How Does Congestion Affect the Evaluation of Recreational Gate Fees? An Application to Gulf Coast Beaches

Roger H. von Haefen[1]

North Carolina State University

Frank Lupi

Michigan State University

August 2021

Abstract: We investigate how congestion influences the welfare, revenue-raising, and distributional implications of gate fees at outdoor recreational sites. A simple conceptional framework decomposes the effects of gate fees into three distinct components which are then quantified in a multi-site recreation demand application to Gulf Coast beaches. Simulation results suggest that when people are willing to pay to avoid congested beaches, the deadweight loss from gate fees is smaller, the revenue raised is higher, and leakage to untaxed sites is less relative to when congestion feedback effects are not accounted for. Congestion feedbacks do not substantively change our distributional analysis which implies that the gate fees we consider are regressive, do not disproportionately impact minorities, and privilege local recreators at the expense of visitors from further away.

Keywords: congestion, gate fees, Gulf Coast beaches

JEL Codes: Q26, Q51, R41

---

[1] Corresponding author. Department of Agricultural and Resource Economics, NCSU Box 8109, Raleigh, NC 27695-8109. Email: roger_von_haefen@ncsu.edu.
Both authors are grateful for helpful comments from Spencer Banzhaf, Dan Phaneuf and participants at the Property and Research Center's "What Price to Play: The Future of Outdoor Recreation and Public Land Funding" workshop in Bozeman, MT, November 7-9, 2019.

Introduction

Most public lands are managed by federal, state and local agencies based on the public trust doctrine. As such, recreational access is typically granted to all at no cost, and overuse and congestion often result. This tragedy of the commons reflects a mismatch between the private cost of access (which is typically only one's roundtrip out-of-pocket and time costs of traveling to a site) and the social cost of access which includes congestion externalities. The textbook economic solution to this situation is a tax on entrance, whereby those who use the resource and impose congestion externalities on others internalize these costs.[2] By reducing aggregate demand and, in turn, congestion at the taxed site, these gate fees can simultaneously correct a market failure and raise valuable revenue that can be used to address a variety of resource management needs.

Dating back to at least Clawson and Knetch (1963), environmental economists have recognized both virtues of charging gate fees. However, empirical studies of these fees (Ji et al., this issue; Lupi et al., this issue) have generally ignored how they may generate feedback effects on aggregate demand and congestion. Moreover, most studies assume the gate fee applies to all sites in the study area and thus do not account for potential spillover effects to untaxed sites. These limitations – driven in part by the complexity of modeling congestion in a behaviorally consistent manner – may influence estimated welfare losses, revenues raised, and the distributional impacts from gate fees.

In this paper, we combine a simple conceptual framework and a more detailed empirical analysis to investigate how accounting for congestion feedback effects influences the economic evaluation of gate fees. The conceptual framework highlights three distinct effects from gate fees: 1) a pure price effect, whereby higher fees reduce demand at taxed sites, *ceteris paribus*; 2) a taxed site congestion effect, where the lower demand at taxed sites reduces congestion, which, all else equal, increases demand at these sites; and 3) a non-taxed site congestion effect, where the fee also generates a substitution or "leakage" effect whereby individuals substitute to other beaches not subject to the fee and, in the process, raise congestion levels at these untaxed sites. Using the largest and most

[2] For example, Clawson and Knetsch (1963) point out the potential of using prices to control crowding.

extensive recreational data set for shoreline recreation in the Gulf Coast region ever collected, we then empirically evaluate the magnitude of these competing effects as well as the revenue-raising and distributional implications of gate fees within a multi-site travel cost model of participation and site choice. Our model combines econometrically-estimated and calibrated parameter values in a way that permits us to evaluate gate fees across a range of assumptions about people's willingness-to-pay to avoid congestion which highlights the important role of this parameter. We also explore the distributional implications of gate fees, and similar to Ji et al. (this issue) and Lupi et al. (this issue), we find these fees to be regressive. Moreover, we do not find evidence that they disproportionally impact minorities but privilege local residents at the expense of visitors from further away.

The paper proceeds as follows. We begin in the next section by developing a simple conceptual framework that highlights the different behavioral effects of congestion. We then turn in the following section to a discussion of our recreation application and the key modeling assumptions that underly our investigation of gate fees. We then present our main findings, and in the last section, conclude with a discussion of fruitful avenues for future research.

Conceptual Framework

In this section, we use a simple demand model to investigate how accounting for congestion affects the revenue raised and deadweight loss generated from gate fees. The model adopts a representative consumer approach and therefore does not permit us to consider distributional impacts, although we will investigate these concerns in our Gulf Coast application. Moreover, our model considers only the gross costs of gate fees and not the direct benefits to recreators from lower congestion levels at visited sites. These gains are proportional to the number of recreational trips ultimately taken and may be substantial in practice. Nevertheless, our model suggests that ignoring congestion feedback effects as in Ji et al. (this issue) and Lupi et al. (this issue) will lead to an overestimate of the fee-induced demand response if people are willing-to-pay to avoid congestion. By implication, this implies that the revenue raised will be underestimated and the deadweight loss will be overestimated if congestion effects are ignored. We also consider leakage of beach goers to other recreation sites that are not subject to gate fees. In our view, this is an important effect to consider because no fee in practice will have complete geographic (or temporal) coverage. From a benefit-cost perspective, all benefits and costs from gate fees should be accounted for, so understanding how fees in one region might affect use, congestion and welfare in others is important to quantify (Cesario, 1980).

