Appendix A: Calculation of Utilities and The Value of Continued Search

In this section, we derive the maximum utilities conditional on availability and show how the value of continued search can be calculated recursively.

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

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

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

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

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

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

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

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

$$+ \int_{P\leq \frac{v_{rtd}+\epsilon_{irtd}-\eta_i d(b_i^*,b_{k+1})-V_i^{\text{garage}|\text{o}}}{\theta_i h_i}} V_i^{\text{park}}(b_{k+1},P)\bar{F}^{\epsilon}_{rtd}\left(\frac{V_i^{\text{search}}(b_{k+1})-V_i^{\text{park}}(b_{k+1},P)}{s_i}\right)f^{P|A}_{rtd}(P|A=1)dP$$
$$+ V_i^{\text{garage}|\text{o}}\bar{F}^{P|A}_{rtd}\left(\frac{v_{rtd}+\epsilon_{irtd}-\eta_i d(b_i^*,b_{k+1})-V_i^{\text{garage}|\text{o}}}{\theta_i h_i}|A=1\right)\bar{F}^{\epsilon}_{rtd}\left(\frac{V_i^{\text{search}}(b_{k+1})-V_i^{\text{garage}|\text{o}}}{s_i}\right), \quad (2)$$

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

$$\iint \max_{a=\{0,1,2\}} u_i(b,P,0,\epsilon;a)f^{P|A}_{rtd}(P_{rtdb_{k+1}}|A=0)f^{\epsilon}_{rtd}(\epsilon)dPd\epsilon$$
$$= \int_{\epsilon<\frac{V_i^{\text{search}}(b_{k+1})-V_i^{\text{garage}|\text{o}}}{s_i}} \left(-s_i\epsilon + V_i^{\text{search}}(b_{k+1})\right)f^{\epsilon}_{rtd}(\epsilon)d\epsilon$$
$$+ V_i^{\text{garage}|\text{o}}\bar{F}^{\epsilon}_{rtd}\left(\frac{V_i^{\text{search}}(b_{k+1})-V_i^{\text{garage}|\text{o}}}{s_i}\right) \quad (3)$$

In sum, we see that the value $V_i^{\text{search}}(b_k)$ is a function of the expected values to continue searching from the adjacent blocks, $V_i^{\text{search}}(b_{k+1})$, the expected value of parking at the adjacent blocks, $V_i^{\text{park}}(b_{k+1},P)$, and the values to stop searching $V_i^{\text{garage}|\text{o}}$.

Appendix B: Simulated Methods of Moments Estimation Procedure

In this section, we provide the detailed steps of implementing Simulated Methods of Moments Estimation. Researchers use SMM instead of GMM when it is difficult (or impossible) to derive moment conditions from the model directly. For example, in our setting it is impossible to derive an explicit analytical expression for the equilibrium. Therefore, we solve it numerically using simulations. Given an admissible set of parameters Θ, we simulate the driving decision and parking location for every consumer in the market. We then calculate the number of people who park at each block and in the garage, and customers' total parking duration, and match these to the corresponding moments we observe in the data.

Step 1: Solve the Model. Given a set of parameters Θ and simulated shocks, we solve for the decision of each consumer: whether she drives, and if so, where she parks.

1. For each consumer i in region r at time t on day d, draw the ideal location b_i^* from the ideal location distribution $\omega_{ry}(b), b\in B_r$. Draw a search cost, distance disutility and price sensitivity (s_i,η_i,θ_i) from the multivariate lognormal distribution $lnN(\mu_{s,\eta,\theta},W_{s,\eta,\theta})$. Finally, we need a draw of parking duration h_i. Observe from Figure A.4 that the distribution of parking duration does not fit common distributions such as normal, lognormal, or extreme value. Rather, there are often spikes at 30-minute, 1-hour, 2-hour, 3-hour, and 4-hour marks. Therefore, estimating the distribution of parking duration assuming it follows certain distribution is problematic. Instead, we draw parking durations from the empirical distribution and conduct sensitivity analyses around it. The details are discussed in Appendix D.4.

