} \Big(-s_i\epsilon + V_i^{\text{search}}(b_{k+1})\Big)
\end{aligned}$$

$$
\begin{aligned}
&\cdot \bar{F}_{rtd}^{P|A,U_{b_{k+1}}}\left(\frac{s_i\epsilon - V_i^{\text{search}}(b_{k+1}) + v_{rtd} + \epsilon_{irtd} - \eta_i d(b_i^*, b_{k+1})}{\theta_i h_i}|A^{U_{b_{k+1}}} = 1\right) f_{rtd}^{\epsilon}(\epsilon)d\epsilon \\
&+ \int_{P^{U_{b_{k+1}}} \le \frac{v_{rtd}+\epsilon_{irtd}-\eta_i d(b_i^*, b_{k+1}^*) - V_i^{\text{garage|o}}}{\theta_i h_i}} V_i^{\text{park}}(b_{k+1}^*, P^{U_{b_{k+1}}}) \\
&\cdot \bar{F}_{rtd}^{\epsilon}\left(\frac{V_i^{\text{search}}(b_{k+1}) - V_i^{\text{park}}(b_{k+1}^*, P^{U_{b_{k+1}}})}{s_i}\right) f_{rtd}^{P|A,U_{b_{k+1}}}(P|A^{U_{b_{k+1}}} = 1)dP \\
&+ V_i^{\text{garage|o}} \bar{F}_{rtd}^{P|A,U_{b_{k+1}}}\left(\frac{v_{rtd} + \epsilon_{irtd} - \eta_i d(b_i^*, b_{k+1}^*) - V_i^{\text{garage|o}}}{\theta_i h_i}|A^{U_{b_{k+1}}} = 1\right) \\
&\cdot \bar{F}_{rtd}^{\epsilon}\left(\frac{V_i^{\text{search}}(b_{k+1}) - V_i^{\text{garage|o}}}{s_i}\right),
\end{aligned} \tag{15}
$$

where $F_{rtd}^{\epsilon}(\epsilon)$ is the CDF of ϵ, $F_{rtd}^{P|A,U}(P|A)$ is the conditional CDF of P for block type U, $\bar{F}_{rtd}^{\epsilon}(\epsilon) = 1 - F_{rtd}^{\epsilon}(\epsilon)$ and $\bar{F}_{rtd}^{P|A,U_{b_{k+1}}}(P|A^{U_{b_{k+1}}}) = 1 - F_{rtd}^{P|A,U_{b_{k+1}}}(P|A^{U_{b_{k+1}}})$.

We can expand the second double integral in Equation (14) as follows:

$$
\begin{aligned}
&\iint \max_{a=\{0,1,2\}} u_i(b_{k+1}, P, 0, \epsilon; a) f_{rtd}^{P|A,U_{b_{k=1}}}(P|A^{U_{b_{k+1}}} = 0) f_{rtd}^{\epsilon}(\epsilon) dP d\epsilon \\
&= \int_{\epsilon < \frac{V_i^{\text{search}}(b_{k+1}) - V_i^{\text{garage|o}}}{s_i}} \Big(- s_i\epsilon \\
&+ V_i^{\text{search}}(b_{k+1})\Big) f_{rtd}^{\epsilon}(\epsilon)d\epsilon + V_i^{\text{garage|o}} \bar{F}_{rtd}^{\epsilon}\left(\frac{V_i^{\text{search}}(b_{k+1}) - V_i^{\text{garage|o}}}{s_i}\right)
\end{aligned} \tag{16}
$$

We can see that the value $V_i^{\text{search}}(b_k)$ is a function of the expected values to continue searching from the adjacent blocks, which allows us to calculate $V_i^{\text{search}}(b_k)$ by solving the equation recursively.

D.4. Parking Duration

To make sure that our approach of drawing the parking durations from the censored empirical distribution is not restrictive, we draw different sets of parking time distributions, which contain different proportions of short and long parking durations such as those shown in Figure 14. Specifically, we draw from the following sets of parking time distributions, which preserve the general shape of the empirical density function of parking durations:

1. The parking time distribution conditional on congestion being low, with 10% more weight for parking durations that are less than 1-hour.
2. The parking time distribution conditional on congestion being low.
3. The parking time distribution conditional on congestion being medium.
4. The parking time distribution conditional on congestion being high.
5. The parking time distribution conditional on congestion being high, with 10% less weight for parking durations that are less than 1-hour.