To begin, consider a representative consumer's demand for a single site, $x = g(p, c)$, where *x* is the number of trips, *p* is the travel cost, and *c* is congestion at the site, which, consistent with our Gulf Coast application, is operationally defined as trips per mile of coastline over a given time period (i.e., $c = x/L$ where *L* is miles of coastline). Recognizing that a gate fee or tax, *F*, influences aggregate congestion at the site by raising costs to all visitors, we can write demand as a function of entrance fees as follows:

$$x = g(p + F, c(F)). \qquad (1)$$

Now consider a marginal change in *F* and its impact on demand. By totally differentiating (1) and rearranging, we see that:

$$\frac{dx}{dF} = \frac{\frac{\partial g}{\partial p}}{1 - \frac{\partial g}{\partial c} / L} \qquad (2)$$

where $\frac{\partial g}{\partial p}$ captures the "partial equilibrium" demand response associated with the price change, and $\frac{\partial g}{\partial c}$ captures the demand response from congestion. Assuming the law of demand holds and that congestion is a bad, the denominator in (2) is greater than one, and the full demand response to an increase in entrance fees, $\frac{dx}{dF}$, is muted relative to the partial equilibrium demand response. As we show in Figure 1, this has important implications for the revenue raised and deadweight loss from gate fees.

For simplicity, Figure 1 approximates demand with linear functions. At a travel cost of *p*, demand is initially x_{base}. With the introduction of the gate fee or tax, the partial equilibrium demand response (ignoring congestion feedbacks) reduces demand to $x_{partial}$. Since all visitors are subject to the fee and reduce their demands accordingly, congestion levels at the site fall, and thus some of the pure price effect of the gate fee is mitigated, resulting in a net response of x_{full}. This implies that accounting for congestion feedback effects *raises* the estimated government revenue by $F \times (x_{full} - x_{partial})$ and *decreases* the deadweight loss by approximately $.5 \times F \times (x_{full} - x_{partial})$ compared to measures using the partial equilibrium demand response that ignores congestion feedbacks.

If we extend the current analysis to a multi-site framework, a related issue arises when the entrance fee or tax applies to only a subset of sites. This case is likely relevant when sites span multiple jurisdictions (e.g., across neighboring states or federal versus state-managed sites) and different jurisdictions adopt different policies. A particular concern is leakage, whereby the jurisdiction not adopting the tax experiences a net increase in demand for its sites, an often unwelcomed spillover effect that exacerbates congestion concerns. To shed some light on this, consider the demand for two sites where only the first site is subject to an entrance fee (i.e., F_1). In this case, the overall demand effect of an increase in F_1 on the demand for trips to the second site is (see the appendix of a formal derivation):

$$\frac{dx_2}{dF_1} = \frac{\left(1 - \frac{\partial g_1}{\partial c_1} \Big/ L_1\right)\frac{\partial g_2}{\partial p_1} + \left(\frac{\partial g_2}{\partial c_1} \Big/ L_1\right)\frac{\partial g_1}{\partial p_1}}{\left(1 - \frac{\partial g_1}{\partial c_1} \Big/ L_1\right)\left(1 - \frac{\partial g_2}{\partial c_2} \Big/ L_2\right) - \left(\frac{\partial g_2}{\partial c_1} \Big/ L_1\right)\left(\frac{\partial g_1}{\partial c_2} \Big/ L_2\right)}. \quad (3)$$

In general, not much can be said about the sign of $\frac{dx_2}{dF_1}$ and, in turn, leakage, although intuition might suggest that the direct effect of the gate fee on demand for the untaxed site will likely dominate any indirect congestion effects implying that leakage will remain a policy concern.

The above discussion suggests that the effects of gate fees on recreational demand are threefold: 1) a pure price effect, whereby the fee reduces demand for the taxed good and (assuming the sites are substitutes) increases demand for the untaxed good, *ceteris paribus*; 2) a taxed site congestion effect, which increases demand at the taxed sites and decreases demand at the untaxed sites; and 3) a non-taxed site congestion effect, which likely reduces demand at the sites not subject to the tax and increases demand at the taxed sites. Moreover, we can separately identify the welfare implications of these three effects by decomposing the compensating variation (CV) for a change from (p_1, p_2, c_1^0, c_2^0) to $(p_1 + F, p_2, c_1^1, c_2^1)$, i.e.,

$$CV = E(p_1, p_2, c_1^0, c_2^0) - E(p_1 + F, p_2, c_1^1, c_2^1), \tag{4}$$

where $E(\cdot)$ is the expenditure function evaluated at different price and congestion levels. In particular, CV can be rewritten as:

$$\begin{aligned} CV = {} & E(p_1, p_2, c_1^0, c_2^0) - E(p_1 + F, p_2, c_1^0, c_2^0) \\ & + E(p_1 + F, p_2, c_1^0, c_2^0) - E(p_1 + F, p_2, c_1^1, c_2^0) \\ & + E(p_1 + F, p_2, c_1^1, c_2^0) - E(p_1 + F, p_2, c_1^1, c_2^1), \end{aligned} \tag{5}$$

where the first line monetizes the welfare implications of the pure price effect, the second line monetizes the taxed site congestion effect, and the last line monetizes the non-taxed site congestion effect. Equation (5) will be helpful when interpreting the implications of accounting for congestion in our application, which we describe in the next section.