2. Simulate the random utility shocks $\epsilon_{i0},\epsilon_{ig},\epsilon_{is}$ from i.i.d normal distributions with mean 0 and standard deviation σ. Also simulate a sequence of search cost shocks $\epsilon_{irtdb_k}, k=1,2,3,...$ from the standard log-normal distribution.

3. Calculate the utility of the outside option, u_{i0}, the utility of parking at the garage, u_{ig}, and the utility of driving and starting searching on street, u_{is}. While it is straightforward to calculate the first two utilities, to calculate u_{is}, we first need to solve the dynamic spatial search model. We explain the details below.

4. At each step of the dynamic spatial search, the consumer can choose whether to park at the current block, continue to search, or abandon searching. Given the ideal location, the parameters, and the simulated shocks, it is straightforward to calculate the utility from parking at the current block and from giving up search. However, to calculate the expected utility from continuing to search, $V_i^{\text{search}}(b_k)$, we need to solve Equation (1) recursively. Observe from Equations (1), (2) and (3), that $V_i^{\text{search}}(b_k)$ is a function of the expected utility from continuing to search at each of the nearby blocks, $V_i^{\text{search}}(b_{k+1})$, where $b_{k+1}\in B_{b_{rk}}$. That is, it is possible to solve for the fixed point of the vector $V_i^{\text{search}}(b)$ using the system of $|B_r|$ equations. Note that ϕ_{rtd} and the conditional distribution $f^{P|A}_{rtd}$ are calculated based on observations in the data under the rational expectation assumption. In the counterfactual analyses, however, we calculate new equilibrium distributions following the procedure outlined in Appendix E.

Once we calculate the utility from continuing to search, we solve for the optimal decision at each step according to the optimal decision rule. Finally, we calculate the expected utility of a consumer who chooses to drive and start searching on street, u_{is}.

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

Step 2: Calculate Simulated Moments. Based on the simulation, for each region, time, and day, calculate 1) the number of consumers who choose to drive and end up parking at each block, 2) the number of consumers who choose to drive and end up parking at the garage, 3) the total minutes parked at each block, and 4) the total minutes parked at the garage.

Step 3: Match Simulated Moments to Observed Moments. Solve the moment conditions in Equation (4) to obtain the parameter estimates $\hat{\Theta}$.

Appendix C: Heterogeneous Welfare Impacts

To further understand the effects of congestion pricing on welfare, we take advantage of the heterogeneity of consumers and examine changes in welfare by different consumer segments in Marina and Fillmore in Table A.1. First, we compare changes in consumer surplus by price sensitivity levels. Consumers with low price sensitivity benefit from congestion pricing more than consumers with high price sensitivity. This makes intuitive sense because consumers who are not very sensitive to price are more willing to trade off monetary payments with congestion costs (search and distance disutility). Second, we compare changes in consumer surplus by the popularity of ideal locations. We define an ideal location's popularity level based on the occupancy rate in year 2011; the popular locations account for more than 64% of consumers in Marina and Fillmore. Consumers whose destinations are at more popular locations are more likely to benefit from congestion pricing. To explain, after the implementation of congestion pricing, popular blocks become more available, which allows consumers who demand these blocks to park there. Therefore, consumers whose ideal locations are popular benefit from congestion pricing more on average. At the same time, with congestion pricing, more consumers park at less popular blocks. As a result, less popular blocks become more congested than with fixed pricing. Consumers whose ideal locations are less popular incur higher search costs and distance disutility and are therefore relatively worse off.

Appendix D: Robustness Tests

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

D.1. Market Size

In the baseline model, we set the market size to be twice the average number of drivers in the before period, which yields a market size of 700 in Marina, $1,135$ in Fillmore, and $1,420$ in Mission. We perform the sensitivity analysis by choosing different levels of market size, which are 1.5 and 2.5 times the average number of drivers in the before period. This choice rule yields market sizes of 525 and 875 for Marina, 850 and $1,420$ for Fillmore, and $1,065$ and $1,775$ for Mission. Results in Figure A.1 shows that changes in consumer surplus, social welfare, and search traffic are robust to the choice of market size.

