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Congestion pricing provides an appealing solution to urban parking problems. By charging varying rates across areas based on their congestion levels, congestion pricing shifts demand and allows a better allocation of limited resources. It aims to increase the accessibility of highly desired public goods for commuters who value them, and reduce traffic caused by drivers searching for available parking spaces. Using data from the City of San Francisco both before and after a congestion pricing scheme was implemented in 2011, 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. These estimates then allow us to conduct welfare comparisons. We find that congestion pricing increases consumer welfare in popular areas, but when implemented in less-congested areas, it may actually hurt consumer welfare. In one of the districts under study, consumers ended up searching more, parked further away and paid more. Interestingly, despite the improved availability, congestion pricing may actually increase traffic due to cruising (searching for parking), as price sensitive consumers start to search for inexpensive parking spaces, particularly when prices are highly dispersed geographically. Through counterfactual analyses, we find that a simple three-tier pricing policy, which eliminates the search for a lower price, can significantly increase welfare and achieve more than 50% of the welfare increase achieved by a full price information benchmark.

Key words: Congestion Pricing, Consumer Welfare, Search Model

1. Introduction

Traffic congestion and lack of parking are the two most prevalent transportation problems in large urban areas (Rodrigue et al. 2006). They are also interrelated because the process of looking for a parking space (or "cruising") creates additional delays and contributes to traffic. While cruising to find parking, drivers waste time and fuel, add to traffic congestion, and pollute the air. Shoup

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(2006) summarized sixteen studies that were conducted between 1927 and 2001. These studies found that it took between 3.5 and 14 minutes to find an on-street parking space in congested city centers, and that 30 percent of the traffic, on average, was caused by drivers cruising for parking rather than driving to their real destinations.

One way to resolve these problems is to implement a congestion pricing policy that charges varying prices to match demand with limited supply. Congestion pricing has long been proposed as a solution to manage traffic congestion (Vickrey 1952). However, it is not until very recently that it has been put into practice, due to technological challenges associated with the implementation. To implement congestion pricing, cities will have to install technologies such as cameras or sensors to track congestion levels at frequent intervals.

A few cities have recently 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).[1] These programs have varying levels of complexity. Some only vary prices by time of day (e.g., NYC's PARK Smart), while others also vary prices by location (e.g., SF*park* and GoBerkeley) and duration (e.g., GoBerkeley). All programs reported increased availability of parking spaces and reduced time spent searching for parking (see program reports for details).[2]

Besides transportation, many other industries facing fixed and limited capacity have successfully used dynamic pricing to match supply with demand. Airlines and hotels have long adopted revenue management practices to adjust prices to shift demand from popular travel dates (or times) to less popular ones or shift late booking to early booking (Boyd 2007, Talluri and van Ryzin 2004). American Airlines and Delta Airlines credit revenue management techniques for a revenue increase of $500 and $300 million per year, respectively (Boyd 1998). Similarly, Marriott's successful execution of Revenue Management has added between $150 million and $200 million in annual revenue (Marriott and Cross 2000). More recently, national sports leagues (such as NBA, NHL, MLB clubs) and concert planners have also adopted dynamic pricing to manage demand given limited seats (Shapiro and Drayer 2014, Tereyagoglu et al. 2016, Xu et al. 2016).

The congestion pricing used to control parking demand works similarly to revenue management in the airline or hotel industries — it uses prices to shift demand and to allocate limited capacity — yet the objective is different. While airlines and hotels use revenue management to maximize revenue (or profit), cities implement congestion pricing to increase availability and accessibility of public goods. Even though both strategies eventually distribute services or products to consumers

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[1] PARK Smart: http://www.nyc.gov/html/dot/html/motorist/parksmart.shtml. SF*park*: http://SF*park*.org/. GoBerkeley: http://www.goberkeley.info/.

[2] 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.

according to their willingness to pay, in the case of city parking, the primary objective of the demand redistribution is to allow consumers to easily find parking when they really need it, not to increase total revenue.

For the same reason, the central goal of our analysis is to evaluate the change in total commuter welfare following the implementation of congestion pricing. The question of whether consumers benefit from or are harmed by congestion pricing is not trivial. First, congestion pricing reduces congestion levels at popular locations by increasing prices and increases congestion levels at unpopular locations by decreasing prices. The benefits from the former may not always outweigh the latter, especially in non-congested regions. Second, even if congestion pricing reduces availability-based searching, it may introduce price-based searching: commuters who are price sensitive may decide to continue cruising even if they find parking at the perfect location. If the additional search costs induced by higher price dispersion outweigh the reduced search costs due to better availability, congestion pricing may actually be harmful to commuters and to the city. In addition to the ambiguous effect on search costs, congestion pricing may result in changes in the total demand for parking (i.e., the number of commuters who decide to drive) as well as the allocation of that demand, which then affects the parking and inconvenience costs (parking too far away from the desired destination) incurred by commuters.

Therefore, to evaluate the change in commuter welfare, we estimate the change in parking payments, inconvenience costs and search costs. The estimation of search costs is particularly important in our analysis, because the most prominent problem with an inefficient city parking program is the extensive cruising that it creates. Unlike purchasing airline tickets or hotel rooms, where a traveler can search for availability and prices ahead of time at minimal cost, a driver has to incur substantial physical costs when searching for available and affordable parking spaces. Moreover, parking availability is more transient and dynamic compared to the availability of airline seats and hotel rooms, i.e., a space that is available now may not be available in just five minutes, and may become available again in a short period of time. Even though there are ways to make availability information accessible in real time, it can often be costly and many times unreliable. In the case of SF*park*, for instance, the city created a mobile app which intended to provide real time availability and price information. However, the app has been criticized for running slowly and being dangerous to use while driving.[3] Moreover, parking sensor batteries started to fail in 2013 and by December of that year, availability information was no longer available.

In order to estimate the search cost as well as other costs a commuter incurs to park, we model commuters' decisions to drive to the desired destination and the process of searching for

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[3] Want to Add to Congestion? Then It's Going to Cost You. The New York Times. May 5, 2011.

parking spaces as a two-stage dynamic structural model. In the first stage, a commuter decides whether to drive to the destination based on her value for the trip and her expected cost of driving. In the second stage, we model a commuter's dynamic search for parking. Our model allows for heterogeneity in commuters' values for the trip, inconvenience costs, search costs, and price sensitivity. Incorporating heterogeneity along these dimensions allows commuters with different characteristics to park at different final locations even though their ideal locations may be the same.

We estimate the structural model 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 and, in particular, on inconvenience costs, search costs and payments.

Our empirical results indicate that the effect of congestion pricing on consumer welfare is indeed ambiguous — congestion pricing may either increase or decrease consumer welfare depending on the characteristics of the district we study. We find that, congestion pricing led to welfare increases in popular districts with moderate to high congestion levels. However, it actually resulted in welfare decreases when implemented in less-congested areas. In one of the districts under study, we find that consumers ended up paying more, searching more and parking further away as a result of the newly implemented congestion pricing program. Moreover, fewer consumers choose to drive, which led to lower total trip valuation and even lower welfare.

With regards to the effect of congestion pricing on searching, as hypothesized, it typically reduces the high costs of searching for an available parking space, because popular blocks become more available after prices increase on those blocks. However, though unintended, congestion pricing may also generate an alternative form of searching — searching for better prices. With an increasing level of price dispersion after the implementation of congestion pricing, drivers start searching for lower prices, particularly when they are price sensitive and when prices are highly dispersed geographically, and updated dynamically (every two to three months in the case of SF*park*). There are situations where a driver continues searching when passing an available spot thinking that if he drives just one more block he may find another spot available at a lower rate. As drivers start to substitute availability-based searching with price-based searching, the intended benefits of congestion pricing may diminish.

The more detailed congestion pricing gets, the better it becomes in managing availability, but at the same time, it induces more searching for better prices. To strike a balance between the positive availability effect and the negative price effect, we conduct a series of counter-factual analyses in which we examine the welfare effects induced by varying levels of sophistication of congestion pricing. While the granular and periodic rate adjustments have induced unnecessary confusion in prices, we show that adopting a simpler three-tier parking rate structure can achieve more than

50% of the welfare increase that can be achieved with full price information. We believe that our results contribute to a better understanding of the implications of congestion pricing on welfare when managing scarce public resources, such as parking spaces in metropolitan areas.

2.   Literature Review

This paper is related to three streams of literature: congestion pricing, welfare effects of price discrimination and theoretical and empirical work that incorporate consumer-driven demand models in operations management. We discuss the relevant literature in each of these streams below.

Congestion Pricing The paper contributes to literature on congestion pricing that examines how a firm or a social planner can control congestion by changing prices. In the literature of service operations, queueing theory is the most commonly used tool to model congestion. In this setting, consumers decide whether to join the queue based on their value for the service relative to the costs of accessing the service (i.e., actual price paid for the service plus the cost of waiting). By varying service prices, the firm or the social planner can control the rate at which consumers entering the system. Naor (1969), in a seminal paper, found that a per-use price can maximize social welfare; however, a firm that aims at maximizing profits will not choose the welfare maximizing price. Hassin and Haviv (2003) provide a comprehensive summary of this literature.

Though related, our context differs from theirs in a number of ways. First, most congestion pricing models in the queueing literature focus on per-use prices (Randhawa and Kumar 2008 and Cachon and Feldman 2011 that study subscription pricing are some exceptions), while parking fees are charged on a per-unit of time basis. Second, in a queueing setting, service providers control service rates and may choose to invest in speeding up the services, whereas the time commuters spend parking is determined by their own needs and are not easily influenced by city planners. Finally, to manage parking demand, congestion pricing varies prices by location and by time of the day. Therefore, this paper is concerned not only with controlling the total arrival rate of consumers, but also with geographical redistribution of demand.

The revenue management literature has a similar flavor — it also uses prices to shift demand and allocate limited capacity (see Talluri and van Ryzin 2004 for a summary). However, this line of research focuses mostly on revenue maximization rather than welfare implication.

Welfare Effects of Price Discrimination As opposed to the literature on congestion pricing and revenue management that is mostly concerned with profit maximization, our paper, to the best of our knowledge, is one of a few that is trying to answer a welfare question: do consumers benefit from congestion pricing? As discussed in the introduction, this is a natural question faced by city planners who are concerned with the welfare of their citizens.

There are a few recent papers that are, at least indirectly, concerned with welfare implications of different pricing strategies. The most related ones are Leslie (2004) and Lazarev (2013) who, like us, use structural models to study the effects of pricing on welfare. Leslie (2004) examines second- and third-degree price discrimination of ticket sales for a Broadway show and finds that while price discrimination led to a 5% increase in profits, consumer welfare was hardly affected relative to static pricing. Using airline data, Lazarev (2013) compares a model of inter-temporal price discrimination (i.e., revenue management) to alternative price schemes (free resale, zero cancellation fees and third degree price discrimination) and finds that the welfare implications are ambiguous — different schemes affect the welfare of business and leisure travelers in different ways. Given the mixed results from Leslie (2004) and Lazarev (2013), and the different context we study (i.e., public goods rather than commercial products), it is a priori unclear what the welfare implications might be when congestion pricing is applied to parking.

In addition to the empirical studies, Aflaki et al. (2016) and Chen and Gallego (2016) are two recent modeling papers in operations management that examine the effects of different pricing schemes on consumer welfare. Chen and Gallego (2016), assume that consumers are myopic (in our model, consumers are strategic) and find that dynamic pricing always benefits consumers. Aflaki et al. (2016) endogenize consumers' decisions and find that consumer welfare is higher under dynamic pricing than under price commitment.

Consumer-Driven Demand Until relatively recently, most research in operations management assumed that consumer behavior is exogenous to the model. For example, demand is random and drawn from a probability distribution that is not affected by strategies employed by the firm. Therefore, previous work did not explicitly model decisions that consumers make as a response to firms' decisions, and may prescribe the wrong strategies to the firm.