Empirical Application

Our empirical application uses data collected by researchers associated with the natural resource damage assessment for the 2010 Deepwater Horizon oil spill (English et al., 2018). As part of that assessment, two general population phone surveys were used to collect recreation data for roughly 2,000 miles of coastline stretching from Texas to Georgia in 2012-13 – see Figure 2. Over 41,000 adults (≥ 18) residing throughout the contiguous (lower 48) United Sates provided information on over 27,500 primary-purpose recreational trips which serve as the foundation of our analysis. Table 1 provides summary statistics for the trips. Importantly, about 17 percent of trips were for more than one day, and a nontrivial number of trips involved one-way driving distances of more than 1,000 miles. These two factors led to the construction of travel costs in a novel way that reflects the reality that individuals may choose to drive or fly to their preferred recreational destination. As described in English et al. (2018), separate estimates of flying and driving from each resident's home to every coastal destination from Texas to Georgia were constructed. It was assumed that everyone within a one-way driving distance of 500 miles of their destination drives, but beyond 500 miles, individuals may choose to fly or drive. Using the reported frequency of flying to recreation sites in the data, an "expected travel cost" was constructed for every origin-destination pair, where weights proportional to the frequency of flying from alternative distance bands and varying by household income and size were used to construct a weighted average of flying and driving travel costs.

The current analysis modifies the recreation data used by English et al. in two key ways. First, while English et al. aggregated the 2,000 miles of coastline from Texas to Georgia into 83 sites, we employ a more disaggregated site definition of 167 sites. Second, we disaggregate the data temporally and estimate separate models by three-month quarters. This disaggregation adds to the richness of our data and allows us to consider the behavioral and welfare implications of alternative gate fees at finer spatial and temporal scales.

A second key difference between English et al. and the current analysis is that given our focus on gate fees, we must construct a measure of congestion for every site by quarter. Our approach to doing so recognizes that site congestion is more a function of user days than trips, a distinction that is especially salient when a nontrivial fraction of trips are multi-day as is the case with our data.[3] This raises two key issues: 1) for many trips in our data set, we do not observe trip duration, i.e., the number of recreation days; and 2) the length of a trip is endogenously chosen by recreators (McConnell, 1992). To avoid these difficulties, we make the simplifying assumption that trip duration is a function of one-way driving distance. To be more precise, we group trips for which we observe the count of recreation days into one of six cells based on one-way driving distance (< 50 miles, 50-100 miles, 100-250 miles, 250-500 miles, 500-1000 miles, and > 1000 miles). For each cell, we then estimate the mean number of recreation days and use these cell means to construct the total number of user days from the trip data for each site in a quarter. We note that these trip durations are monotonically increasing with distance and range from 1.02 days

[3] By specifying congestion as a function of user days instead of trips here, our empirical model differs from the theoretical framework put forward in the previous section that effectively assumed that all trips were for a single day. This divergence was motivated by our desire to keep the theoretical model simple, and we strongly suspect that the model's implications carry over to our more nuanced empirical setting.

for trips < 50 miles and 4.84 days for trips ≥ 1000 miles, which is consistent with the observation of McConnell (1975). When forecasting how congestion changes with gate fees, we assume these one-way driving distance / recreation user day relationships are deterministic, which obviates the endogenity issue that we alluded to previously.

Another advantage of using a more disaggregated model in the current application is that it allows us to specify congestion in a more refined way. In particular, congestion clearly has spatial and temporal dimensions which we should account for. As Bujosa et al. (2015) point out, a 10-square mile site with 1,000 visitors is far less congested than 1-square mile site with 1,000 visitors. To translate this estimate of the aggregate number of user days by site and quarter into a daily, per mile of coastline congestion measure, we divide it by 90 days and the site's estimated coastline length, or *L*.[4] Our data suggests that there are about 1,245 daily visitors per coastline mile for the average site in our application, although some sites in some quarters have well over 20,000 daily visitors per mile of coastline.

Before moving on to a discussion of our modeling framework, it is worth briefly discussing the structure of the gate fees which we will consider in our policy simulations. Consistent with our specification of congestion, we assume gate fees are charges on a per-user day basis, meaning a person on a long weekend trip who visits the beach on three consecutive days pays triple the amount a person on a single-day trip pays. We assume the charge applies to visitors of any coastal area in Mississippi, Alabama and the Gulf Coast-side of Florida (Perdido Key to Key West) excluding the coastline from Apalachicola to just north of Tampa where sandy beaches are largely absent. Recognizing that many user fees provide discounts for locals, we assume residents of these three states pay a $5 daily fee for access, whereas those coming from other states pay a $10 daily user fee. Since our data

[4] Determining the length of a coastline is a well-known measurement problem that has no exact answer (Manderbrot, 1967). We use a simplified approach where we approximate a site's coastline length with the straight-line distance between the two specific locations within a site that are mentioned by survey respondents and furthest apart from each other. McConnell, in an early application of contingent valuation of the effect of congestion at beaches on WTP, measures congestion as attendance per acre. More generally, Jakus and Shaw (1997) discuss alternative concepts and approaches to measuring congestion. Schuhmann and Schwabe (2004) examine several measures of congestion in a site choice RUM with non-linear congestion effects but without accounting for endogeneity in estimation and in welfare measurement.

only includes trips for adults 18 and older, we assume that children do not have to pay the fee.