We re-estimate the model and re-calculate the counterfactual equilibrium. The results are displayed in Figure 12, and the changes in consumer welfare, social welfare and search traffic are very robust to the different parking duration distributions used.

Appendix E: Algorithm for Computing the Counterfactual Equilibrium

In the counterfactual analysis, we compute the counterfactual equilibrium following the procedure below:

1. For each region r, time t and day d, start with an initial guess of each consumer's driving and parking decision. Compute the number of consumers parking at each block, $q_{rtd}(b), \forall b \in B_r$, and the total parking minutes at each block, $Q_{rtd}(b), \forall b \in B_r$. Also compute the number of consumers parking at the garage, q_{rtdg}, and the total minutes parked, Q_{rtdg}.

2. Calculate the occupancy rate at each block for region r, time t and day d. Then compute the availability at each block $\hat{\phi}_{rtdb}, \forall b \in B_r$ by solving Equation (8).

3. Given the estimated parameters and the availability vector $\hat{\phi}_{rtdb}, \forall b \in B_r$, re-calculate each consumer's driving and parking decision based on the optimal decision rule derived in the paper. Update $q\prime_{rtd}(b), Q'_{rtd}(b), \forall b \in B_r$, q'_{rtdg}, and Q'_{rtdg}.

4. Repeat the above steps until convergence, i.e., $\left| \begin{array}{c} q\prime_{rtd}(b) - q_{rtd}(b), \forall b \\ Q'_{rtd}(b) - Q_{rtd}(b), \forall b \\ q\prime_{rtdg} - q_{rtdg}, \\ Q'_{rtdg} - Q_{rtdg} \end{array} \right| < \epsilon = 10^{-4}$.