In recent years, a burgeoning body of literature in operations management is concerned with the effects that consumer behavior has on firms' decisions. Within this literature, most related to ours are papers that consider pricing. Several types of consumer behaviors have been analyzed in the literature, including choosing whether or not to arrive to a queueing system, whether to buy now or wait for later, and whether to shop given limited information, to name just a few. The majority of these papers find that such strategic consumer behavior negatively impacts profit, and many have proposed to use price commitment to mitigate this behavior (Aviv and Pazgal 2008, Elmaghraby et al. 2008, Su and Zhang 2008, Mersereau and Zhang 2012). Other studies, however, find that dynamic pricing can outperform price commitment in certain contexts (Cachon and Swinney 2009 and Aflaki et al. 2016). Cachon and Feldman (2015) find that a commitment to frequent discounts can further increase firms' profits compared to static price commitment, when consumers strategically choose whether to visit a firm.

Empirical work that incorporates consumer models is also growing. This type of study estimates structurally how consumers make decisions given firms' current strategy, and then simulate counterfactual profits or revenues if firms adopt a different strategy. Both static and dynamic consumer decision models have been applied in various settings. Among static models, one that sees most application is the discrete choice model used to analyze consumers' choices among competing products or services. It has been successfully applied in settings such as airline (Vulcano et al. 2010, Newman et al. 2014), hospitality (Lederman et al. 2014), retailing (Fisher et al. 2015) and the sharing economy (Kabra et al. 2015). More closely related to our work are those which model consumers' inter-temporal decisions, for example, whether to buy or to wait for future price decreases in the air-travel setting (Li et al. 2014), whether to abandon or to continue waiting in the call center setting (Akşin et al. 2013, Yu et al. 2016), whether to buy now or engage in constant price monitoring in online retailing (Moon et al. 2016). In our paper, we use a dynamic model to describe commuters' process of searching for available and affordable parking spaces. What complicates our model is that consumer decisions are done in two stages: they first decide whether to engage in the dynamic search process or not (i.e., to drive or not and if drive, to search or to park at the garage directly) before the search process begins (i.e., search for on-street parking spaces), and their first stage decision depends on where their real destination is, which is unobserved and needs to be estimated.We describe how we uncover the distribution of commuters' real destinations as well as other heterogeneous consumer parameters in the estimation section.

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 as well as provide summary statistics of the parking rates and occupancy levels prior to and following the implementation of the program.

3.1. The SF*park* program

The SF*park* program is a new parking program implemented by the City of San Francisco. Its goal is to address the parking problem in San Francisco by employing congestion pricing, a policy that better allocates the limited capacity of parking spaces through a redistribution of demand. Rather than charging a constant rate at all locations and at all times, the program adjusts parking rates according to demand. In areas with high demand (e.g., in blocks and at times where it is difficult to find a parking space), SF*park* charges a higher hourly parking rate to dampen demand. In areas with plentiful demand (e.g., in blocks and at times where it is easy to find parking), SF*park* charges a lower rate to increase 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, in order to track availability and evaluate changes in utilization that resulted from the new parking program. The sensor is a device designed to detect a parked vehicle and then transmit the occupancy data. The smart meter records transaction-level payment data and time intervals paid for by each commuter. The adoption of these two technologies enabled SF*park* to implement a data-driven pricing strategy on city parking.

The San Francisco Municipal Transportation Agency (SFMTA) designated seven parking management districts as SF*park* pilot areas. The pilot started in August 2011 and ended in June 2013. These pilot areas included 6,000 metered spaces, which amounts to roughly a quarter of the total metered parking spaces in San Francisco. 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 2011.

Here we provide the details of how SF*park* adjusts hourly parking rates dynamically based on observed occupancy rates. The program divides each parking day (Monday to Saturday) into three time windows during which commuters have to pay for on-street parking: 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. The occupancy rate is defined as the fraction of the total available time that a block is occupied, i.e., total occupied seconds divided by the sum of total vacant seconds and total occupied seconds. For instance, if a block with 6 parking spaces is occupied for 45360 seconds in a three-hour window, its average occupancy is $45360/(3600*6*3) = 70\%$.

SF*park* started tracking the occupancy rates of the designated pilot areas in April 2011, four months before the official start of the pilot program. The occupancy data during that period served as the basis for how prices would be adjusted when the pilot started in August 2011. SF*park* adjusted prices based on the following rules:

1. If the occupancy rate is between 80 and 100 percent, the hourly rate is raised by $0.25.
2. If the occupancy rate is between 60 and 80 percent, the hourly rate is not changed.
3. If the occupancy rate is between 30 and 60 percent, the hourly rate is lowered by $0.25.
4. If the occupancy rate is less than 30 percent, the hourly rate is lowered by $0.50.

In addition to street parking, SF*park* also adjusted the hourly rates of off-street parking locations (city-managed parking garages and lots) using similar rules:

1. If the occupancy rate is between 80 and 100 percent, the hourly rate is raised by $0.50.
2. If the occupancy rate is between 40 and 80 percent, the hourly rate is not changed.
3. If the occupancy rate is less than 40 percent, the hourly rate is lowered by $0.50.

Finally, SF*park* set an upper- and a lower-bound for the hourly rate—the rate could not exceed $6.00 per hour or go below $0.25 per hour. Over the course of the two-year period starting in August 2011, SF*park* made ten on-street rate adjustments and eight off-street rate adjustments according to these rules. This resulted in parking rate changes at a frequency of about every eight to twelve weeks. As a result of this program, parking rates vary by block, time of day, day of week and month. All SF*park* rate adjustments were announced in the program's website at least seven days before the changes went into effect.

3.2. Data

SF*park* made data available both before and after the implementation of congestion pricing in August 2011. In our analysis, we mainly used three datasets: parking sensor data, on-street meter payment data and off-street garage data. We discuss each dataset in detail.

Parking Sensor Data Parking sensor data consists of hourly block-level occupancy rates from April 2011 until June 2013. Starting late 2012, the sensor data became incomplete due to battery failures (sensor batteries reached their end of life)—dead batteries were not replaced. In addition, there was a sensor outage for the week of December 10-17, 2012. During that week, no data was recorded. While the geographical distribution of battery failures appears to be random, battery failures created significant noise in the data starting late 2012, as many block-hour occupancy rates were missing.

On-Street Meter Payment Data The on-street smart meter payment data contains all parking transactions starting in the first quarter of 2011.[4] The payment data is rich and includes the start and end time paid for in each transaction, the payment type (credit card, coin, smart card, pay by phone) and the transaction amount. The meter payment data is more reliable than the parking sensor data because it is not subject to battery failures. However, it is inaccurate to use meter payment data to infer availability, because drivers can park for longer or shorter periods than paid for or they can park illegally without paying at all. Therefore, as long as the sensors have not experienced massive failures, the sensor data is a more accurate source of occupancy rates. We therefore used the meter payment data to determine parking locations and durations, but not to infer occupancy rates.

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[4] The starting dates of payment data collection depend on the dates smart meters were installed and therefore differ between districts. However, all sensors were installed before April 1, 2011, when the parking sensor data first became available.

Off-Street Garage Data The off-street garage data contains usage data for publicly-owned garages. There are a total of 12250 parking spaces in the seven piloted districts, which amounts to 75 percent of the off-street spaces managed by the SFMTA. We observe transaction-level payment data that is as detailed as the meter payment data. However, the garage transaction data is not subject to illegal or under/overtime parking—drivers cannot leave the garage without paying, and payment is determined at the end of the parking period and is therefore based on actual parking time.

Data Construction Due to the increased occurrences of 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 following months: April to July 2011 (the before period), and the same months, April to July in 2012 (the after period). 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 (i.e., neither vacant nor occupied) and indicates the duration of the failure (in seconds). We exclude the "unknown" time from the calculation of occupancy rates. We focus on the time period during which commuters have to pay to park on the street, i.e., Monday through Saturday, 9am to 6pm.
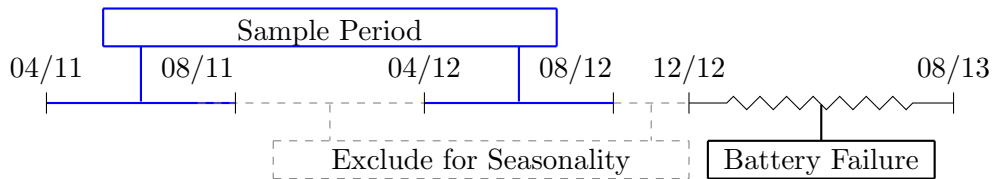
Figure 1   Timeline

The SFMTA extended the parking time limit in the pilot areas from 2 to 4 hours in late April, 2011.[5] To make fair comparisons, we exclude the days in April 2011 in which the parking time limit was only 2 hours. Due to the 4 hour on-street parking limit, commuters who needed to park their vehicles for longer than 4 hours must either park in garages or seek other transportation options. Only commuters who require short-term parking (less than 4 hours) consider parking on the street.[6] These commuters decide whether to start searching for on-street parking and choose

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[5] For the Fillmore, Marina, and Mission districts, the parking time limit changed from 2 hours to 4 hours on 04/25/11, 04/11/11 and 04/22/11, respectively.

[6] We acknowledge that there may be cases in which commuters park for longer periods of time, but return to add funds after parking for the maximum time allowed. However, we believe such behavior is rare in this case, as street parking is normally intended for short term parking and especially since the parking limit in this dataset has increased to 4 hours.

when to stop searching and park at a garage. Therefore, we exclude commuters who parked in a garage for more than 4 hours from our study. We do account for these commuters for garage occupancy rate calculations.

Given that we only have access to usage data of public-owned garages, not to privately-owned ones, we select only districts with limited numbers of private garages— the Fillmore, Marina and Mission districts. These districts have at most three private garages, and are neighborhoods mixed with both residential and shopping areas.

Table 1 presents the summary statistics of the hourly parking rates and occupancy rates for the three areas in the before and after periods. We divided the parking blocks to high, medium, and low-utilization blocks based on the average occupancy rates in the before period and according to the guidelines set by SF*park*: High utilization blocks are blocks averaging occupancy rates greater than 80%, medium utilization blocks are those averaging between 60% and 80%, and low utilization blocks are those averaging below 60%. During the before period, the parking rates were $2 per hour for all blocks at all times. The rates during the after period were adjusted according to the rules and became geographically dispersed. The mean parking rate increased by around 150% for high-utilization blocks, and decreased by between 40% - 70% for low-utilization blocks relative to the before period in the Fillmore and Marina districts. In the Mission district there were no blocks with utilization higher than 80% in the before period, and the parking rates at the low utilization rate decreased only slightly.[7] The rates at the parking garages also changed during the after period, and they either increased or decreased compared to the before period. 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 to shifts in demand as a response to congestion pricing.

4. The Structural Model

We use a two-stage structural model to analyze a commuter's choice to drive to her desired destination as well as her process of searching for a parking space. In the first stage, a commuter decides whether to drive to the destination or choose an outside option (e.g., stay at home or use other modes of transportation). A commuter decides whether to drive based on her value for the trip and her expected cost if driving. In the second stage, we model a commuter's search for parking using a dynamic model. We estimate the model using the SF*park* data. Our model allows for heterogeneity along multiple dimensions, including commuters' trip values, distance disutility, search costs, and price sensitivity.

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

We now describe the model in detail. As a commuter's first stage decision depends on her expectation of the total cost she would incur in the second stage, we start by explaining the dynamic search model (Stage II). We then describe the choice of whether to drive and the starting location (Stage I).

4.1. Stage II: Dynamic Search Model

We model a commuter's search for on-street parking as a dynamic optimal stopping problem. Commuter i with trip value v_i needs to find a parking space for t_i hours.[8] Each commuter i, has an ideal location b_i^*, which is her desired destination and the location she would like to park at if a parking space were available and absent of any costs. For example, the ideal location of a commuter whose trip purpose is to buy a new iPhone is next to the Apple store. However, a parking space at the ideal location may not be available, in which case the commuter will continue to search or park at the nearby garage.[9]

In particular, we assume that commuter i incurs two types of costs: (1) a search cost s_i, which is commuter i's per unit cost for each block searched while looking for a parking space, and (2) a distance disutility η_i, which is commuter i's per unit cost for parking one block away from the ideal location (e.g., her disutility from "walking" one additional block from the parked location to the ideal destination). In addition, each commuter has a price-sensitivity θ_i, which may affect her decision of where to park, with variable parking rates. Note that commuters are heterogenous in all of these dimensions.