Modeling Framework

Our recreational model builds on the revealed preference approach introduced by Timmins and Murdock (2007). Within a site selection model, they model how congestion arises from a Nash bargaining framework in which individuals make choices given expectations about the decisions of others. In equilibrium, expectations of congestion match realized congestion for every individual and site, and assuming congestion is a bad, a Nash equilibrium exists. We extend the Timmins and Murdock model by allowing the total trips to all sites (i.e., participation) to be endogenous. We do so within the repeated discrete choice framework (Morey et al., 1993), whereby the time horizon of choice (e.g., three-month quarter) is comprised of a series of choice occasions. On each choice occasion, an individual makes a discrete choice of whether to take a recreation trip, and if so, a conditional choice of which site to visit. Because these decisions are made across multiple choice occasions and aggregate demand is the sum of these separate choices, the total quantity of trips as well as their distribution across multiple sites is endogenous. We assume that conditional on taking a trip, preferences can be represented by the following indirect utility function:

$$\begin{aligned} V_{ijqt} &= v_{ijq} + \varepsilon_{ijqt} \\ &= \beta_{tc} tc_{ij} + \underbrace{\beta_c c_{jq} + \delta_{jq}}_{\delta^*_{jq}} + \varepsilon_{ijqt}, \end{aligned} \tag{7}$$

where tc_{ij} is individual *i*'s travel cost to site *j*, c_{jq} is the total count of user days per mile of beach at site *j* in quarter *q*, δ_{jq} is a fixed effect for site *j* and quarter *q* that nonparametrically controls for unobserved and observed site characteristics in that quarter, and ε_{ijqt} captures idiosyncratic factors specific to the individual, site, quarter and choice occasion *t*. Note that congestion and unobserved site characteristics in a quarter are perfectly correlated, and thus cannot be separately identified without additional structure.

Following convention in the recreation literature, the utility associated with not taking a trip is specified as a linear function of demographic variables ($\mathbf{z}_i$) specific to individual *i* and an idiosyncratic error:

$$\begin{aligned} V_{i0qt} &= v_{i0q} + \varepsilon_{i0qt} \\ &= \eta \mathbf{z}_i + \varepsilon_{i0qt}. \end{aligned} \tag{8}$$

Assuming the idiosyncratic errors are random draws from the GEV variant of the Type I extreme value distribution, the probability taking a trip to site *j* on choice occasion *t* in quarter *q* is:

$$P_{ijqt} = P_{iqt}(j \mid trip) \times P_{iqt}(trip) = \frac{e^{\left(v_{ijq}/\lambda\right)}}{\sum_{j=1}^{J} e^{v_{ijq}/\lambda}} \frac{\left[\sum_{j=1}^{J} e^{v_{ijq}/\lambda}\right]^{\lambda}}{e^{v_{i0q}} + \left[\sum_{j=1}^{J} e^{v_{ijq}/\lambda}\right]^{\lambda}} = \frac{e^{\left(v_{ijq}/\lambda\right)} \left[\sum_{j=1}^{J} e^{v_{ijq}/\lambda}\right]^{\lambda-1}}{e^{v_{i0q}} + \left[\sum_{j=1}^{J} e^{v_{ijq}/\lambda}\right]^{\lambda}}, \tag{9}$$

And the probability of not taking a trip is:

$$P_{i0qt} = P_{iqt}(no\ trip) = \frac{e^{v_{i0q}}}{e^{v_{i0q}} + \left[\sum_{j=1}^{J} e^{v_{ijq}/\lambda}\right]^{\lambda}}. \tag{10}$$

Estimation of model parameters $(\beta_{tc}, \beta_c, \lambda, \eta, \delta_{1q}^*, \ldots, \delta_{Jq}^*)$ proceeds by maximum likelihood and incorporates the population weights for each person in the sample.

With these parameters in hand, we could, in principle, follow Timmins and Murdock and recover the marginal (dis-)utility of congestion through a second-stage regression that decomposes the alternative specific constants $(\delta_{1q}^*, \ldots, \delta_{Jq}^*)$ into part-worths associated congestion and other observed site characteristics. Because unobserved site characteristics are likely correlated with these observable characteristics, the regression suffers from a classic endogeneity problem. To address this, Timmins and Murdock (2007) adopt an instrumental variables approach that employs nonlinear functions of the observed characteristics of neighboring sites as instruments (as do Melstrom and Welniak 2020 and Phaneuf et al. 2009), whereas Bujosa et al. (2015) use a control function approach. Here we do not estimate the congestion parameter through either approach, but instead evaluate the sensitivity of gate fees to alternative calibrated parameter values that are consistent with different assumptions about what people would pay to avoid additional congestion on a beach trip. Given the relatively small number of recreation studies using credible econometric methods and data to estimate the marginal value of congestion, our approach allows us to speak to the issue of how much demand, welfare and revenue change across a range of plausible parameter values.