5. Repeat the above steps to obtain the equilibrium parking locations for all regions, times and days.

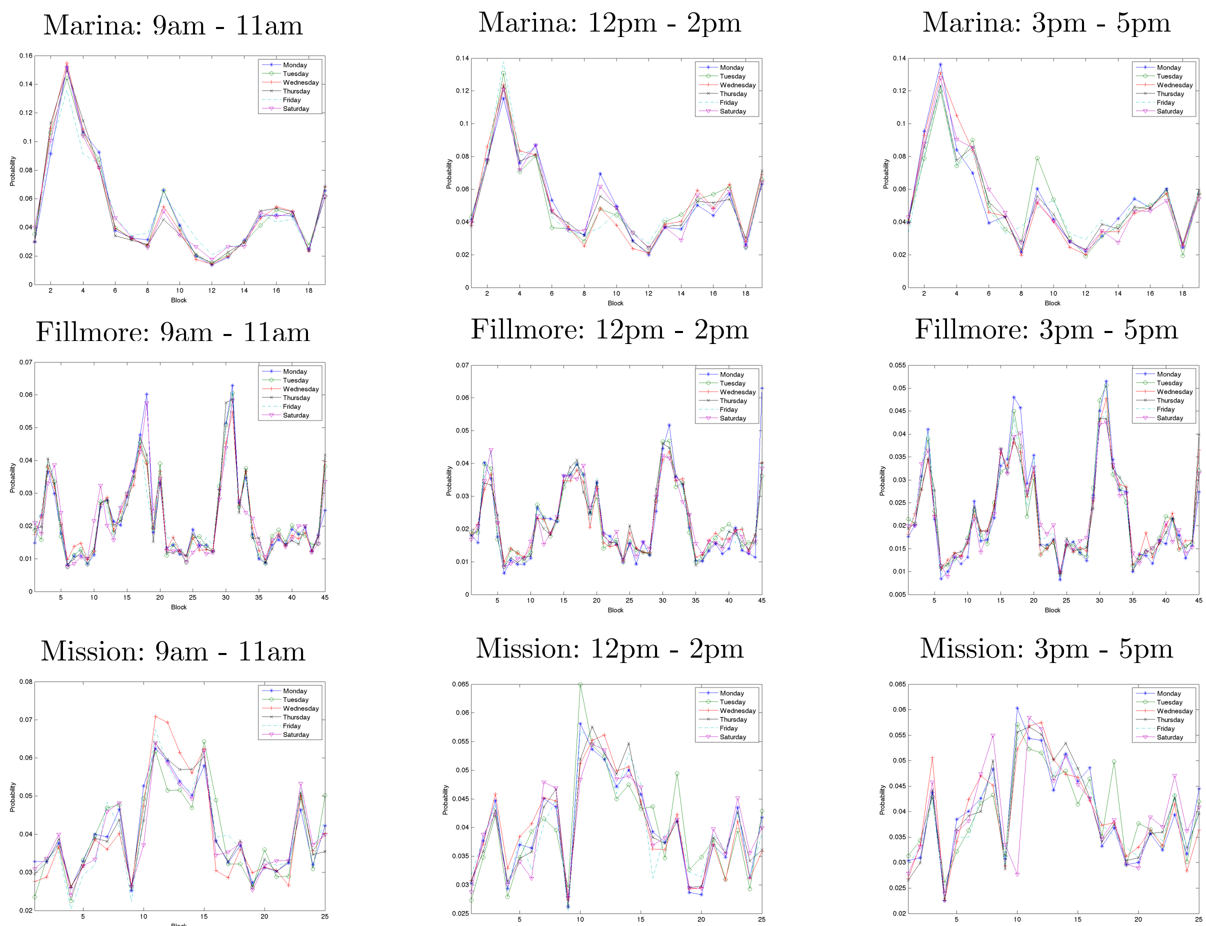


Figure 8 Ideal Location Demand Estimates

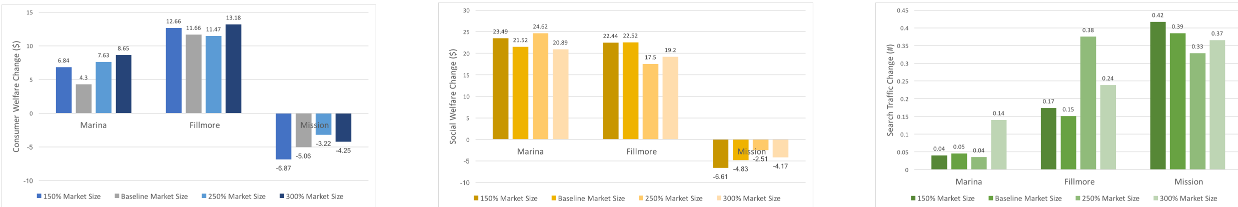


Figure 9 Robustness Test: Market Size

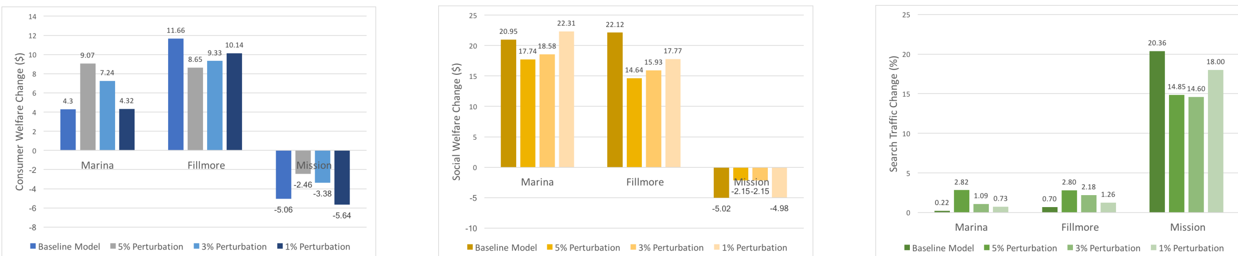


Figure 10 Robustness Test: Ideal Location

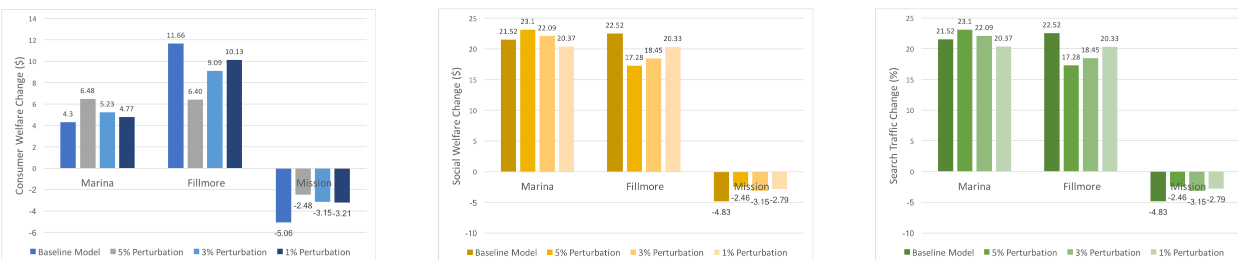


Figure 11 Robustness Test: Consumer Belief

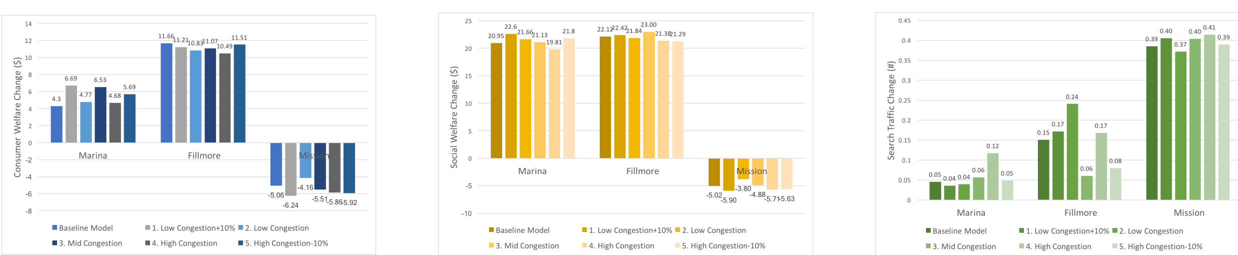


Figure 12 Robustness Test: Parking Duration

Table 9 Estimates of γ and δ

	9am - 11am						12pm - 2pm						3pm - 5pm					
	Mon.	Tues.	Wed.	Thur.	Fri.	Sat.	Mon.	Tues.	Wed.	Thur.	Fri.	Sat.	Mon.	Tues.	Wed.	Thur.	Fri.	Sat.
									Marina									
γ_0	-1.13	-1.49	-0.59	-1.15	-0.44	0.26	0.29	0.30	0.55	-0.72	-0.97	0.30	0.14	-0.57	-0.16	-0.31	0.38	-0.05
γ_1	-1.43	-2.88	-1.30	-0.65	-1.24	0.69	0.08	0.12	0.31	-0.97	-1.22	0.17	0.15	-0.93	-0.80	-0.84	0.39	-0.49
γ_2	-1.56	-3.54	-1.68	-0.17	-1.44	1.02	-0.05	-0.01	0.12	-1.08	-1.02	0.09	0.18	-1.17	-0.82	-0.87	0.32	-0.71
γ_3	2.55	3.30	2.21	1.70	1.17	0.46	0.25	0.25	0.36	1.59	2.04	0.19	0.26	0.71	1.14	1.09	-0.21	0.69
γ_4	-0.40	-0.71	-0.40	-0.28	-0.29	-0.01	0.01	-0.05	-0.05	-0.31	-0.35	0.02	-0.05	-0.16	-0.27	-0.23	0.05	-0.21
γ_5	0.15	1.78	0.30	-0.09	0.91	-0.95	-0.35	0.05	-0.26	0.59	0.34	-0.37	-0.09	0.72	0.49	0.50	-0.19	0.59
δ_0	0.65	1.14	1.31	1.77	1.08	1.70	1.28	1.50	1.86	1.26	1.59	0.93	1.55	0.75	2.19	1.47	1.09	1.40