Let $b_i(k)$ denote the block that commuter i arrives at after searching k blocks, and $d(b_i^*, b_i(k))$ denote the distance between her ideal location b_i^* and the block $b_i(k)$, which is measured by driving distance rather than Euclidean distance. If she decides to park there, she incurs the following costs: (1) search cost: she has searched for k blocks and therefore she incurs a total search cost of ks_i; (2) distance disutility: she needs to travel (e.g., "walk") a distance of $d(b_i^*, b_i(k))$ to get to her ideal location once parked. We assume that the disutility cost depends linearly on this distance and

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[8] While the choice of a parking location is endogenously determined in the model, we assume that demand for *parking time*, t_i, is exogenous. Even though parking time could presumably be endogenous (i.e., commuters choose to park for fewer hours when the parking rate is high), using the meter payment data we verify that the overall distribution of parking time did not change before and after the implementation of congestion pricing.

[9] In this model, we assume that commuters arrive to their ideal location and start searching from there. An alternative model lets commuters search *toward* their ideal locations (Weber 2010). However, the alternative model is problematic for at least two reasons. First, it assumes a commuter stops searching and incurs a large penalty cost if she finds parking unavailable at her ideal location, whereas commuters often continue searching when they drive past their ideal location. Second, estimating the alternative model would require identification of the ideal locations and the starting locations, which is infeasible with the data we have. We provide a detailed explanation in the identification section. We acknowledge that assuming that commuters start searching from their ideal location may be restrictive as well. Starting from the ideal location is more realistic if commuters do not have prior information about the occupancy rate of blocks. Therefore, in the full information counterfactual analyses, we let commuters choose their starting location, and allow them to be different from their ideal location.

therefore the total disutility cost commuter i incurs if parking at block $b_i(k)$ is $\eta_i d(b_i^*, b_i(k))$ and that $E[d(b_i^*, b(k))] \leq E[d(b_i^*, b(k+1))]$, so that a commuter is looking for a parking space away from her destination in *expectation*;[10] and (3) parking payment: she parks at block $b_i(k)$ for t_i hours and pays a total of $\theta_i p_{b_i(k)} t_i$, where $p_{b_i(k)}$ represents the hourly parking rate at block $b_i(k)$.

Commuter i looks for a parking space that minimizes her total costs. We can write the sequential search problem as a dynamic program. In particular, after searching for k blocks, a commuter decides whether to park or to continue searching. This decision depends on three state variables: (1) k, the number of blocks searched; (2) $A_{b_i(k)}$, a binary variable denoting the availability of the block arrived at after k searches, where $A_{b_i(k)} = 1$ if there is *at least* one parking spot available in block $b_i(k)$, and 0 otherwise; and (3) $p_{b_i(k)}$, hourly parking rate of the block arrived at after k searches. Note that $p_{b_i(k)}$ is constant across blocks in the case of fixed pricing. Let $f_i(b_i(k), p_{b_i(k)})$ denote commuter i's cost of parking at block $b_i(k)$,

$$f_i(b_i(k), p_{b_i(k)}) = \eta_i d(b_i^*, b_i(k)) + \theta_i p_{b_i(k)} t_i + \epsilon_{ik},$$

where ϵ_{ik} is the i.i.d. idiosyncratic disutility shock to commuter i at kth search, which follows standard type I extreme value distribution . Let $F_i(k, A_{b_i(k)}, p_{b_i(k)})$ denote commuter i's cost-to-go upon arriving at block $b_i(k)$ and observing availability $A_{b_i(k)}$ and price $p_{b_i(k)}$.

If commuter i finds the kth block unavailable, i.e., $A_{b_i(k)} = 0$, she needs to decide whether to stop searching and park at a nearby garage or continue to search the $(k+1)$th block for a parking space. If she stops searching and parks at the nearby garage located at block b_g, she incurs a total cost of $f_i(b_g, p_{b_g}) = \eta_i d(b_i^*, b_g) + \theta_i p_{b_g} t_i + \epsilon_{ig}$ (cost of driving to garage is negligible), where ϵ_{ig} is the idiosyncratic disutility shock to commuter i if she parks at the garage, and follows standard type I extreme value distribution as well. However, if she continues searching, she incurs the cost of searching for an additional block, s_i, and the expected cost-to-go $E[F_i(k+1, A_{b_i(k+1)}, p_{b_i(k+1)})]$.

If commuter i finds the kth block available, i.e., $A_{b_i(k)} = 1$, she needs to decide whether to park at that block and incur a cost of $f_i(b_i(k), p_{b_i(k)})$ or act as if it is not available, i.e. continue searching or park at the garage. Specifically,

$$F_i(k, 0, p_{b_i(k)}) = \min \begin{cases} f_i(b_g, p_{b_g}), \text{ park at garage} \\ s_i + E[F_i(k+1, A_{b_i(k+1)}, p_{b_i(k+1)})], \text{ keep searching} \end{cases}$$

[10] Note that the condition requires that after searching for one additional block, *in expectation* a commuter will get no closer to her ideal location. It is not a restrictive assumption given that it only needs to hold in expectation, but does not need to hold for every sample path. With simulated samples of 1000 commuters for each region under study, we verify that indeed only 0.6% to 1.2% of commuters would ever experience an decreasing distance to their ideal locations in expectation when searching from a particular block. Expected decreasing distances only happen only when commuters have searched for more than eight blocks and arrived at a boundary of the region.

$$F_i(k, 1, p_{b_i(k)}) = \min \begin{cases} f_i(b_i(k), p_{b_i(k)}), & \text{park on street} \\ F_i(k, 0, p_{b_i(k)}), & \text{keep searching or park at garage,} . \end{cases} \quad (1)$$

Note that $F_i(k, 0, p_{b_i(k))})$ does not actually depend on the price $p_{b_i(k))}$, so we can equivalently write $F_i(k, 0, p_{b_i(k))}) = F_i(k, 0)$. The following lemma derives several useful properties of the dynamic problem given in (1):

LEMMA 1. *The following properties hold: (i) $F_i(k, 0, p_{b_i(k)}) \leq f_i(b_g, p_{b_g})$ and is non-decreasing in k; and (ii) $F_i(k, 1, p_{b_i(k)}) \leq f_i(b_g, p_{b_g})$ and is non-decreasing in k.*

All proofs appear in the appendix.

Fixed Pricing Under fixed pricing, $p_{b_i k} = p$ for every block. The following proposition formalizes the solution to the dynamic problem under fixed pricing:

PROPOSITION 1. *Let $\phi = Pr(A_b = 1)$ be the probability to find at least one parking space available upon arrival at block b. Then, there exists a unique threshold, k_i^*, that defines the maximum number of blocks commuter i searches,*

$$k_i^* = \max \left\{ k : d(b_i^*, b_i(k)) \leq d(b_i^*, b_g) + \frac{\theta_i}{\eta_i}(p_{b_g} - p)t_i - \frac{s_i}{\eta_i}\frac{1}{\phi}, k = 1, 2, 3, ... \right\}. \quad (2)$$

Furthermore, commuter i's optimal action at the kth block, $a_i(k, A_{b_i(k)})$, satisfies,

$$a_i(k, 0) = \begin{cases} \text{keep searching,} & \text{if } k < k_i^* \\ \text{park at garage,} & \text{if } k = k_i^* \end{cases}$$

$$a_i(k, 1) = \begin{cases} \text{park at kth block,} & \text{if } k < k_i^* \\ \text{park at garage,} & \text{if } k = k_i^*. \end{cases}$$

Proposition 1 proves that the optimal stopping policy is a threshold policy, where commuter i will search for up to k_i^* blocks and park at the first block that she finds available. If after k_i^* searches, no block is available, she will park at the garage. The threshold k_i^* depends on commuter i's distance dis-utility η_i, search cost s_i, and price sensitivity θ_i. As is intuitive, the threshold is low if the search cost is high and the price sensitivity is low. The effect of distance disutility on the threshold is less clear and depends on the difference between two distances: the distance between the current and the ideal location and the distance between the ideal location and the parking garage. The threshold will also be low if the availability is low. Note that ϕ is not equivalent to one minus the observed occupancy rate, unless there is only one parking spot in the block. We discuss the details of how to estimate ϕ using an M/G/S/0 Erlang loss system in Section 5.2.1.

4.1.1. Congestion Pricing Under congestion pricing, the commuter faces a more complex decision process, as the following proposition suggests:

PROPOSITION 2. *There exists a unique threshold k_i^* and a series of prices, $p_i^*(k), k = 1, 2, ..., k_i^*$, such that commuter i's optimal action at the kth block, $a_i(k, A_{b_i(k)}, p_{b_i(k)})$, satisfies*

$$a_i(k, 0, p_{b_i(k)}) = \begin{cases} keep\ searching, & if\ k < k_i^* \\ park\ at\ garage, & if\ k = k_i^* \end{cases}$$

$$a_i(k, 1, p_{b_i(k)}) = \begin{cases} park\ at\ kth\ block, & if\ k < k_i^*, p_{b_i(k)} \le p_i^*(k) \\ keep\ searching, & if\ k < k_i^*, p_{b_i(k)} > p_i^*(k) \\ park\ at\ garage, & if\ k = k_i^*. \end{cases}$$

Furthermore, $p_i^*(k)$ is non-decreasing in k.

Again, the optimal stopping policy is a threshold policy, but it is a more complicated one: commuter i will search for at most k_i^* blocks. However, at the kth block, she will park only if the current block is available and if the hourly parking rate is below an acceptable threshold $p_i^*(k)$. As is intuitively appealing, the series of price, $p_i^*(k)$, is non-decreasing in k: a commuter is more likely to accept a high price closer to the end of the search, while in the early stages of search, she only accepts relatively low prices.

Under the threshold policy, the expected cost-to-go depends on the probabilities of several events occurring and is given by:

$$\begin{aligned} &E[F_i(k+1, A_{b_i(k+1)}, p_{b_i(k+1)})] \\ &= Pr\big(A_{b_i(k+1)} = 0\big) F_i(k+1, 0) \\ &+ Pr\big(A_{b_i(k+1)} = 1, p_{b_i(k+1)} > p_i^*(k+1)\big) F_i(k+1, 0) \\ &+ Pr\big(A_{b_i(k+1)} = 1, p_{b_i(k+1)} \le p_i^*(k+1)\big) E[f_i(b_i(k+1), p_{b_i(k+1)}) | A_{b_i(k+1)} = 1, p_{b_i(k+1)} \le p_i^*(k+1)] \end{aligned}$$

To explain, when commuter i arrives at the $(k+1)$th block, three scenarios can occur: (1) there is no available parking space, i.e., $A_{b_i(k+1)} = 0$, and therefore she incurs a cost of $F_i(k+1, 0, p_{b_i(k+1)})$; (2) there is a parking space available, but the parking rate is too high, i.e., $A_{b_i(k+1)} = 1, p_{b_i(k+1)} > p_i^*(k+1)$, and therefore she will incur a cost as if the block is unavailable, $F_i(k+1, 0, p_{b_i(k+1)})$; or (3) there is a parking space available and the parking rate is acceptable, i.e., $A_{b_i(k+1)} = 1, p_{b_i(k+1)} \le p_i^*(k+1)$, and therefore, she will park and incur a cost of $f_i(b_i(k+1), p_{b_i(k+1)})$. We assume commuters have rational expectations about the probability of each scenario and do not update their beliefs based on previous observations.

Heuristic Policy. To reduce the computational complexity of estimating a dynamic structural model with changing stopping criteria, we simplify the search process under congestion pricing by assuming that commuters adopt a fixed price threshold $p_i^* = p_i^*(k_i^*)$.[11] This heuristic is cognitively appealing for the commuter. It can be considered as the reservation price of commuter i and it is dependent on her price sensitivity and search cost, as we show below.