D.2. Consumer Beliefs

Although consumers may not have complete knowledge of the states of every individual block, it may be restrictive to assume that consumers' price and availability beliefs are identical for all blocks. We analyze an alternative partial-knowledge model. In this model, we group blocks into three levels (high, medium, and low) according to their popularity before the implementation of congestion pricing,

and allow consumers to form different beliefs of price and availability for high-, medium- and low-popularity blocks, $\{P^H_{rtd}, A^H_{rtd}\}, \{P^M_{rtd}, A^M_{rtd}\}, \{P^L_{rtd}, A^L_{rtd}\}$. We also assume that consumers know which block is high-, medium-, and low-popularity block. Empirically, we determine whether a block has a high, medium, or low popularity based on SF*park*'s definition. High popularity blocks are those with an average occupancy rate of 80% or higher before implementation. Medium popularity blocks are those with average occupancy rates of between 60% and 80%. Low popularity blocks are those with average occupancy rates of 60% or lower.

Under such assumptions, consumers' decisions differ from those derived under identical beliefs in two ways. First, consumers may choose to start their search from a block that is not their destination given their knowledge of all blocks' popularity. Second, consumers will derive an optimal search path instead of following a random walk strategy at the intersection: they choose where to go next based on which block yields the highest expected utility. We now derive the transition probability and the optimal decision rule under such assumptions.

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

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

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

$$
\begin{aligned}
&V_i^{\text{search}}(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k}) \\
&= E\big[\max_{a=\{0,1,2\}, b_{k+1} \in B_{rb_k}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{rtdb_{k+1}}; a) | (b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{rtdb_k})\big] \\
&= \max_{b_{k+1} \in B_{rb_k}} E\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{rtdb_{k+1}}; a) | (b_{k+1}, b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{rtdb_k})\big] \\
&= \max_{b_{k+1} \in B_{rb_k}} E\big[\max_{a=\{0,1,2\}} u_i(b_{k+1}, P_{rtdb_{k+1}}, A_{rtdb_{k+1}}, \epsilon_{rtdb_{k+1}}; a) | (b_{k+1}, b_k)\big] \\
&\equiv \max_{b_{k+1} \in B_{rb_k}} V_i^{\text{search}}(b_{k+1}, b_k) \equiv V_i^{\text{search}}(b_k). \qquad (4)
\end{aligned}
$$

Optimal Decision Rule. The optimal decision rule now concerns two decisions: (1) whether to park, continue or stop searching, and (2) which block to search next if the search continues. For consumer i, the optimal decision rule $\{a^*_i(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k}), b^*_{k+1}(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k})\}$ can be characterized as follows. If consumer i decides to continue searching, she will drive to block $b^*_{k+1}(b_k, P_{rtdb_k}, A_{rtdb_k}, \epsilon_{irtdb_k})$ such that:

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

The optimal decision $a^*_i(b_k, P_{rtdb_k}, A_{rtdb_k})$ can be characterized similarly as before. When the current block is available, i.e., $A_{rtdb_k} = 1$, a consumer will choose the action that gives her the highest utility:

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

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

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

Note that $V_i^{\text{search}}(b_k)$ is defined by Equation (4), and can be calculated recursively.

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

$$+\ (1-\phi_{rtd}^{U_{b_{k+1}}})\iint \max_{a=\{0,1,2\}} u_i(b_{k+1},P,0,\epsilon;a) f_{rtd}^{P|A,U_{b_{k+1}}}(P|A^{U_{b_{k+1}}}=0) f_{rtd}^{\epsilon}(\epsilon)dPd\epsilon\Big], \tag{5}$$