Our calibration of the congestion parameter works as follows. On a given trip, the willingness-to-pay (*WTP*) to avoid a change in current congestion levels is:

$$WTP = -\frac{\beta_c \Delta c}{\beta_{tc}}. \tag{11}$$

If we have an econometric estimate of β_{tc} and assume a change in congestion Δc, we can back out the congestion coefficient, β_c, for alternative *WTP* values. We assume Δc corresponds to a doubling of congestion levels at the average site in our data set and consider alternative *WTP* values for avoiding this change that range from \$0 to \$25 in \$5 increments. We then evaluate gate fees for each of the implied values for β_c.[5] It is important to note that the linearity of (11) in Δc rules out the possibility of convex congestion costs, i.e., a doubling of congestion at a congested site has a larger impact on demand and welfare than a doubling of congestion at an uncongested site. In this way, it is likely that the implied demand and welfare effects of congestion reported in the next section may be conservative relative to a richer model that allows for such nonlinearities.

With the estimation or calibration of our model parameters complete, we can turn our attention to identifying the congestion levels after the introduction of a fee. There are two related questions here: 1) is there a unique Nash equilibrium with the fee? And 2) if so, how does one solve for it? As discussed in Bayer and Timmins (2005), the assumption that

[5] To preserve the accuracy of model predictions, the calibrated effect of congestion on utility, $\beta_c c^0$, must be subtracted from the alternative specific constants $(\delta^*_{1q},\ldots,\delta^*_{Jq})$ estimated in the first stage.

congestion is a bad guarantees that a unique Nash equilibrium exists.[6] Solving for the new equilibrium with the gate fee can be achieved through a contraction mapping where the congestion estimates at each site are updated iteratively until they have converged to their true values, c^*. The algorithm we use works as follows. We initially assume congestion levels are fixed at their pre-tax level, c^0, and then solve for the implied congestion levels with the gate fee, $c^1 = c(c^0)$. We repeat this step by solving for $c(c^1)$ and then update our congestion estimate in the following way:

$$c^j = c^{j-1} + d\left[c(c^{j-1}) - c^{j-1}\right], j \geq 2, \qquad (12)$$

where d is a dampening parameter, $0 < d < 1$. We repeat this step until $abs\left|c^j - c^{j-1}\right| \leq k$ where k is a small positive value, which implies the contraction mapping has converged to c^*.

Once we have solved for the new equilibrium level of congestion, we can monetize the full change in economic value induced by the gate fee using the well-known "log-sum" formula as presented in English et al. (2018).

Results

Table 2 reports first-stage parameter estimates for the travel cost (β_{tc}) and dissimilarity (λ) coefficients across alternative models, with the other parameters not reported for brevity. In the first column, all participation and site choice data are pooled across the four quarters, whereas the remaining four columns report separate models by quarter. Focusing first on the travel cost coefficient, we find that it is consistently negative and significant. The coefficient is generally larger during the summer months and smaller during the winter months, implying that trips during the winter months are modestly

[6] If congestion is a good, i.e., there are agglomeration effects at play, Bayer and Timmins (2005) show that a unique equilibrium may or may not exist, and assuming it exists, finding the equilibrium is often more difficult in practice.

higher value (Haab and McConnell, 2002).[7] The dissimilarity coefficients, which by theory must fall between zero and one, are centered around .2 and highly significant.

Table 3 reports key findings from our simulations. These results are aggregated across the four quarters and represent annual predictions for calendar year 2012. We focus first on column 1 where we assume the per trip *WTP* to avoid a doubling of congestion is zero, which is the implicit assumption in Ji et al. (this issue), Lupi et al. (this issue), and the vast majority of published recreation studies investigating access fees. Our model predicts that the gate fee will raise $424 million in revenue from 44 million trips, which corresponds to an average gate fee of roughly $9.65 per trip. Relative to the pre-tax baseline, the fee generates a 22.4% reduction in trips at Gulf Coast sandy beaches in Mississippi, Alabama and Florida subject to the fee and a 6.9% increase in trips to other coastal areas in the six-state region. The behavioral response in terms of user days is larger – a 33.6% reduction in user days at taxed Gulf Coast beaches and a 10.8% increase at other coastal sites – suggesting that multi-day trips – which are subject to higher average fees per trip – are more affected by the gate fee than single-day trips.

Column 1 of Table 3 also reports the compensating variation (*CV*) associated with the gate fee, which equals $556 million. The decomposition of *CV* shows that this loss is entirely due to the increase in the price of recreation trips induced by the fee because, by assumption, congestion does not affect the marginal value of a trip. Finally, we report two measures of the efficiency costs of the gate fee. The first is net surplus, or the sum of revenue raised and compensating variation, which equals -$132 million, or roughly 31% of the total revenue raised. The second measure is the traditional Harberger triangle measure of deadweight loss, $\frac{1}{2}\triangle Trips_G \times Avg\ Fee$, where $\triangle Trips_G$ equals the change in trips to Gulf Coast sandy beaches. This commonly used approximation of deadweight loss equals -$61 million as reported in column 1. Given that recreators are assumed to not value changes in congestion in this case, there is no welfare gain from declines in congestions, and thus the two measures are in theory comparable. In practice, however, they diverge by a factor of two. Our sense is that this difference is driven by the Harberger triangle's reliance on

---

[7] While there are fewer trips in quarters 1 and 4, these trips tend to come from greater distances and hence have higher travel costs, especially in the first quarter.

average price and average change in trips which masks the substantial heterogeneity that arises in our data and is accounted for in the *CV* calculations.[8] Although quantitively different, both measures nonetheless suggest that there is substantial excess burden generated by the gate fee.