We now derive the optimal thresholds k_i^* and p_i^*. Commuter i's search for on-street parking continues as long as the cost of continued searching is no greater than the cost of parking at the garage. In other words, commuter i will search for up to k_i^* blocks such that

$$k_i^* = \max \left\{ k : d(b_i^*, b_i(k)) \leq d(b_i^*, b_g) + \frac{\theta_i}{\eta_i}\left(p_{b_g} - E[p|A=1, p \leq p_i^*]\right)t_i \\ -\frac{s_i}{\eta_i}\frac{1}{Pr(A=1, p \leq p_i^*)}, n = 1,2,3,... \right\} \tag{3}$$

At block k_i^*, commuter i chooses to park at the block when it is available as long as the observed price is no greater than the price threshold, i.e. $p_{b_i(k_i^*)} \leq p_i^*$, and park at the garage otherwise. That is, p_i^* satisfies

$$d(b_i^*, b_i(k_i^*)) + \frac{\theta_i}{\eta_i}p_i^* t_i = d(b_i^*, b_g) + \frac{\theta_i}{\eta_i}p_i(b_g)t_i \tag{4}$$

The next proposition shows how the thresholds change with the parameter values:

PROPOSITION 3. *The threshold k_i^* decreases in s_i and η_i, and increases in θ_i and t_i. The threshold p_i^* increases in s_i and decreases in θ_i and t_i. The disutility parameter η_i does not affect p_i^*.*

Note that the directional results of k_i^* are consistent with the findings under fixed pricing.

4.2. Stage I: Choice of Driving

Prior to searching for an on-street parking space, in stage I each commuter decides whether to drive or choose an outside option (e.g., travel by other means of transportation or not go at all). If a commuter chooses to drive to her destination, she may start searching from her ideal location or go directly to the garage. Suppose she starts from her ideal location, then she incurs an expected cost of:

$$C_i(b_i^*, b_i^*) = Pr\big(A_{b_i^*} = 0\big)E[F_i(1, 0, p_{b_i^*})|A_{b_i^*} = 0] \\ + Pr\big(A_{b_i^*} = 1, p_{b_i^*} > p_i^*\big)E[F_i(1, 0, p_{b_i^*})|A_{b_i^*} = 1, p_{b_i^*} > p_i^*] \\ + Pr\big(A_{b_i^*} = 1, p_{b_i^*} \leq p_i^*\big)E[f_i(b_i^*, p_{b_i^*})|A_{b_i^*} = 1, p_{b_i^*} \leq p_i^*]$$

[11] With this heuristic, the price threshold according to which the commuter will park is slightly higher than under the optimal stopping policy (they are equal at k_i^*). Therefore, compared to the optimal policy, with the heuristic, commuters will search less for better prices. As we show later, even with such a conservative assumption, we still observe that commuters searching for prices can contributes to a negative welfare change post congestion pricing.

If she starts from the garage, she incurs a cost of: $C_i(b_i^*, b_g) = f_i(b_g, p_{b_g})$ The commuter chooses the starting block b_i^o to minimize the total expected cost of driving,

$$b_i^o = \underset{b \in \{b_i^*, g\}}{\arg\min} C_i(b_i^*, b) \tag{5}$$

Let $C_i^*(b_i^*) = C_i(b_i^*, b_i^o)$. A commuter chooses to drive if her trip valuation minus the expected cost from driving is greater than the value of the outside option, which we normalize to 0. Therefore, commuter i drives if and only if

$$v_i - C_i^*(b_i^*) \geq 0.$$

5. Identification and Estimation

In this section, we discuss how we identify the primitive parameters using the SF*park* data as well as the details of estimation.

5.1. Identification

The primitives of the model that we wish to identify are the distribution of ideal location, the *joint* distribution of search cost, distance dis-utility and price sensitivity, and the distribution of trip valuation. We discuss the identification of each primitive.

5.1.1. Distribution of Ideal Locations
In the case of fixed pricing, a commuter will always park if the block she arrives at is available. Without capacity constraints, the observed demand is a direct mapping of the distribution of ideal locations. In the presence of capacity constraints, however, commuters are not always able to park at their ideal location because that block may not be available, which results in the need to search. The policy function in the case of fixed pricing yields predictions of the equilibrium of final parking locations, which allow us to infer the distribution of ideal locations using the moments of occupied times in the before period.

We now describe how we construct the moment conditions. There are two types of drivers who park at a block j: those whose ideal locations are indeed block j, and those whose ideal locations are not block j, but ended up parking there after searching. The latter are the commuters who discover all blocks they have arrived at before block j are full. Regardless of where their ideal locations are, what is common about these commuters is that 1) they all have arrived at an adjacent block j' to block j and find it unavailable; 2) they decided to continue searching and then arrived at block j, rather than giving up and parking at the garage after finding block j' unavailable.

We start with several definitions. We are interested in identifying the distribution of ideal locations at every hour t. That is, for every time t and for every block j, we are interested in the percentage of customers whose ideal location is j, denoted as g_{jt}^*. We define q_{jtd}^* as the total parking

minutes *demanded* (rather than observed) at block j as the ideal location in hour t on day d. It can be expressed as the product of 1) the total number of commuters who choose to drive in hour t on day d, $M_{td} = \sum_j q_{jtd} + q_{gtd}$; 2) the fraction of commuters whose ideal locations are j conditional on driving, which equals to the unconditional probability g_{jt}^*; and 3) the fraction of consumers whose ideal locations are j and also decide to start searching from j rather than directly parking at the garage, $\pi(\phi_{td}, d(j, g))$. Specifically,

$$q_{jtd}^* = M_{td} \cdot g_{jt}^* \cdot \pi(\phi_{td}, d(j, b_g)),$$

Note that $\pi(\cdot)$ is a function of the (expected) availability at time t and day d, ϕ_{td}, and the distance between block j and the garage b_g.

Observe that while the total parking minutes, q_{jtd}^*, is a function of expected average availability on day d, and therefore depends on d, we assume that the distribution of ideal locations, g_{jt}^*, is constant across all weekdays and across all weekends, respectively.

Furthermore, as explained above, due to capacity constraints, the parking time observed at a block is likely different than the parking time demanded. Specifically, the *observed* parking minutes at block j in hour t on day d, q_{jtd}, is the minimum between demand and capacity and is given by:

$$q_{jtd} = \min \left\{ q_{jtd}^* + \sum_{j': d(j',j)=1} \frac{1}{N_{j'}} \rho(\Delta d_{j',j}, \phi_{td}) h_{j'td}, \bar{q}_j \right\}, \ \forall j. \tag{6}$$

To explain, the second term in the minimum operator is the capacity (i.e., total parking minutes available) at block j. Note that while q_{jtd}^* and q_{jtd} may vary by hour and by day, capacity $\bar{q}_j$ is constant across time and day.

The first term in the minimum operator is the total parking minutes demanded at block j, time t and day d and includes both the demand at j of commuters for whom j is the ideal location and the demand of commuters for whom j is not the ideal location, but arrive at block j from an adjacent block of distance one, j', after searching. We denote the number of blocks adjacent to block j' by $N_{j'}$ and assume that a commuter who does not find the block j' available and decides to continue searching, instead of parking at the garage, will choose the next block randomly. That is, she arrives at block j with probability $\frac{1}{N_{j'}}$.

We then define $\rho(\Delta d_{j,j'}, \phi_{td})$ as the fraction of commuters who will decide to continue searching once they find block j' is full, rather than park at the garage, and is a function of the expected availability of a block ϕ_{td} and of the relative difference of distances, $\Delta d_{j',j} \equiv d(j', j) - d(j', b_g)$. To see this, let us examine the condition under which a commuter will continue searching. According to Equation (2), given $(s_i, \theta_i, \eta_i, t_i)$ and the ideal location j, whether commuter i continues to search

at block j' depends on the availability, ϕ, and the difference in distances, $\Delta d_{j,j'}$. Assuming that the distributions of the parameters $(s_i, \theta_i, \eta_i, t_i)$ are time-invariant, the fraction ρ will be a function of $\Delta d_{j,j'}$ and ϕ_{td} only. According to Equation (2), this fraction is larger when the garage is *relatively* further away from the ideal location and when the expected availability is high.

Finally, we define h_{jtd} as the unsatisfied demand at block j, time t and day d. h_{jtd} is expressed recursively:

$$h_{jtd} \equiv \max\{q^*_{jtd} + \sum_{j':d(j',j)=1} \frac{1}{N_{j'}} \rho(\Delta d_{j,j'}, \phi_{td}) h_{j'td} - \bar{q}_j, 0\}.$$

In addition to Equation (6), which expresses the observed parking minutes in block j, we can write the observed parking minutes at the garage, q_{gtd}, as:

$$q_{gtd} = \sum_j g^*_{jt}(1 - \pi(\phi_{td}, d(j,g))) M_{td} + \sum_j \sum_{d(j',j)=1} \left(1 - \rho(\Delta d_{j,j'}, \phi_{td})\right) h_{jtd}, \tag{7}$$

The observed parking minutes at the garage is composed of the demanded minutes of consumers who decide not to search for on street parking and immediately go to the garage (the first term) and from consumers who do not find a parking space at block j, and decide to drive to the garage instead of continuing to search at any of the adjacent blocks j' of any block j (the second term).

Solving the system of equations (6) and (7), we are able to back out the distribution of ideal locations g^*, the function $\rho(\cdot)$, which is approximated using a polynomial function of ϕ_{td} and $\Delta d_{j,j'}$, and the function $\pi(\cdot)$, which is approximated using a polynomial function of ϕ_{td} and $d(j, b_g)$. Note that the functions and parameters are identified because we have multiple days during a month, and our system of equations is observed daily, except on Sundays when parking is free.

Note that we are not able to identify the distribution of ideal locations using the same strategy in the case of congestion pricing because commuters may not park at a block with prices exceeding their reservation price, even if they find a space available. We assume that, for the same calendar month, the distribution of ideal locations in the after period in 2012 is the same as in the before period in 2011. That is, we allow the total number of commuters to vary, but require that the distribution remains the same in the before and after periods. The months included in the before and after periods are the same, so while the total market size may differ, it's unlikely that the distribution of ideal locations varies significantly.

5.1.2. Distributions of Commuter Attributes and Trip Valuations The model maps commuters' attributes to their final parking locations, and the moments of the final locations allow us to identify the joint distribution of these attributes.

Note that we can always divide both sides of the policy functions by any of the three parameters, i.e., s_i, θ_i, η_i, without changing commuters' decisions. That is, the three parameters, s_i, θ_i and η_i are

not separately identifiable. In our estimation, we normalize the parameter η_i, and identify the two ratios, $\frac{\theta_i}{\eta_i}$ and $\frac{s_i}{\eta_i}$, using the variations in price and availability.[12] The intuitions are the following. If commuters are very price sensitive, we expect more commuters to park at blocks with lower prices in the after period under congestion pricing compared to the before period under fixed pricing. Similarly, if commuters have high search costs, we expect to observe that more commuters park closer to their ideal locations. The difference between the distribution of ideal locations and that of the final parking locations identifies the distribution of search costs.

We identify the distribution of trip valuations by tracking how the total number of commuters who drive varies with the expected availability. The higher a commuter's valuation for the trip, the more likely a commuter will drive on a congested day.

5.2. Estimation

Next, we discuss how we estimate 1) the probability that a block is available, ϕ, from the observed occupancy rate; 2) the distribution of ideal locations; 3) the *joint* distribution of commuter search cost, price sensitivity and distance disutility; 4) and the distribution of trip valuations.

5.2.1. Availability

The availability of a block, ϕ, is defined as the probability of finding at least one empty parking space in a block. Note that while the occupancy rates can be easily derived from the sensor data, it is not an accurate measure of availability. To explain, consider two blocks that have the same occupancy rate, but different capacity levels (i.e., different number of parking spaces). The block with the higher capacity has a higher availability than the block with the lower capacity, even though both have the same occupancy rates. In other words, keeping the occupancy rate constant, the probability of finding an available parking space is higher in blocks with more parking spaces.