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

We can further expand the first double integral in Equation (5) as follows:

$$\begin{aligned}
&\iint \max_{a=\{0,1,2\}} u_i(b_{k+1},P^{U_{b_{k+1}}},1,\epsilon;a) f_{rtd}^{P|A,U_{b_{k+1}}}(P|A^{U_{b_{k+1}}}=1) f_{rtd}^{\epsilon}(\epsilon)dPd\epsilon\\
=&\int_{\epsilon\le \frac{V_i^{\text{search}}(b_{k+1})-V_i^{\text{garage|o}}}{s_i}} \Big(-s_i\epsilon+V_i^{\text{search}}(b_{k+1})\Big)\\
&\cdot \bar{F}_{rtd}^{P|A,U_{b_{k+1}}}\left(\frac{s_i\epsilon-V_i^{\text{search}}(b_{k+1})+v_{rtd}+\epsilon_{irtd}-\eta_i d(b_i^*,b_{k+1})}{\theta_i h_i}|A^{U_{b_{k+1}}}=1\right) f_{rtd}^{\epsilon}(\epsilon)d\epsilon\\
+&\int_{P^{U_{b_{k+1}}}\le \frac{v_{rtd}+\epsilon_{irtd}-\eta_i d(b_i^*,b_{k+1}^*)-V_i^{\text{garage|o}}}{\theta_i h_i}} V_i^{\text{park}}(b_{k+1}^*,P^{U_{b_{k+1}}})\\
&\cdot \bar{F}_{rtd}^{\epsilon}\left(\frac{V_i^{\text{search}}(b_{k+1})-V_i^{\text{park}}(b_{k+1}^*,P^{U_{b_{k+1}}})}{s_i}\right) f_{rtd}^{P|A,U_{b_{k+1}}}(P|A^{U_{b_{k+1}}}=1)dP\\
+&\ V_i^{\text{garage|o}}\bar{F}_{rtd}^{P|A,U_{b_{k+1}}}\left(\frac{v_{rtd}+\epsilon_{irtd}-\eta_i d(b_i^*,b_{k+1}^*)-V_i^{\text{garage|o}}}{\theta_i h_i}|A^{U_{b_{k+1}}}=1\right)\\
&\cdot \bar{F}_{rtd}^{\epsilon}\left(\frac{V_i^{\text{search}}(b_{k+1})-V_i^{\text{garage|o}}}{s_i}\right),
\end{aligned} \tag{6}$$

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

We can expand the second double integral in Equation (5) as follows:

$$\begin{aligned}
&\iint \max_{a=\{0,1,2\}} u_i(b_{k+1},P,0,\epsilon;a) f_{rtd}^{P|A,U_{b_{k=1}}}(P|A^{U_{b_{k+1}}}=0) f_{rtd}^{\epsilon}(\epsilon)dPd\epsilon\\
=&\int_{\epsilon< \frac{V_i^{\text{search}}(b_{k+1})-V_i^{\text{garage|o}}}{s_i}} \Big(-s_i\epsilon+V_i^{\text{search}}(b_{k+1})\Big) f_{rtd}^{\epsilon}(\epsilon)d\epsilon\\
+&\ V_i^{\text{garage|o}}\bar{F}_{rtd}^{\epsilon}\left(\frac{V_i^{\text{search}}(b_{k+1})-V_i^{\text{garage|o}}}{s_i}\right)
\end{aligned} \tag{7}$$

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

We re-estimate the model parameters and re-calculate welfare changes under the above consumer belief specification. Results presented in Figure A.2 shows that changes in consumer and social welfare as well as search traffic are robust to consumers' having heterogeneous beliefs across blocks.

D.3. Updating of Beliefs

Even though it is unlikely that consumers are armed with the sophistication to update their beliefs continuously, consumers may be able to update them periodically. In this subsection, we estimate a variant of the model where we allow consumers to update their beliefs once arriving at their ideal location and observing whether it is available or not. Under rational expectation, the updated belief is the expected availability of the all other blocks conditional on the ideal location's availability, which can be calculated empirically using the panel availability data. In Table A.2, we show that the parameter estimates are robust when allowing for consumer to update their beliefs.

D.4. Parking Duration

To make sure that our approach of drawing the parking durations from the censored empirical distribution is not restrictive, we draw different sets of parking time distributions, which contain different proportions of short and long parking durations such as those shown in Figure A.4. Specifically, we draw from the following sets of parking time distributions, which preserve the general shape of the empirical density function of parking durations: (1) the parking time distribution conditional on congestion being low, with 10% more weight for parking durations that are less than 1-hour; (2) the parking time distribution conditional on congestion being low; (3) the parking time distribution conditional on congestion being medium; (4) the parking time distribution conditional on congestion being high; (5) the parking time distribution conditional on congestion being high, with 10% less weight for parking durations that are less than 1-hour.