We now turn to the second column where we assume the per trip *WTP* to avoid a doubling of congestion levels on a trip is $5. Comparing these results to those in the first column, we find several differences. First, the gate fee raises an additional $30 million (7.1%) in revenue under the assumption of a $5 *WTP* to avoid a doubling of congestion relative to a $0 *WTP.* This increase is driven more so by a smaller decline in trips to the taxed beaches (-18.4% versus -22.4%) than a higher average fee per trip (which rises by only $0.17, or 1.8%). Second, leakage, or the increase in trips to non-taxed sites, is smaller in column 2 relative to column 1 (4.6% versus 6.9%). Third, a similar pattern of behavioral differences arises if one focuses instead on user days instead of trips. Fourth, the welfare losses to consumers (i.e., *CV*) are greater by $10 million (or 1.7%) when recreators have a $5 *WTP* to avoid a doubling of congestion. The decomposition suggests that while there are significant additional benefits ($99 million) from the reduction in congestion levels at the taxed sites, there are even more ($108 million) additional costs associated with the higher congestion levels at the untaxed sites. Finally, the efficiency measures suggest that the net benefits (revenue raised plus *CV*) of the gate fee are higher (or less negative) when congestion is a disamenity to recreators. The Harberger triangle measure of deadweight loss, which does not account for the welfare gains from reduced congestion, remains substantially below the sum of revenue raised and compensating variation.

We now consider the final four columns of Table 3 where the *WTP* to avoid a doubling of congestion is gradually increased in $5 increments from $10 to $25. Comparing these results to those reported in the first two columns reveals several interesting trends. First, revenue raised increases with *WTP* for avoided congestion, albeit

---

[8] To drive home the importance of heterogeneity in the current context, an example is illustrative. Imagine there are two beach goers – one who faces a $1 gate fee and reduces her demand by one trip and a second who faces a $7 gate fee and reduces her demand by seven trips. The deadweight loss for each person is $1 and $24.50, respectively, or $12.75 on average. By contrast, the representative individual faces a $4 gate fee and reduces demand by four trips, implying a deadweight loss of $8.

at a declining rate. In particular, revenue raised increases by $16 million when moving from column 2 to 3 (*WTP* changing from $5 to $10) but only by $9 million when moving from column 5 to 6 (*WTP* changing from $20 to $25). This trend appears to be due more so to the gradual increase in the predicted number of trips to taxed beaches (which increases from 46 to 50 million between columns 2 and 6) than to the more modest increase in the average fee per trip (which increases from $9.83 to $10.07). Second, we also find that leakage to non-Gulf Coast beaches declines as the value for avoided congestion increases, and these patterns are similar if we focus on user days as our relevant metric.

Third, the welfare costs of the gate fee as measured by *CV* decline as recreator's value for avoiding congestion increases. The decline seems to decelerate with higher values for avoided congestion. The decomposition results suggest that the welfare gains from less congestion at the taxed sites trends upward while the welfare losses from more congestion at the non-taxed sites trends downward. However, the gains from the reduced congestion at taxed sites grows faster than the losses at taxed sites. The net result is that overall welfare losses to recreators declines to such a degree that, combined with the gradual increases in revenue raised, social welfare (*Revenue Raised* + *CV*) is positive when recreators value congestion reductions most highly ($8 and $39 million in columns 5 and 6, respectively). This implies that when recreators value avoided congestion highly, gate fees can be potential Pareto improving, even when the revenues are only returned lump sum. Finally, it is worth pointing out that value of the Harberger triangle approximation as a proxy for welfare change degrades with higher values for avoided congestion to the point that it can be misleading both in sign and magnitude (again, see columns 5 and 6). This result is due to the increasing welfare gains to recreators from reduced congestion that the Harberger triangle approximation does not account for.

Table 3 also shows results for implied price elasticities associated with the fee regime. Elasticities for the complex pattern of price changes are approximated by taking the percentage change in total Gulf Coast beach trips and dividing by the percentage change in average price. A similar calculation is performed for the total trips to all beaches (final row). With no congestion effects (column 1), the Gulf Coast beach trips are elastic with an elasticity of about 1.8, which is similar to the elasticities reported in Lupi et al. (this issue).

When looking at total trips, the results are inelastic because the change in total trips is lessened by the substitution away from Gulf to non-Gulf Coast beaches where prices do not change. As the simulations include increasing amounts of congestion effects, the Gulf Coast beach trips become less elastic, and at a WTP for avoiding a doubling of congestion of $25 (column 6) Gulf Coast beach trips are inelastic due to the net effects of the price and congestion changes.

In terms of the distribution of benefits and costs, the underlying demand model reported in Table 2 controls for several observable demographic characteristics that influence trip-taking, allowing us to examine the effects of the fee regime by race, geographic origin of trips and income. These results are presented in Tables 4 and 5. Beginning with Table 4, non-whites, who make up 25% of the sample, take only 17% of total trips with the gate fee but reduce their demand by relatively more compared to whites (17-28% versus 11-21% depending on scenario considered). Non-whites, however, bear a modestly smaller percentage of total welfare losses (compensating variation) from the fee relative to their population share (21-24%) and pay a lower percentage of gate fees (20-21%). Taken as a whole, these results do not suggest that gate fees are disproportionately born by minorities.