To derive an accurate measure of availability from the occupancy rate data, we model the parking process as an M/G/s/0 Erlang loss system, where s is number of servers (parking spaces in a block) and 0 is the maximum number of cars waiting and therefore denotes a loss system. Approximating the parking process as an Erlang loss system allows us to derive the availability as a function of the occupancy rate and the number of parking spaces in a block. According to an Erlang loss formula, the probability that a car arriving to an M/G/s/0 system finds at least one parking spot available, and therefore is not "lost," is:

$$\phi = 1 - \frac{\frac{(\frac{\lambda}{\mu})^s}{s!}}{\sum_{k=0}^{s} \frac{(\frac{\lambda}{\mu})^k}{k!}}, \tag{8}$$

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[12] η_i is normalized to 10 for the purpose of presentation. It can be normalized to any other positive value.

where λ is the commuter arrival rate, i.e., the rate at which drivers are arriving at a block looking for parking, and μ is the service rate that can be translated from the average parking time. The effective, or actual, arrival rate, $\hat{\lambda}$ can be expressed as $\hat{\lambda} = \phi\lambda$, and can also be inferred using occupancy rate $OccRate$ observed from the data. That is,

$$\hat{\lambda} = \phi\lambda = OccRate \cdot s \cdot \mu, \tag{9}$$

The second equality follows from Little's Law, the average number of parked cars in a block, $OccRate \cdot s = \hat{\lambda}/\mu$. We solve equations (8) and (9) numerically to obtain the hourly block-level availability, ϕ.

5.2.2.   Distribution of Ideal Locations We now estimate the distribution of ideal locations. We solve the moment condition in the before period with the least squared estimator:

$$m_1(g_{jt}^*, \rho(\cdot), \pi(\cdot)) = E\left[q_{jtd} - \hat{q}_{jtd}\big(g_{jt}^*, \rho(\cdot), \pi(\cdot)\big)\right] = 0, \forall j, t, d \tag{10}$$

where q_{jtd} are the *observed* parking minutes for block j in hour t on day d, while $\hat{q}_{jtd}$ are the *predicted* demanded minutes for block j in hour t on day d, given the distribution of ideal locations g_{jt}^*, the functions $\rho(\cdot)$ and $\pi(\cdot)$. We choose a flexible functional form for $\rho(\cdot)$ and $\pi(\cdot)$. Specifically, we use the following second-order approximation:

$$\rho(\Delta d_{j,j'}, \phi_{td}) \approx \beta_0 + \beta_1\phi_{td} + \beta_2\Delta d_{j,j'} + \beta_3\phi_{td}\Delta d_{j,j'} + \beta_4\phi_{td}^2 + \beta_5\Delta d_{j,j'}^2 \tag{11}$$

$$\pi(\phi_{td}, d(j, b_g)) \approx \gamma_0 + \gamma_1\phi_{td} + \gamma_2 d(j, b_g) + \gamma_3\phi_{td}d(j, b_g) + \gamma_4\phi_{td}^2 + \gamma_4 d^2(j, b_g) \tag{12}$$

We then solve for the moment conditions in Equation (10). The error terms have mean zero at the true vector of distribution g_{jt}^*, function $\rho(\cdot)$ and function $\pi(\cdot)$. This allows us to non-parametrically estimate the distribution of ideal locations.

5.2.3.   Commuter Attributes and Trip Valuation Once we obtain estimates of the distribution of ideal locations, we can simulate the parking location for each profile of parameters $(s_i, \theta_i, \eta_i, t_i, v_i)$, which can then be aggregated to compute the total parking demand for each block.

We specify the joint distribution of search cost and price sensitivity to follow a multivariate log normal distribution $lnN(\mu_{s,\theta}, W_{s,\theta})$, and the distribution of trip valuation to follow a normal distribution $N(\mu_v, \sigma_v)$. Let $\omega = \{\mu_{\{s,\theta\}}, W_{\{s,\theta\}}, \mu_v, \sigma_v\}$. We choose a sufficiently large market size for each district[13] and recover the primitives of the model from mapping the *observed* parking minutes

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[13] The hourly market size in the estimation is 500 commuters for Marina, 800 commuters for Fillmore, and 1000 commuters for Mission.

q_{jtd} to the simulated parking minutes $\hat{q}_{jtd}$, as well as mapping the *observed* number of commuters who drive M_{jtd} to the simulated number of commuters who drive $\hat{M}_{jtd}$. If the model is correctly specified, the error terms have mean zero at the true parameter vector ω_0:

$$m_2(\omega_0) = E\left[\begin{array}{c} q_{jtd} - \hat{q}_{jtd}(\omega; g^*) \\ M_{jtd} - \hat{M}_{jtd}(\omega; g^*) \end{array}\right] = 0 \tag{13}$$

Our reliance on simulation motivates the choice of Simulated Method of Moments estimators over maximum likelihood estimators, which are highly nonlinear in search probabilities. The variance-covariance matrix and the standard errors are calculated numerically. Appendix E contains a more detailed discussion of our estimation procedure.

6. Results

Table 2 displays the summary statistics of the availability for high-, medium-, and low-utilization blocks during our sample periods. Recall that availability is defined as the probability that a commuter will find at least one parking spot available at a given block. We note the directional changes in availability are consistent with the changes in occupancy rates as shown in Table 1, but the magnitude of change is different, because the availability also depends on the number of parking spaces in each block, as explained previously. The pattern of changes in availability before and after the implementation of congestion pricing illustrates the geographical re-distribution of demand: high-utilization blocks experienced an increase in availability due to the higher prices charged at those blocks, while low utilization blocks experienced a decrease in availability due to the lower prices charged at those blocks.

The estimation results are shown in Table 3. Recall that our estimation contains two parts: we first estimate the distribution of ideal locations using data from the before period, and then estimate the model parameters (commuter attributes and trip valuations) using data from both before and after periods. Appendix F contains the detailed estimation results of the distribution of ideal locations for each district under study. The R-squares of ideal location estimation are reported at the bottom of Table 3 (58.75%, 51.11% and 53.36%, for each region respectively). Table 3 also shows the estimates of the joint distribution of commuter attributes and the distribution of trip valuations for each district. The estimates are similar across the three districts we analyzed. In order to understand the meaning of these estimated values, we convert all parameter estimates into dollar values based on the estimates of price sensitivty. The average cost incurred from searching one additional block is approximately $0.5. The average cost incurred from walking for one additional block is slightly higher than search cost, at around $0.6. Relative to the outside option, the value

of which is normalized to zero, the trip valuation has an average of \$3 and a standard deviation of \$1.2. As expected, the correlations between price sensitivity and search cost are negative. That is, less price sensitive customers also value their time more (i.e., dislike searching).[14] The R-squares from this stage of estimation is shown at the bottom of the table (50.88%, 44.77% and 44.24%, respectively).

We then use the estimates in Table 3 to quantify the effect of congestion pricing on consumer welfare and compare the changes in trip valuation and incremental costs incurred from parking. In calculating the welfare effects for commuters, we take into account the utility obtained by those commuters who chose the outside option. Therefore, consumer welfare W is defined as

$$W = \sum_i \frac{1}{\theta_i}\big(v_i - c_i N_i - \eta_i d(b_i^*, b_i(N_i)) - \theta_i p_{b_i(N_i)} t_i\big) \mathbb{1}\{v_i \geq C_i^*(b_i^*)\}$$

where N_i denotes number of searches the commuter has made before finding a parking space, $b_i(N_i)$ denotes the final parking location for commuter i. Following the convention in the literature, we scaled welfare by price sensitivity θ_i to normalize it to dollar values.

Our results show that consumer welfare increased in Fillmore and Marina but decreased in Mission. We now explain why it is the case. In Fillmore and Marina, even though the higher prices in high-utilization areas increase payments, consumer welfare still increases. Three reasons contribute to this increase. First, the total distance cost decreased. As a result of the improved availability of popular blocks under congestion pricing, commuters are now able to park closer to their ideal locations when they really need to. Even though some consumers may have to park further away because of their aversion to higher prices, the overall distance cost decreases in both Fillmore and Marina.

Second, the total search cost decreased. Congestion pricing may have two effects on search. While it reduces availability-based searching because highly desired parking spots become more available, it also introduces price-based searching, especially when prices are highly dispersed geographically as shown in Figure 2. The added fraction of consumers who search due to price dispersion is almost equal to the reduction in the fraction of consumers who search for availability (2 to 3%). However, because price-sensitive consumers tend to have lower search costs, the total search cost in Fillmore and Marina still decreased.

Finally, the total trip valuation increased. As a result of the better availability achieved by congestion pricing, more commuters find driving and parking on-street is a more appealing option than the outside option, so more commuters decided to drive to their destinations. The gains from

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[14] To be precise, given that we normalize the distance disutility η_i, the correlation we estimate here is the correlation between $\frac{s_i}{\eta_i}$ and $\frac{\theta_i}{\eta_i}$.

the reduced distance disutility and search cost and increased total trip valuation more than offset the increased payments, resulting in the overall increase of consumer welfare in both districts.

On the contrary, we found that consumer welfare decreases in Mission. Similar to Fillmore and Marina, commuters pay more for parking with congestion pricing. However, in Mission congestion pricing did not result in a significant improvement in availability since the availability in the Mission was already high prior to the implementation of congestion pricing (0.97 vs. 0.79 and 0.78 in Fillmore and Marina). The additional search resulting from price dispersion outweighed the decreased search from availability. The total search costs actually increased. Moreover, congestion pricing led to an increase in distance costs: with fixed pricing, 98% of the consumers parked at their ideal locations because of the already high availability. After congestion pricing, however, some commuters actually parked further away from their ideal location, either because they were searching for lower prices or because the availability in low-utilization blocks decreased significantly. Finally, because of the increased search costs, distance costs and payment, fewer commuters choose to drive, which resulted in a decrease in total trip valuation. Together with increased total payments, this leads to a decrease in consumer welfare for Mission after congestion pricing was introduced.

The welfare results have two main implications. First, implementation of congestion pricing in non-congested areas (such as the Mission) may actually hurt consumer welfare. Second, congestion pricing may result in consumers searching for better prices when prices are dispersed geographically — there were twenty or more price levels in a district at any given time during our sample period. Furthermore, the frequent SF*park* price adjustments (every 8 to 10 weeks) made the price structure even more complicated. Commuters' confusion about prices resulted in more people searching for lower prices while giving up available parking spots. Besides the direct impact on consumer welfare, such behavior also generates a negative externality by causing more traffic, which may further decrease the attractiveness of congestion pricing.

7.   Counterfactual Analysis

The granular and periodical rate adjustments by SF*park* have induced an unnecessary confusion with prices, especially when prices are updated dynamically and highly dispersed geographically, across time of day and day of week. Even though price adjustments are announced in advance, commuters do not seem to have accessed such information. Based on a survey conducted following the congestion pricing program, 81.8% of the 1584 respondents who parked on street answered that they are unaware of the ways to get information to help them park. Even among those who responded that they were "aware" that the information is available, 83.6% responded that they

either never or rarely accessed the information that are available on multiple channels, including 511.org phone and website, SF*park* APP and website and other.

We examine whether a simpler parking rate structure would actually lead to an increase in consumer welfare. To quantify the benefit, we first calculate the consumer welfare that could be achieved given the current complex parking rate structure but consumers have full price information. While we believe that the welfare derived in the full price information case is unachievable, it can used as a benchmark. We then calculate the consumer welfare achieved with a simpler three-tier price structure and compare it to the status quo and to the full price information benchmark.

7.1. Full Information

We first consider the case when commuters are fully informed about the hourly parking rate, i.e., commuters know the exact price for every single block in the district. With full information, commuters will not search on price anymore because they already know whether they would be willing to accept the price before arriving at the block. If they are not willing to accept the price of a block, they would even not drive there. Moreover, with full price information, consumers will also be able to derive rational expectations on the availability of a block based on the price charged. Under such assumptions, consumers would even choose to start from a location that is different from their ideal location, if the expected cost is lower due to either low price or better availability.