We re-estimate the model and re-calculate the counterfactual equilibrium. The results are displayed in Figure A.3, and the changes in consumer surplus, social welfare, and search traffic are very robust to the different parking duration distributions used. For example, in Mission, assuming consumers know which block is high-, medium-, and low-popularity block increases the welfare in the after period from 499.66 to 513.76, and increases the welfare in the before period from 458.60 to 458.79. That is, the welfare change is of 0.04%–2.82%.

Appendix E: Algorithm for Computing the Counterfactual Equilibrium

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

1. For each region r, time t and day d, start with an initial guess of each consumer's driving and parking decision. Compute the number of consumers parking at each block, $q_{rtd}(b), \forall b \in B_r$, and the total parking minutes at each block, $Q_{rtd}(b), \forall b \in B_r$. Also compute the number of consumers parking at the garage, q_{rtdg}, and the total minutes parked, Q_{rtdg}.
2. Calculate the occupancy rate at each block for region r, time t and day d. Then compute the availability at each block $\hat{\phi}_{rtdb}, \forall b \in B_r$ by solving Equation (3).
3. Given the estimated parameters and the availability vector $\hat{\phi}_{rtdb}, \forall b \in B_r$, re-calculate each consumer's driving and parking decision based on the optimal decision rule derived in the paper. Update $q\prime_{rtd}(b), Q'_{rtd}(b), \forall b \in B_r$, q'_{rtdg}, and Q'_{rtdg}.
4. Repeat the above steps until convergence, i.e., $\left| \begin{array}{c} q\prime_{rtd}(b) - q_{rtd}(b), \forall b \\ Q'_{rtd}(b) - Q_{rtd}(b), \forall b \\ q\prime_{rtdg} - q_{rtdg}, \\ Q'_{rtdg} - Q_{rtdg} \end{array} \right| < \epsilon = 10^{-3}$.
5. Repeat the above steps to obtain the equilibrium parking locations for all regions, times and days.