δ_1	0.66	-0.05	0.21	0.05	-0.56	0.12	0.11	0.25	0.16	0.12	0.13	0.21	0.10	0.25	-0.62	-0.19	0.11	0.12
δ_2	-0.41	-0.22	-0.69	-0.92	0.06	-1.13	-0.73	-0.69	-1.12	-0.61	-0.70	-0.30	-0.92	-0.22	-0.56	-0.59	-0.68	-0.71
δ_3	0.16	0.21	-0.05	-0.22	0.36	-0.16	0.14	-0.15	-0.27	0.09	-0.24	0.17	-0.08	0.41	-0.16	0.06	0.25	0.19
δ_4	-0.03	-0.03	-0.02	0.00	-0.06	-0.02	-0.05	0.01	-0.01	-0.03	0.00	-0.03	-0.01	-0.04	-0.01	-0.04	-0.05	-0.05
δ_5	0.00	-0.06	0.18	0.27	0.01	0.33	0.16	0.05	0.29	0.06	0.20	0.00	0.20	-0.18	0.20	0.17	0.07	0.04
									Fillmore									
γ_0	-0.50	-0.86	-0.16	-0.58	-0.96	0.00	-0.31	-0.88	-0.19	-0.31	-0.57	0.20	0.11	0.07	0.35	0.35	0.03	-0.01
γ_1	-0.39	-0.52	-0.11	-0.34	-0.67	-0.18	-0.28	-0.69	-0.31	-0.39	-0.52	-0.06	0.01	0.03	0.23	0.21	-0.04	-0.03
γ_2	-0.27	-0.28	-0.08	-0.17	-0.46	-0.27	-0.26	-0.54	-0.37	-0.42	-0.45	-0.22	-0.06	0.01	0.15	0.11	-0.08	-0.03
γ_3	0.71	0.38	0.44	0.55	0.53	0.60	0.59	0.50	1.10	1.24	0.73	0.78	0.63	0.30	0.30	0.63	0.49	0.10
γ_4	-0.05	-0.06	-0.02	-0.03	-0.06	0.00	-0.02	-0.05	-0.05	-0.06	-0.05	-0.02	-0.03	-0.03	-0.02	-0.03	-0.02	-0.03
γ_5	-0.17	0.44	-0.15	-0.09	0.36	-0.62	-0.38	0.22	-0.68	-0.73	-0.08	-0.76	-0.42	0.07	-0.16	-0.43	-0.28	0.21
δ_0	2.49	2.12	1.22	1.59	1.65	1.36	1.55	2.43	1.86	1.60	1.92	0.78	1.18	0.67	1.09	1.47	0.92	0.98
δ_1	-0.41	-0.34	0.13	-0.07	-0.08	-0.11	-0.07	-0.17	0.04	0.10	-0.06	0.24	0.24	0.42	0.33	0.21	0.31	0.17
δ_2	-2.12	-1.82	-0.58	-1.10	-1.15	-0.99	-1.07	-1.76	-1.11	-0.83	-1.30	-0.10	-0.39	0.25	-0.14	-0.62	-0.10	-0.35
δ_3	-0.52	-0.29	-0.16	-0.23	-0.22	-0.19	-0.29	-0.32	-0.28	-0.18	-0.21	0.06	0.04	0.25	0.07	-0.16	-0.04	0.04