We apply the following procedure to calculate the new equilibrium under full price information. Given certain belief about availability at each block, a commuter decides whether to drive, where to start searching, and how many blocks she's willing to search before parking at the garage, as in the model presented in Section 4 except for that the availability ϕ is now block specific. Given each commuter's decision, we could simulate occupancy levels at each block and then use the Erlang loss formula in Section 5.2.1 to calculate availability. We thus solve for the equilibrium availability recursively.

In Table 5, we report the consumer welfare obtained with full price information. Compared with the baseline results shown in Table 4, consumer welfare improves in all the three districts. This increase is mostly driven by the fact that consumers no longer search for prices upon arrival. We see that the total fraction of consumers who search decreases significantly, which leads to a decrease in total search costs, especially for the Fillmore and Marina where prices are highly dispersed. While the consumer welfare change pre and post congestion pricing is positive in Fillmore and Marina, it remains negative in Mission even with full price information. To explain why it is the case, we note that although the availability in medium-utilization blocks increased, the availability in low-utilization blocks decreased significantly. As a result, the decreased search cost in medium-utilization blocks is dominated by the increased search cost in low-utilization blocks, and the

total search cost increased. This happened in Mission but not in Fillmore or Marina because low-utilization blocks represent a significantly larger proportion of the entire Mission district compared to the other districts — 88 out of 261 spaces (33.7%) in Mission, compared to 138 out of 714 spaces (19.3%) in Fillmore and 62 out of 319 spaces (19.4%) in Marina as shown in Table 2. This reinforces our previous conclusion that implementing congestion pricing in non-congested regions such as the Mission may harm consumer welfare.

7.2. Three-Tier Price Structure

Of course, it is unreasonable to expect that consumers know the prices charged at all blocks in all districts at all times. We therefore examine a simpler pricing policy where there are only three price levels, each corresponds to the high, medium, and low-utilization blocks, respectively. To simplify the analysis and allow for a fair comparison, we set each of the three price levels equal to 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 availability under the three-tier rate structure similarly as we did for the full price information case, and report consumer welfare in Table 6. The results from this counterfactual analysis suggest that adopting a simpler three-tier parking rate scheme can achieve a higher consumer welfare for all three districts compared to the complex congestion pricing policy that is currently in place. We then compare the increase in consumer welfare with that achieved by full price information and find that the three-tier price scheme can capture more than 50% of the increase in consumer welfare relative to the full price information, as seen in Table 7.

These results illustrate that a simple pricing scheme, that is not too complex cognitively for commuters, has two benefits: it is good at controlling congestion and at the same time does not require consumers to search extensively for a low price. It thus balances the two types of search and generates higher consumer welfare.[15]

8. Conclusion

Congestion pricing is often considered to be an effective tool to match demand with supply. With data from SF*park*, we find that congestion pricing indeed helps to increase parking availability in congested areas, which reduces searching and allows commuters to park closer to their destination when they really need to. These benefits outweigh the increased payment and lead to an overall increase in consumer welfare.

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[15] As we noted above, for simplicity, we set the three prices equal to the average prices of the current policy according to utilizations. The three-tier pricing policy could be improved further, if the three prices were chosen optimally to maximize consumer welfare.

On the other hand, we also find that cities should be cautious when implementing congestion pricing in non-congested areas, and perhaps should consider design their pricing rules differently. In one of the district under study, congestion pricing impacted consumer welfare negatively. Before congestion pricing, the majority of the commuters (98%) already parked at their ideal locations without searching. After congestion pricing, they ended up searching more, parked further and paid more. This is partially due to the increased searching due to price dispersion. However, even if we allow consumers to have perfect information about prices, congestion pricing still hurt consumer welfare in Mission. This is because there was no high utilization blocks in the district but only medium and low-utilization blocks, therefore, the low utilization blocks represent a significant portion of the district. The reduced availability in low-utilization blocks thus dominates the mildly increased availability in medium-utilization blocks, leading to worse parking conditions on average.

We also note that cities implementing congestion pricing policies should be mindful of unnecessarily complicated pricing rules. Even though congestion pricing is intended to reduce search and traffic, it may actually unintentionally introduce another type of search. When prices are dispersed geographically, consumers may choose to bypass available but expensive parking spots hoping to find lower priced ones. Therefore, even though more sophisticated pricing policies may result in better availability across all blocks, the overall result may not always be desirable to consumers. Thus, to achieve the best welfare outcome, it is important to balance the desired availability targets with the complexity of the pricing policy.

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<div align="center">**Table 1   Descriptive Statistics**</div>

	Rate		Occupancy		Number of Blocks
	Before April July 2011	After April July 2012	Before April July 2011	After April July 2012	
Fillmore	2.00 (0.00)	2.23 (-0.93)	0.72 (0.19)	0.70 (0.19)	45
High	2.00 (0.00)	3.21 (0.38)	0.85 (0.14)	0.81 (0.17)	13
Mid	2.00 (0.00)	2.02 (0.83)	0.69 (0.16)	0.67 (0.17)	25
Low	2.00 (0.00)	1.41 (0.57)	0.56 (0.18)	0.58 (0.20)	7
Garage	2.00 (0.00)	2.22 (0.41)	0.26 (0.12)	0.23 (0.14)	1
Marina	2.00 (0.00)	2.36 (0.85)	0.75 (0.16)	0.74 (0.16)	19
High	2.00 (0.00)	3.24 (0.45)	0.83 (0.11)	0.81 (0.12)	6
Mid	2.00 (0.00)	2.51 (0.71)	0.75 (0.14)	0.74 (0.14)	10
Low	2.00 (0.00)	1.00 (0.77)	0.56 (0.16)	0.57 (0.16)	3
Garage	2.50 (0.00)	1.72 (0.40)	0.14 (0.05)	0.19 (0.05)	1
Mission	2.00 (0.00)	2.29 (0.74)	0.63 (0.18)	0.69 (0.18)	25
High	- -	- -	- -	- -	0
Mid	2.00 (0.00)	2.46 (0.74)	0.65 (0.17)	0.70 (0.17)	6
Low	2 (0.00)	1.97 (0.78)	0.56 (0.19)	0.64 (0.17)	19
Garage	2.11 (0.00)	2.00 (0.41)	0.07 (0.01)	0.19 (0.05)	2

[*] 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.

Table 2   Statistics of Availability

	Availability		Number of Spaces
	Before April July 2011	After April July 2012	
Fillmore	0.79 (0.27)	0.81 (0.26)	714
High	0.51 (0.32)	0.60 (0.33)	93
Mid	0.90 (0.13)	0.91 (0.14)	483
Low	0.90 (0.18)	0.85 (0.23)	138
Garage	1.00 (0.00)	1.00 (0.00)	920
Marina	0.78 (0.25)	0.80 (0.25)	319
High	0.64 (0.31)	0.67 (0.32)	95
Mid	0.82 (0.19)	0.84 (0.18)	162
Low	0.97 (0.07)	0.96 (0.06)	62
Garage	1.00 (0.00)	1.00 (0.00)	205
Mission	0.97 (0.06)	0.95 (0.12)	261
High	- -	- -	0
Mid	0.97 (0.06)	0.93 (0.11)	173
Low	0.99 (0.05)	0.98 (0.74)	88
Garage	1.00 (0.00)	1.00 (0.00)	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.

Table 3   Model Estimates

	Fillmore	Marina	Mission
Search cost (log scaled) mean	2.21	2.14	2.18
	(0.28)	(0.36)	(0.37)
Search cost (log scaled) standard deviation	0.71	0.64	0.54
	(0.05)	(0.09)	(0.07)
Price sensitivity (log scaled) mean	2.79	2.70	2.77
	(0.54)	(0.45)	(0.28)
Price sensitivity (log scaled) standard deviation	0.93	1.09	1.02
	(0.17)	(0.07)	(0.08)
Trip valuation mean	52.52	46.02	54.54
	(1.21)	(1.45)	(2.12)
Trip valuation standard deviation	21.05	22.85	19.93
	(0.93)	(1.53)	(0.72)
Price sensitivity (log scaled) $\times$ Search cost (log scaled)	-0.65	-0.84	-0.67
	(0.27)	(0.26)	(0.15)
Search cost dollar value	$0.56	$0.57	$0.54
Distance cost dollar value	$0.61	$0.67	$0.63
Trip Valuation dollar value	$3.32	$3.08	$3.42
R-square (ideal location estimation)	0.5875	0.5111	0.5336
R-square (parameter estimation)	0.5083	0.4477	0.4424

Table 4   Consumer Welfare

	Fillmore		Marina		Mission	
	Before	*After*	*Before*	*After*	*Before*	*After*
Search Cost	92.49	77.46	144.48	124.45	12.09	14.65
Distance Cost	42.76	34.15	57.56	45.46	5.68	8.64
Payment	91.56	98.75	72.76	90.41	82.60	88.35
Trip Valuation	620.07	628.26	768.27	774.06	694.10	683.43
Welfare Change	+24.64		+20.27		-21.94	
Go with Car (%)	70	72	69	72	77	73
Search on Availability (%)	14.97	12.69	14.06	11.43	2.55	2.20
Search on Price (%)	0.00	1.98	0.00	2.28	0.00	0.60

* Consumer welfare is normalized to dollar value at the size of a hundred commuters.

Results are based on 50 rounds of simulations.

Table 5   Consumer Welfare with Full Information

	Fillmore		Marina		Mission	
	Before	*After*	*Before*	*After*	*Before*	*After*
Search Cost	92.49	68.44	144.48	105.84	12.09	14.07
Distance Cost	42.76	47.75	57.56	63.12	5.68	10.45
Payment	91.56	76.87	72.76	73.22	82.60	88.54
Trip Valuation	620.07	641.89	768.27	784.40	694.10	699.58
Welfare Change	+55.57		+48.75		-7.21	
Go with Car (%)	70	82	69	77	77	79
Search on Availability (%)	14.97	10.38	14.06	10.85	2.55	2.05
Search on Price (%)	0.00	0.00	0.00	0.00	0.00	0.00

* Consumer welfare is normalized to dollar value at the size of a hundred commuters.

Results are based on 50 rounds of simulations.

|	Table 6	Consumer Welfare with Three-Tier Price Structure				
	Fillmore		**Marina**		**Mission**	
	Before	*After*	*Before*	*After*	*Before*	*After*
Search Cost	92.49	68.03	144.48	114.38	12.09	14.11
Distance Cost	42.76	31.36	57.56	44.73	5.68	5.43
Payment	91.56	95.87	72.76	85.46	82.60	91.95
Trip Valuation	620.07	630.47	768.27	776.19	694.10	690.73
Welfare Change	+41.95		+38.15		-14.49	
Go with Car (%)	70	73	69	72	77	75
Search on Availability (%)	14.97	11.63	14.06	11.57	2.55	2.15
Search on Price (%)	0.00	0.00	0.00	0.00	0.00	0.00

* Consumer welfare is normalized to dollar value at the size of a hundred commuters.

Results are based on 50 rounds of simulations.