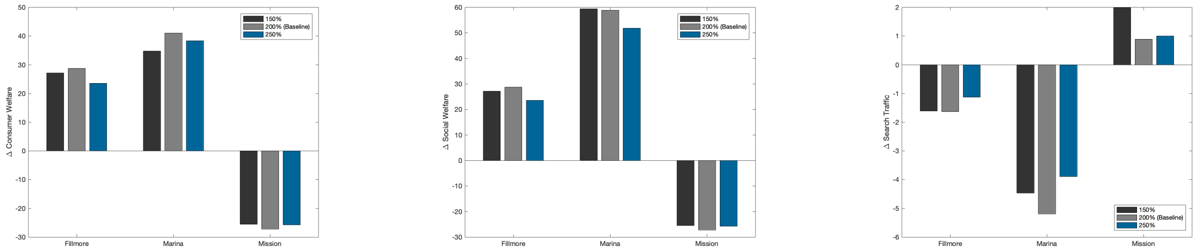


Figure A.1 Robustness Test: Market Size

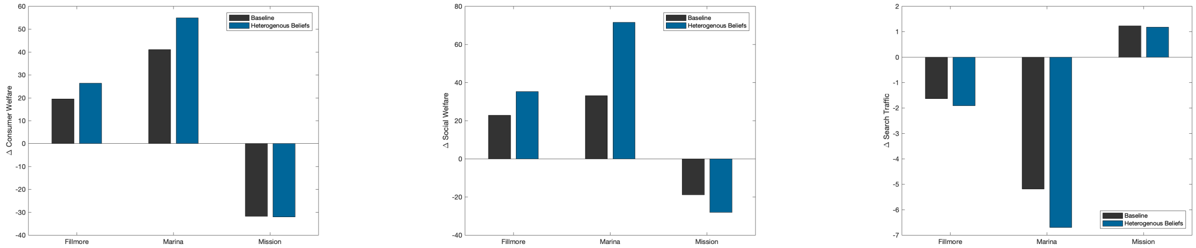


Figure A.2 Robustness Test: Consumer Belief

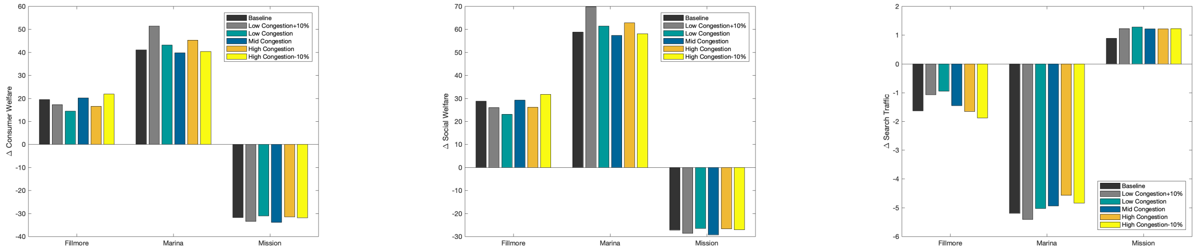


Figure A.3 Robustness Test: Parking Duration

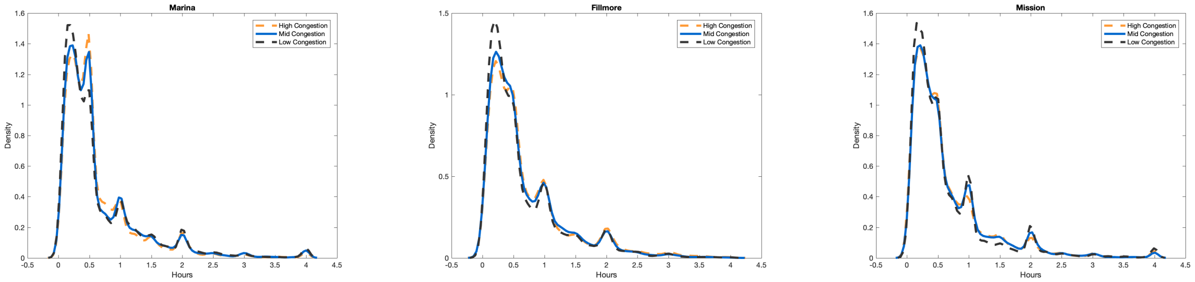


Figure A.4 Parking Time Distribution

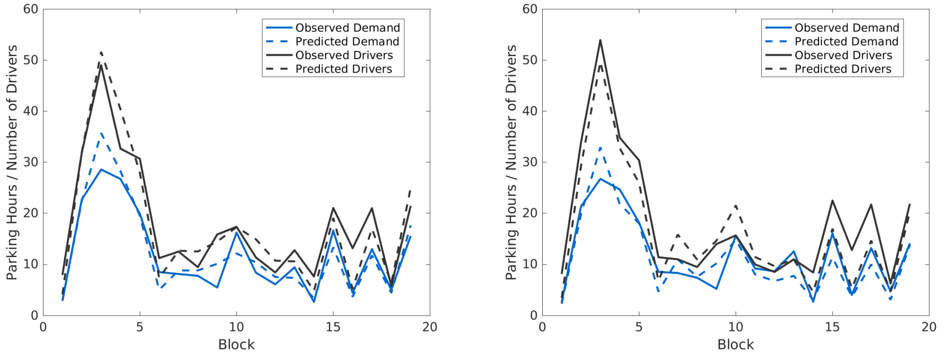
Table A.1 Impacts of Congestion Pricing on Consumer Surplus by Consumer Segment

	Consumer surplus Change ($)		Fraction of Consumers (%)	
	Marina	Fillmore	Marina	Fillmore
Consumer Segments by Price Sensitivity				
High	-6.40	-11.66	50.00	50.00
Low	47.46	31.16	50.00	50.00
Consumer Segments by Ideal Locations				
High-Popularity Blocks	28.19	24.65	68.52	64.19
Low-Popularity Blocks	12.87	-5.15	31.48	35.81