δ_4	-0.01	-0.01	0.00	-0.01	-0.01	-0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
δ_5	0.75	0.57	0.24	0.41	0.36	0.45	0.31	0.32	0.27	0.17	0.25	-0.10	-0.05	-0.35	-0.16	0.12	0.02	-0.05
									Mission									
γ_0	-0.07	0.04	-0.08	0.13	-0.55	0.01	0.00	0.09	0.13	0.02	-0.05	-0.03	0.14	0.14	0.27	0.30	-0.07	0.20
γ_1	-0.09	0.02	-0.10	0.12	-0.56	-0.01	-0.03	0.04	0.11	0.01	-0.07	-0.04	0.04	0.03	0.23	0.24	-0.10	0.07
γ_2	-0.10	0.01	-0.12	0.11	-0.57	-0.02	-0.06	0.00	0.10	0.01	-0.08	-0.06	-0.04	-0.07	0.19	0.19	-0.12	-0.03
γ_3	-0.14	-0.02	-0.21	-0.03	-2.07	0.01	0.11	-0.05	0.15	0.00	-0.06	-0.02	0.16	0.19	0.36	0.37	-0.13	0.41
γ_4	0.07	0.02	0.24	0.04	0.89	0.02	0.00	0.04	-0.08	-0.01	0.03	0.04	-0.01	0.00	-0.10	-0.10	0.10	-0.09
γ_5	-0.25	-0.11	-0.32	-0.08	-2.16	-0.07	-0.04	-0.24	0.12	-0.01	-0.12	-0.10	-0.17	-0.23	0.26	0.17	-0.29	-0.02
δ_0	1.59	1.12	1.85	1.42	1.85	1.21	0.94	0.93	0.93	0.54	1.04	0.78	1.30	1.43	0.87	1.60	1.19	1.50
δ_1	0.30	0.26	0.28	0.32	0.17	0.28	0.28	0.30	0.28	0.30	0.27	0.27	0.29	0.23	0.26	0.27	0.28	0.22
δ_2	-0.85	-0.51	-0.98	-0.66	-1.24	-0.54	-0.31	-0.27	-0.30	0.10	-0.41	-0.21	-0.59	-0.84	-0.28	-0.92	-0.53	-0.92
δ_3	-0.24	-0.08	-0.64	-0.26	-0.29	-0.07	0.16	0.21	0.21	0.36	0.13	0.31	-0.05	-0.06	0.15	-0.24	0.01	-0.28
δ_4	0.00	-0.01	0.03	0.01	-0.02	0.00	-0.01	-0.01	-0.01	0.00	-0.01	-0.01	0.00	-0.02	-0.01	0.01	-0.01	-0.01
δ_5	0.22	0.19	0.49	0.18	0.43	0.09	-0.10	-0.14	-0.15	-0.33	-0.08	-0.21	0.06	0.19	-0.07	0.23	0.03	0.36