Table 7   Consumer Welfare Change from Full Price Information vs. Three-Tier Price Structure

	Fillmore	Maria	Mission
Welfare change (full price information - current)	30.93	28.48	14.73
Welfare change (three-tier pricing - current)	17.31	17.88	7.45
Relative welfare change (three-tier to full price information)	55.97%	62.78%	50.58%

* Consumer welfare is normalized to dollar value at the size of a hundred commuters. Results are

based on 50 rounds of simulations.
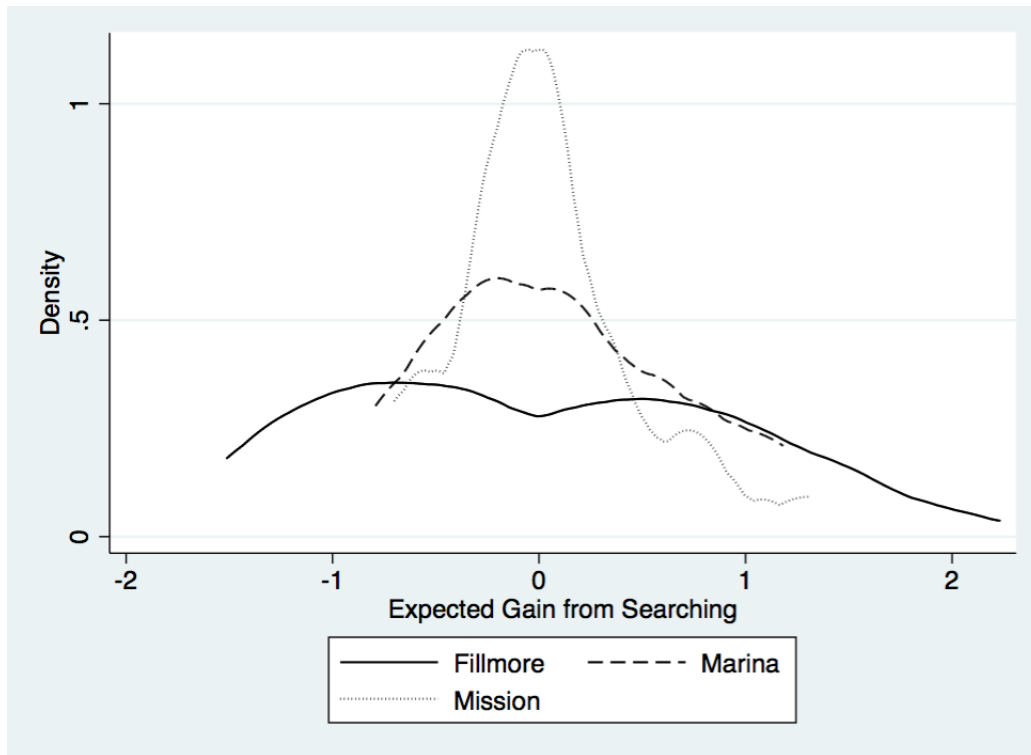
Figure 2   Expected Gain on Price from Searching

Table 8   Index of Blocks

	Marina				
1	AVILA ST 0	8	Marina ST 3300	15	PIERCE ST 3200
2	CHESTNUT ST 2000	9	LOMBARD ST 2000	16	PIERCE ST 3300
3	CHESTNUT ST 2100	10	LOMBARD ST 2100	17	SCOTT ST 3200
4	CHESTNUT ST 2200	11	LOMBARD ST 2200	18	SCOTT ST 3300
5	CHESTNUT ST 2300	12	LOMBARD ST 2300	19	STEINER ST 3300
6	CHESTNUT ST 2400	13	LOMBARD ST 2400		
7	DIVISADERO ST 3200	14	MALLORCA WAY 0		

	Fillmore				
1	BUCHANAN1800	16	FILLMORE2000	31	POST1700
2	CALIFORNIA2300	17	FILLMORE2100	32	POST1800
3	CALIFORNIA2400	18	FILLMORE2200	33	POST1900
4	CLAY2400	19	FILLMORE2300	34	SACRAMENTO2400
5	CLAY2500	20	FILLMORE2400	35	SACRAMENTO2500
6	FILLMORE1000	21	GEARY1500	36	STEINER1500
7	FILLMORE1100	22	GEARY1600	37	SUTTER1800
8	FILLMORE1200	23	GEARY1700	38	SUTTER2000
9	FILLMORE1300	24	GEARY1800	39	WASHINGTON2400
10	FILLMORE1400	25	JACKSON2300	40	WASHINGTON2500
11	FILLMORE1500	26	JACKSON2400	41	WEBSTER1500
12	FILLMORE1600	27	LAGUNA1500	42	WEBSTER1600
13	FILLMORE1700	28	LAGUNA1600	43	WEBSTER2100
14	FILLMORE1800	29	PINE2300	44	WEBSTER2200
15	FILLMORE1900	30	POST1600	45	CALIFORNIA902

	Mission				
1	16TH ST 3000	10	BARTLETT ST 0	19	VALENCIA ST 600
2	16TH ST 3100	11	MISSION ST 2000	20	VALENCIA ST 700
3	17TH ST 3300	12	MISSION ST 2100	21	VALENCIA ST 800
4	18TH ST 3400	13	MISSION ST 2200	22	VALENCIA ST 900
5	19TH ST 3400	14	MISSION ST 2300	23	VALENCIA ST 1000
6	20TH ST 3500	15	MISSION ST 2400	24	VALENCIA ST 1100
7	21ST ST 3200	16	MISSION ST 2500	25	VALENCIA ST 1200
8	22ND ST 3200	17	VALENCIA ST 400		
9	23RD ST 3300	18	VALENCIA ST 500		

Appendix

A. Proof of Lemma 1

(i) First, observe that $F_i(k, 0, p_{b_i(k)}) \leq f_i(b_g, p_{b_g})$ holds by definition. To prove that $F_i(k, 0, p_{b_i(k)})$ is non decreasing in k, note that we can write:

$$F_i(k+1, 0, p_{b_i(k)}) - F_i(k, 0, p_{b_i(k)})$$

$$\geq s_i + E[F_i(k+1, A_{b_i(k+1)}, p_{b_i(k+1)})] - s_i + E[F_i(k, A_{b_i(k+1)}, p_{b_i(k+1)})]$$

$$= A \cdot [F_i(k+1, 0, p_{b_i(k+1)}) - F_i(k, 0, p_{b_i(k+1)})]$$

$$+ B \cdot [F_i(k+1, 0, p_{b_i(k+1)}) - F_i(k, 0, p_{b_i(k+1)})]$$

$$+ C \cdot \eta_i [d(b_i^*, b_i(k+1)) - d(b_i^*, b_i(k))]$$

where

$$A = Pr\left(A_{b_i(k+1)} = 0\right) = Pr\left(A_{b_i(k)} = 0\right)$$

$$B = Pr\left(A_{b_i(k+1)} = 1, p_{b_i(k+1)} > p_i^*(k+1)\right) = Pr\left(A_{b_i(k)} = 1, p_{b_i(k)} > p_i^*(k)\right)$$

$$C = Pr\left(A_{b_i(k+1)} = 1, p_{b_i(k+1)} \leq p_i^*(k+1)\right) = Pr\left(A_{b_i(k)} = 1, p_{b_i(k)} \leq p_i^*(k)\right)$$

Then, it follows that

$$(1 - A - B)[F_i(k+1, 0, p_{b_i(k)}) - F_i(k, 0, p_{b_i(k)})] \geq C \cdot \eta_i [d(b_i^*, b_i(k+1)) - d(b_i^*, b_i(k))] \geq 0 \tag{14}$$

Since A, B, C are probabilities, it must hold that $0 \leq C \leq 1$ and $0 \leq A + B \leq 1$, and therefore the above inequality implies

$$F_i(k+1, 0, p_{b_i(k)}) - F_i(k, 0, p_{b_i(k)}) \geq 0$$

(ii) Observe that $F_i(k, 1, p_{b_i(k)}) \leq f_i(b_g, p_{b_g})$ holds by definition. To prove that $F_i(k, 1, p_{b_i(k)})$ is non decreasing in k, note that we can write:

$$F_i(k+1, 1, p_{b_i(k+1)}) - F_i(k, 1, p_{b_i(k)}) \geq f_i(b_i(k+1), p_{b_i(k)+1}) - f_i(b_i(k), p_{b_i(k)})$$

$$= \eta_i d(b_i^*, b_i(k+1)) + \theta_i E[p_{b_i(k+1)}] t_i - \eta_i d(b_i^*, b_i(k)) + \theta_i E[p_{b_i(k)}] t_i$$

$$= \eta_i \underbrace{[d(b_i^*, b_i(k+1)) - d(b_i^*, b_i(k))]}_{\geq 0} \geq 0$$

∎

B. Proof of Proposition 1

From Lemma 1, it follows that $E[F_i(k, A_{b_i(k)}, p_{b_i(k)})]$ is non decreasing in k and since $f_i(b_g, p_{b_g})$ is constant, there exists some maximum k^* for which a commuter weakly prefers to keep searching. That k^* is the maximum k that satisfies

$$s_i + E[F_i(k, A_{b_i(k)}, p)] \leq f_i(b_g, p_{b_g}), \tag{15}$$

where $f_i(b_g, p_{b_g}) = \eta_i d(b_i^*, b_g) + \theta_i p_{b_g} t_i$.

Under fixed pricing and at k^*,

$$E\big[F_i(k^*, A_{b_i(k^*)}, p_{b_i(k^*)})\big] = E\big[F_i(k^*, A_{b_i(k^*)}, p)\big]$$

$$= Pr(A_{b_i(k^*)} = 0)F_i(k^*, 0) + Pr(A_{b_i(k^*)} = 1)f_i(b_i^*, p)$$

$$= (1 - \phi)f_i(b_g, p_{b_g}) + \phi\eta_i d(b_i^*, b_i(k^*)) + \theta_i p t_i$$

Then Inequality (15) becomes,

$$s_i + \phi\eta_i d(b_i^*, b_i(k^*)) + \theta_i p t_i \leq \phi\eta_i d(b_i^*, b_g) + \phi\theta_i p_{b_g} t_i.$$

Rearranging terms, we get the desired results. ∎

C. Proof of Proposition 2

(1) To show that there exists a unique k_i^* and a unique $p_i^*(k)$ for each $k, k \leq k_i^*$, note that the following two equations hold at the final step k_i^*,

$$d(b_i^*, b_i(k_i^*)) = d(b_i^*, b_g) + \frac{\theta_i}{\eta_i}\Big(p_{b_g} - E[p|A = 1, p \leq p_i^*(k_i^*)]\Big)t_i - \frac{s_i}{\eta_i}\frac{1}{Pr(A = 1, p \leq p_i^*(k_i^*))}, \qquad (16)$$

$$d(b_i^*, b_i(k_i^*)) = d(b_i^*, b_g) + \frac{\theta_i}{\eta_i}\big(p_{b_g} - p_i^*(k_i^*)\big)t_i.$$

If follows that,

$$Pr(A = 1, p \leq p_i^*(k_i^*))\big(p_i^*(k_i^*) - E[p|A = 1, p \leq p_i^*(k_i^*)]\big) = \frac{s_i}{\theta_i}\frac{1}{t_i}$$

We can show the left-hand-side of the above equation is an increasing function of $p_i^*(k_i^*)$ by taking the derivative over $p_i^*(k_i^*)$,

$$\frac{\partial}{\partial p_i^*}Pr(A = 1, p \leq p_i^*)\big(p_i^* - E[p|A = 1, p \leq p_i^*]\big) = Pr(A = 1, p \leq p_i^*) > 0.$$

Therefore, there exists a unique $p_i^*(k)$ at $k = k_i^*$. Plug the unique p_i^* back into the right-hand-side of Equation (16). Given our assumption that drivers only search away from their ideal locations when they search, i.e., $d(b_i^*, b_i(k))$ is a non-decreasing function of k, there exists a unique solution of k_i^* to Equation (16).

We now prove the uniqueness of $p_i^*(k)$ for all $k < k_i^*$. At the kth search, the threshold $p_i^*(k)$ satisfies,

$$f_i(b_i(k), p_i^*(k)) = F(k, 0, p_i^*(k)) = F(k, 0) \qquad (17)$$

By backward induction, given unique $p_i^*(l), k < l \leq k_i^*$ and k_i^*, $F(k, 0)$ equals a constant. Because $f_i(b_i(k), p)$ is an increasing function of p, there exists a unique solution $p_i^*(k)$ to Equation (17).