Additionally, Table 4 breaks down the distributional impacts of the proposed gate fee by locals (i.e., residents of Mississippi, Alabama and Florida) and non-locals. Locals account for 9% of the sample but take 88-90% of total trips after the gate fee is implemented. Their reduction in trips is much lower relative to non-locals, ranging from 3 to 14% compared to 48 to 59% for non-locals. Locals bear about half of the welfare losses from the fee and pay almost two-thirds of all gate fees. However, given that they take the vast majority of trips, it appears that the structure of the gate fee considered – which is proportional to user days and discriminates against non-locals – is effective at shifting the burden of the tax to non-locals.

Finally in Table 5, we consider the distributional impacts across income quintiles. In our empirical model, trip-taking is positively influenced by income, with higher income groups having the largest probability of visiting a beach.[9] This implies that the poorest income quintile takes only 14% of total trips under the gate fee. However, the poorest quintile reduces their demand by the highest percentage (25-37%) and bears a disproportionate amount of the total welfare losses. The 2nd lowest income quintile actually bears a higher percentage of total compensating variation (27%) and total fees (27%) although they take a higher percentage of trips (24%). On the other hand, the highest income quintile takes 22-23% of total trips but bears only 13-14% of the welfare losses and 14-15% of the fee payments. To gain further insight into the distributional impacts of the gate fees by income, we can aggregate the bottom two and top two quintiles. Doing so reveals that the lowest 40% of incomes take a modestly lower percentage of total trips (38%), experience a steep decline in trips after the fee's introduction (13-24%), bear 51-53% of the welfare losses, and pay 48-49% of the total gate fees. This contrasts with the upper 40% who take a slightly higher percentage of trips (41-42%), experience a smaller decline in trips after the fee is implemented (5-13%), and bear only 28-30% of the compensating variation losses and 30-32% of the gate fees. Consistent with Ji et al. (this issue) and Lupi et al. (this issue), these results suggest that gate fees are generally regressive even when congestion feedback effects are accounted for.

Conclusion

This special issue has focused on the need for a significant and reliable revenue stream to pay for maintenance and repair projects on public lands throughout the United States. Our paper contributes to this theme by focusing on an appealing revenue-raising instrument – an access or gate fee – that not only generates funds for maintenance and repair but also mitigates a persistent problem with public resources that are often managed as open-access resources – congestion. By introducing a gate fee, one can address both concerns simultaneously. Economists have long recognized this virtue, but our collective understanding of the behavioral, welfare, revenue-raising, and distributional implications of these taxes remains relatively primitive. In the current paper, we advance

[9] This finding is generally consistent with English et al. (2018).

our understanding of gate fees by developing a simple conceptual framework that predicts the likely behavioral and welfare impacts of gate fees, building a detailed recreation demand model of participation and site choice for shoreline recreation from Texas to Georgia, and then evaluating a gate fee for sandy beaches in Mississippi, Alabama and Florida that is proportional to the number of user days. We identify three distinct behavioral channels that arise from a gate fee – a pure price effect, a taxed site congestion effect, and a non-taxed site congestion effect – that combine to determine the overall social costs of such a fee. In our empirical analysis of Gulf Coast sandy beaches, we find that substantial revenue can be raised by such a fee, and that accounting for how a fee is likely to change congestion levels can reduce the social costs of the fee substantially. In fact, if people have a relatively large willingness-to-pay to avoid congestion, these fees can be potential Pareto improving. Moreover, our distributional analysis suggests that gate fees are generally regressive, do not disproportionally impact minorities, and benefit locals at the expense of visitors from further away.

There remains much to do to further economist's understanding of gate fees, and here we identify two areas that seem promising to us. First, our limited understanding of the marginal value of reducing congestion at beaches and other resources suggests the need for more research. This will require additional data collection efforts and clever identification strategies, and the work by Timmins and Murdock (2007) and Bujosa et al. (2015) certainly represents a good start. We also believe that stated preference approaches like Boxall et al. (2003) can add significant insight, especially in terms of how the value of congestion varies across individuals, sites, and recreational activities. Second, our study investigates one possible gate fee but does not search across alternative gate fees to determine which fee structure is optimal from a net-benefits perspective. And once one sets as a target identifying an optimal gate fee, several questions arise: 1) what are the potential gains of allowing the fee to vary across time and space? 2) should gate fees vary by time of day and the level of aggregate use? 3) what are the social costs of exempting children or seniors from the fee? and 4) should locals be provided a discount relative to non-locals? Economists have made some progress in answering these questions in the context of energy and water consumption demand, but the implications of alternative fee structures merits further study in the recreation context.

References

Bayer, Patrick, and Christopher Timmins. 2005. "On the Equilibrium Properties of Locational Sorting Models," *Journal of Urban Economics* 57:462-477.

Boxall, Peter, Jeffery Englin, and Kim Rollins. 2003. "Heterogeneous Preferences for Wilderness Congestion," *Resource and Energy Economics* 25:177–195.

Bujosa, Angel, Antoni Riera, Robert Hicks, and Kenneth McConnell. 2015. "Densities Rather than Shares: Improving the Measurement of Congestion in Recreation Demand Models," *Environmental and Resource Economics* 61(2):127-140.

Cesario, Frank. 1980. "Congestion and the Valuation of Recreation Benefits," *Land Economics* 56(3):329-338.

Clawson, Marion, and Jack L. Knetsch. 1963. "Outdoor Recreation Research: Some Concepts and Suggested Areas of Study," *Natural Resources Journal* 3(2):250-275.