* Note we estimate all coefficients for each month separately. Since the estimates are very similar across months, for brevity, we report the average across months in the table.

Table 10 Block Index

		Marina		
1 AVILA ST 0	5 CHESTNUT ST 2300	9 LOMBARD ST 2000	13 LOMBARD ST 2400	17 SCOTT ST 3200
2 CHESTNUT ST 2000	6 CHESTNUT ST 2400	10 LOMBARD ST 2100	14 MALLORCA WAY 0	18 SCOTT ST 3300
3 CHESTNUT ST 2100	7 DIVISADERO ST 3200	11 LOMBARD ST 2200	15 PIERCE ST 3200	19 STEINER ST 3300
4 CHESTNUT ST 2200	8 Marina ST 3300	12 LOMBARD ST 2300	16 PIERCE ST 3300	
		Fillmore		
1 BUCHANAN 1800	10 FILLMORE 1400	19 FILLMORE 2300	28 LAGUNA 1600	37 SUTTER 1800
2 CALIFORNIA 2300	11 FILLMORE 1500	20 FILLMORE 2400	29 PINE 2300	38 SUTTER 2000
3 CALIFORNIA 2400	12 FILLMORE 1600	21 GEARY 1500	30 POST 1600	39 WASHINGTON 2400
4 CLAY 2400	13 FILLMORE 1700	22 GEARY 1600	31 POST 1700	40 WASHINGTON 2500
5 CLAY 2500	14 FILLMORE 1800	23 GEARY 1700	32 POST 1800	41 WEBSTER 1500
6 FILLMORE 1000	15 FILLMORE 1900	24 GEARY 1800	33 POST 1900	42 WEBSTER 1600
7 FILLMORE 1100	16 FILLMORE 2000	25 JACKSON 2300	34 SACRAMENTO 2400	43 WEBSTER 2100
8 FILLMORE 1200	17 FILLMORE 2100	26 JACKSON 2400	35 SACRAMENTO 2500	44 WEBSTER 2200
9 FILLMORE 1300	18 FILLMORE 2200	27 LAGUNA 1500	36 STEINER 1500	45 CALIFORNIA 902
		Mission		
1 16TH ST 3000	6 20TH ST 3500	11 MISSION ST 2000	16 MISSION ST 2500	21 VALENCIA ST 800
2 16TH ST 3100	7 21ST ST 3200	12 MISSION ST 2100	17 VALENCIA ST 400	22 VALENCIA ST 900
3 17TH ST 3300	8 22ND ST 3200	13 MISSION ST 2200	18 VALENCIA ST 500	23 VALENCIA ST 1000
4 18TH ST 3400	9 23RD ST 3300	14 MISSION ST 2300	19 VALENCIA ST 600	24 VALENCIA ST 1100
5 19TH ST 3400	10 BARTLETT ST 0	15 MISSION ST 2400	20 VALENCIA ST 700	25 VALENCIA ST 1200