(2) To show $p_i^*(k)$ is increasing in k, rewrite Equation (17) and define

$$y\big(k, p_i^*(k)\big) = f_i(b_i(k), p_i^*(k)) - F(k, 0, p_i^*(k)) = 0$$

Using the implicit function theorem, we can write:

$$\frac{\partial p_i^*(k)}{\partial k} = -\frac{\partial y}{\partial k}\Big/\frac{\partial y}{\partial p_i^*(k)}$$

We first calculate $\partial y / \partial k$. Take partial difference of y over k,

$$y\big(k+1, p_i^*(k)\big) - y\big(k, p_i^*(k)\big)$$
$$= \big[f_i(b_i(k+1), p_i^*(k)) - f_i(b_i(k), p_i^*(k))\big] - \big[F(k+1, 0, p_i^*(k)) - F(k, 0, p_i^*(k))\big]$$
$$= \eta_i \big[d(b_i^*, b_i(k+1)) - d(b_i^*, b_i(k))\big] - \big[F(k+1, 0) - F(k, 0)\big]$$

Based on Equation (14), we have

$$\big[F(k+1, 0) - F(k, 0)\big] = \big[F_i(k+1, 0, p_{b_i(k)}) - F_i(k, 0, p_{b_i(k)})\big]$$
$$\geq \frac{C}{1 - A - B}\eta_i\big[d(b_i^*, b_i(k+1)) - d(b_i^*, b_i(k))\big] = \eta_i\big[d(b_i^*, b_i(k+1)) - d(b_i^*, b_i(k))\big]$$

Therefore,

$$y\big(k+1, p_i^*(k)\big) - y\big(k, p_i^*(k)\big) \leq 0$$

We then calculate

$$\frac{\partial y}{\partial p_i^*(k)} = \frac{\partial f_i(b_i(k), p_i^*(k))}{\partial p_i^*(k)} - \frac{\partial F(k, 0, p_i^*(k))}{\partial p_i^*(k)}$$
$$= \theta_i t_i + Pr(A_{b_i(k)} = 1, p_{b_i(k)} \leq p_i^*(k)))\big[F(k, 0) - f_i(b_i(k), p_i^*(k))\big]$$
$$= \theta_i t_i > 0$$

Note that the last inequality follows from the definition $y\big(k, p_i^*(k)\big) = 0$. Now that we show $\partial y / \partial k \leq 0$ and that $\partial y / \partial p_i^*(k) > 0$, it follows that $\partial p_i^*(k) / \partial k \geq 0$. That is, $p_i^*(k)$ is non-decreasing in k. ∎

D. Proof of Proposition 3

We first show that p_i^* increases in s_i and decreases in θ_i, t_i. k_i^* and p_i^* satisfies the following equations at the final stage

$$d(b_i^*, b_i(k_i^*)) = d(b_i^*, b_g) + \frac{\theta_i}{\eta_i}\Big(p_{b_g} - E[p|A=1, p \leq p_i^*]\Big)t_i - \frac{s_i}{\eta_i}\frac{1}{Pr(A=1, p \leq p_i^*)}$$
$$d(b_i^*, b_i(k_i^*)) = d(b_i^*, b_g) + \frac{\theta_i}{\eta_i}\big(p_{b_g} - p_i^*\big)t_i \tag{18}$$

It follows that,

$$Pr(A=1, p \leq p_i^*)\big(p_i^* - E[p|A=1, p \leq p_i^*]\big) = \frac{s_i}{\theta_i}\frac{1}{t_i} \tag{19}$$

Taking the derivative of the left-hand-side of the above equation over p_i^*, we get:

$$\frac{\partial}{\partial p_i^*}Pr(A=1, p \leq p_i^*)\big(p_i^* - E[p|A=1, p \leq p_i^*]\big) = Pr(A=1, p \leq p_i^*) > 0.$$

That is, the left-hand-side of Equation (19) is increasing in p_i^*. It follows that p_i^* is increasing in s_i and is decreasing in θ_i, t_i. Intuitively, the commuter searches less for prices (p_i^* is higher) when the search cost s_i is high, price sensitivity θ_i is low, and parking duration t_i is short.

We now show that k_i^* decreases in s_i, η_i and increases in θ_i, t_i. Take derivative over θ_i at both sides of the Equation (18), we have

$$\frac{\partial d(b_i^*, b_i(k_i^*))}{\partial k_i^*} \frac{\partial k_i^*}{\theta_i} = \frac{t_i}{\eta_i}\left(p_{b_g} - p_i^*\right) - \frac{\theta_i t_i}{\eta_i}\frac{\partial p_i^*}{\partial \theta_i} \tag{20}$$

Take derivative over θ_i at both sides of the Equation (19), we have

$$Pr(A=1, p \le p_i^*)\frac{\partial p_i^*}{\partial \theta_i} = -\frac{s_i}{\theta_i^2 t_i}$$

$$\frac{\partial p_i^*}{\partial \theta_i} = -\frac{s_i}{\theta_i^2 t_i}\frac{1}{Pr(A=1, p \le p_i^*)} = -\frac{1}{\theta_i}\left(p_i^* - E[p|A=1, p \le p_i^*]\right)$$

Substitute $\frac{\partial p_i^*}{\partial \theta_i}$ back into Equation (20), we obtain

$$\begin{aligned}\frac{\partial d(b_i^*, b_i(k_i^*))}{\partial k_i^*} \frac{\partial k_i^*}{\theta_i} &= \frac{t_i}{\eta_i}\left(p_{b_g} - p_i^* + p_i^* - E[p|A=1, p \le p_i^*]\right) \\ &= \frac{t_i}{\eta_i}\left(p_{b_g} - E[p|A=1, p \le p_i^*]\right) > 0\end{aligned}$$

Given $\frac{\partial d(b_i^*, b_i(k_i^*))}{\partial k_i^*} \ge 0$, we thus have $\frac{\partial k_i^*}{\theta_i} > 0$. Following the exact same procedure, one can prove that $\frac{\partial k_i^*}{t_i} > 0$. Given that p_i^* increases in s_i, one can easily see from Equation (18) that k_i^* decreases in p_i^* and hence it decreases in s_i as well. Also, given that p_i^* is not a function of η_i, one can easily see from Equation (18) that k_i^* decreases in η_i. In sum, we have proven that k_i^* increases in θ_i, t_i and decreases in s_i, η_i. ∎

E. Algorithm for Simulated Moments

We compute the demand for each block and a profile of parameters as follows.

1. Draw an ideal location b_i^* from the estimated distribution g^*.

2. Draw a profile of parameters: search cost s_i and price sensitivity θ_i from $lnN(\mu_{s,\theta}, W_{s,\theta})$, trip valuation v_i from $N(\mu_v, \sigma_v)$, and a parking time t_i from $f(t)$ observed from data. η_i is normalized to 10.

3. Calculate thresholds N_i^* and p_i^* using Equations (3) and (4). Compute the starting location b_i^o using Equation (5) and calculate the expected cost of driving $C_i^*(b_i^*)$.

4. Stage I: If v_i is less than $C_i(b_i^*)$, then the commuter chooses not to drive and we end the program. Otherwise, she will drive and start with the starting location b_i^o. If $b_i^o = g$, the commuter drives directly to the garage and we end the program. Otherwise, the commuter searches for on-street parking starting from block b_i^*. Set $k = 1$ and continue to the next step.

5. Stage II: After k searches, the commuter arrives at block $b_i(k)$. We draw the availability of the block from a Bernoulli distribution with probability ϕ_{jtd} (calculated from data),

   a) If the block is unavailable,

      i. and if the maximum searching threshold has already been reached, i.e., $k = N_i^*$, the commuter parks at the garage and we end the search process;

      ii. otherwise, the commuter enters the next step.

   b) If the block is available,

i. and if the hourly rate $p_{b_i(k)} \leq p_i^*$, the commuter parks at block $b_i(k)$ and we end the search process;

ii. otherwise, the commuter enters the next step.

6. Draw a new block from the adjacent blocks with equal sampling probabilities to be the next block arrived at. Set $k = k + 1$ and return to Step 5.

7. Compute total parking demand $\hat{q}_j$ and the number of commuters who drive $\hat{M}_j$ for all blocks.
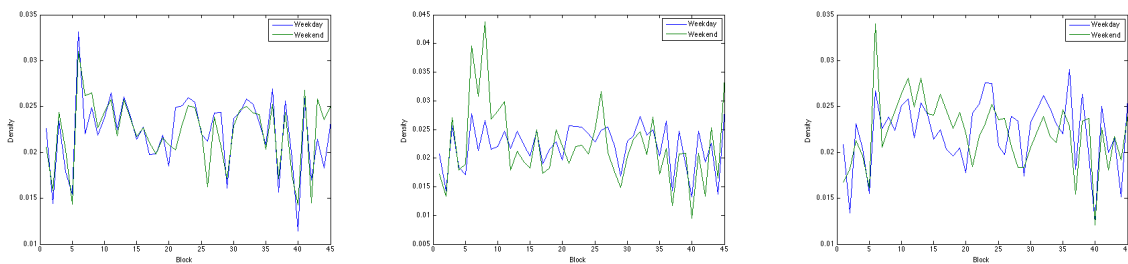
F. Distribution of Ideal Locations

We estimate a distribution of ideal locations for each month during the after period: April, May, June and July, separately for weekdays and weekends (Saturdays). We therefore estimate $3 \times 2 = 6$ distributions of ideal locations in total for each district. Figures 3, 4 and 5 display the non-parametric estimates of the distributions for Fillmore, Marina and Mission. The x-axes of the figures are the numeric indices of blocks. The indices and their corresponding locations can be found in Table 8.

G.   Algorithm for Computing the Counterfactual Equilibrium

This section explains how we compute our counterfactual equilibrium under full price information as well as under the three-tier pricing policy. We do so by finding a fixed point using the following steps:

1. Start with initial demand q_k for each block k.

2. Compute the simulated availability $\hat{\phi}_k$ for each block k by numerically solving equations (8) and (9).

3. Given the estimated parameters and simulated availability $\hat{\phi}_k$ for each block, compute the simulated parking minutes $\hat{q}_k$ as described in the estimation section.

4. Repeat the above steps until convergence, i.e., $\left| \begin{matrix} q_k - \hat{q}_k \\ M_k - \hat{M}_k \end{matrix} \right| < \epsilon = 10^{-4}$.
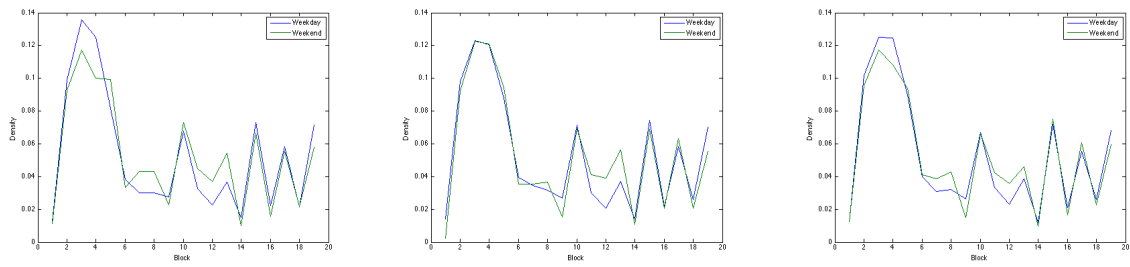

(a) April - May　　　　　　　　　(b) June　　　　　　　　　(c) July

Figure 3   Estimates of Densities of Ideal Location for Fillmore District.
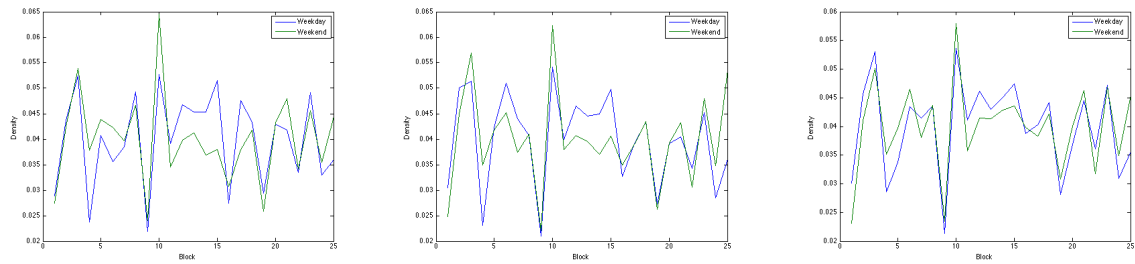
(a) April - May

(b) June

(c) July

Figure 4   **Estimates of Densities of Ideal Location for Marina District.**

(a) April - May

(b) June

(c) July

Figure 5   **Estimates of Densities of Ideal Location for Mission District.**