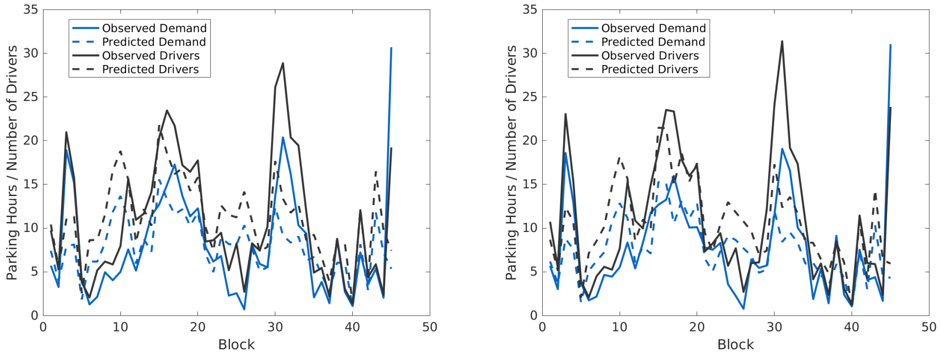
Notes. Consumer surplus is normalized to dollar value at the size of a hundred consumers. Results are based on 50 rounds of simulations. High (low) price sensitivity is categorized by whether the price sensitivity is greater (less) than the 50th percentile. High and low popularity blocks are defined as the blocks which occupancy rate in year 2011 is greater (less) than the 50th percentile.

Table A.2 Updating Belief: Changes in Parameter Estimates

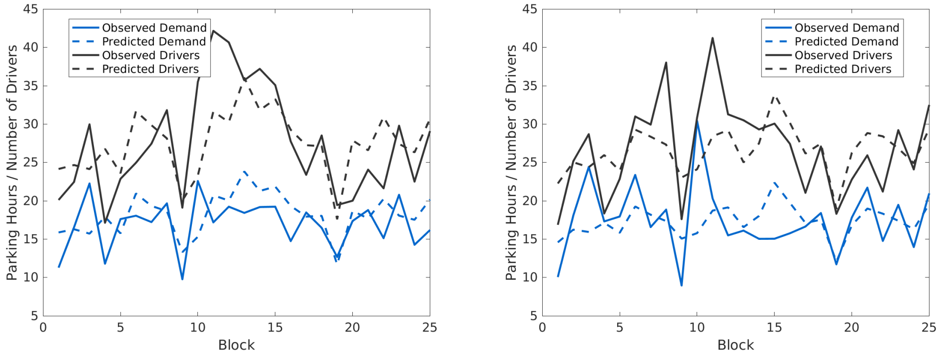
	Marina	Fillmore	Mission
Search cost (log-scaled) mean	0.00	0.00	0.00
Search cost (log-scaled) sd	0.00	0.07	0.00
Distance disutility (log-scaled) mean	0.00	0.00	0.00
Distance disutility (log-scaled) sd	0.00	0.00	0.00
Price sensitivity (log-scaled) mean	0.02	0.00	0.00
Price sensitivity (log-scaled) sd	0.03	0.00	-0.05
Search cost×distance disutility corr	0.00	0.10	0.09
Search cost×price sensitivity corr	0.00	0.00	0.00
Distance disutility ×price sensitivity corr	-0.01	0.10	0.00
Trip valuation—α	0.09	0.00	0.00
Trip valuation—intercept	0.10	0.00	0.00
Trip valuation—June	0.00	0.00	0.00
Trip valuation—July	0.00	0.00	0.00
Trip valuation—weekend	0.00	0.00	0.00
Trip valuation—noon	0.00	0.00	0.00
Trip valuation—afternoon	0.00	0.00	0.00
Destination Model $-\kappa_A$	0.00	0.00	0.00
Destination Model $-\kappa_B$	0.00	0.00	0.00
Destination Model $-\kappa_C$	0.00	0.00	0.00
Destination Model $-\kappa_D$	0.00	0.00	0.00



(a1) Marina - Before (a2) Marina - After



(b1) Fillmore - Before (b2) Fillmore - After



(c1) Mission - Before (c2) Mission - After

Figure A.5 **Moment Fits**