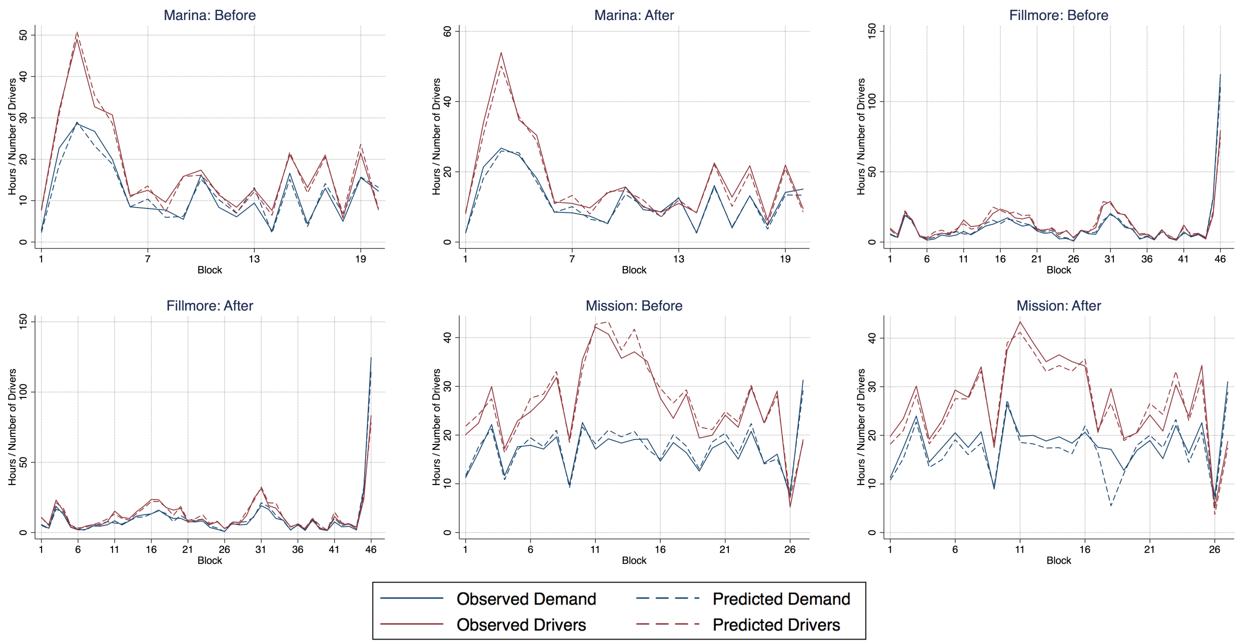


Figure 13 Moment Fits

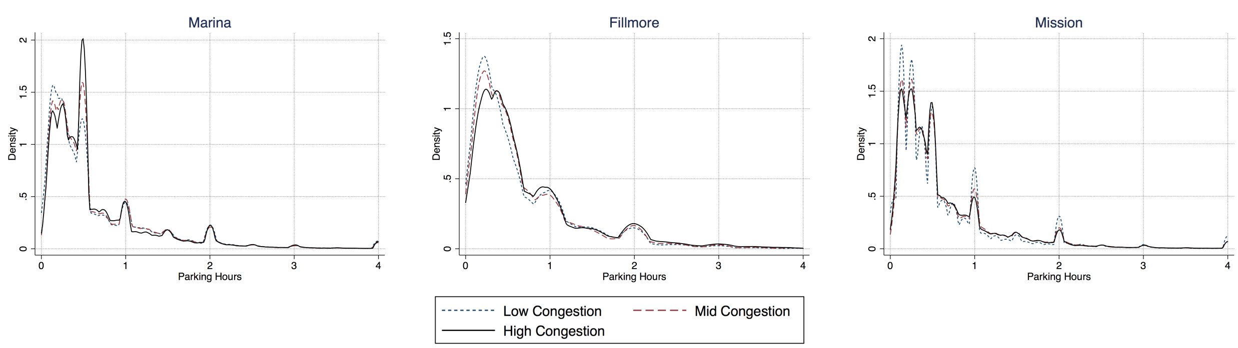


Figure 14 Parking Time Distribution