English, Eric, Roger H. von Haefen, Joseph A. Herriges, Christopher G. Leggett, Frank Lupi, Kenneth E. McConnell, Michael Welsh, Adam Domanski, and Norman Meade. 2018. "Estimating the Value of Lost Recreation Days from the Deepwater Horizon Oil Spill." *Journal of Environmental Economics and Management* 91:26-45.

Jakus, Paul, and W. Douglass Shaw, 1997. "Congestion at Recreation Areas: Empirical Evidence on Perceptions, Mitigating Behaviour and Management Preferences," *Journal of Environmental Management* 50:389-401.

Haab, Timothy C., and Kenneth E. McConnell. 2003. *Valuing Environmental and Natural Resources: The Econometrics of Non-Market Valuation.* Cheltenham: Edward Elgar.

Ji, Yongjie, David A. Keiser, Catherine L. Kling, and Daniel J. Phaneuf. *This Issue*. "Revenue and Distributional Consequences of Alternative Outdoor Recreation Pricing Mechanisms: Evidence from a Micro Panel Data Set."

Lupi, Frank, Roger H. von Haefen, and Li Cheng. *This Issue*, "Distributional Effects of Entry Fees and Taxation for Financing Public Beaches."

Manderbrot, Benoit. 1967. "How Long is the Coast of Britain? Statistical Self-Similarity and Fractional Dimension," *Science* 157(3775):636-638.

Melstrom, Richard T., and Taylor Welniak. 2020. "The Effect of Site Congestion on Valuing Freshwater Fishing for Urban Residents," *Water Economics and Policy* 6(4): 1950008.

McConnell, Kenneth E. 1975. "Some Problems in Estimating the Demand for Outdoor Recreation," *American Journal of Agricultural Economics* 57:330-34.

McConnell, Kenneth E. 1977. "Congestion and Willingness to Pay: A Study of Beach Use," *Land Economics* 53(2):185-195.

McConnell, Kenneth E. 1992. "Onsite Time in the Demand for Recreation," *American Journal of Agricultural Economics* 74:918-925.

Phaneuf, Daniel J., Jared C. Carbone, and Joseph A. Herriges. 2009. "Non-Price Equilibria for Non-Marketed Goods," *Journal of Environmental Economics and Management* 57:45–64.

Schuhmann, Peter, and Kurt Schwabe. 2004. “An Analysis of Congestion Measures and Heterogeneous Angler Preferences in a Random Utility Model of Recreational Fishing,” *Environmental and Resource Economics* 27:429-450.

Timmins, Christopher, and Jennifer Murdock, 2007.” A Revealed Preference Approach to the Measurement of Congestion in Travel Cost Models,” *Journal of Environmental Economics and Management* 53(2): 230-49.

Figure 1 – Demand Response to Gate Fee

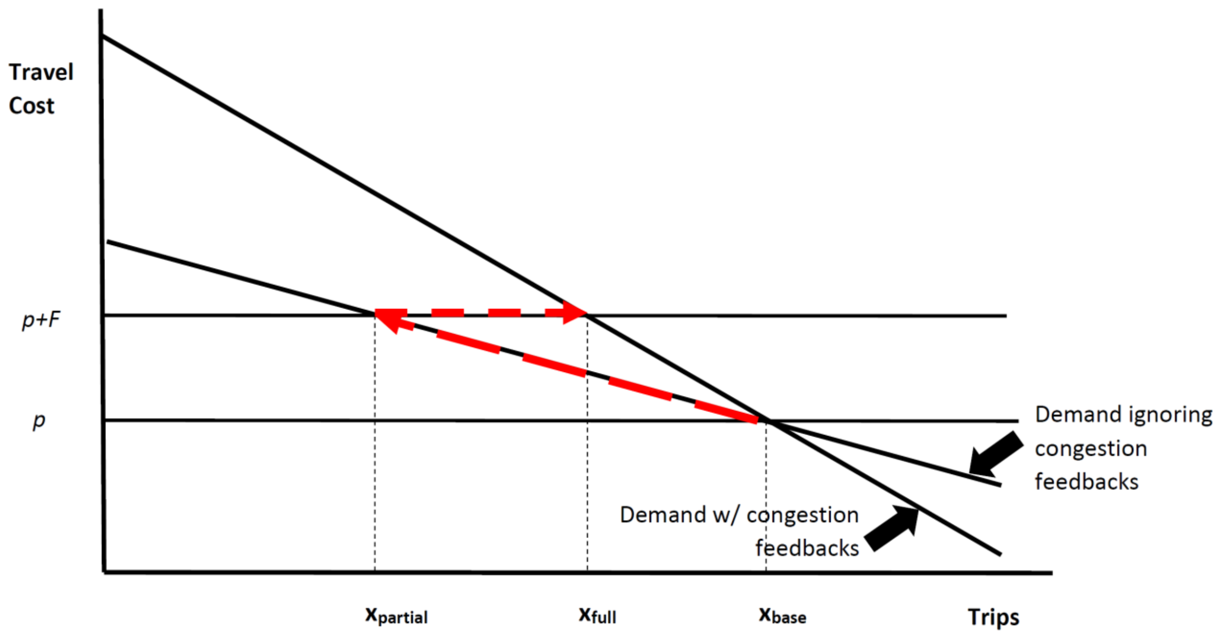
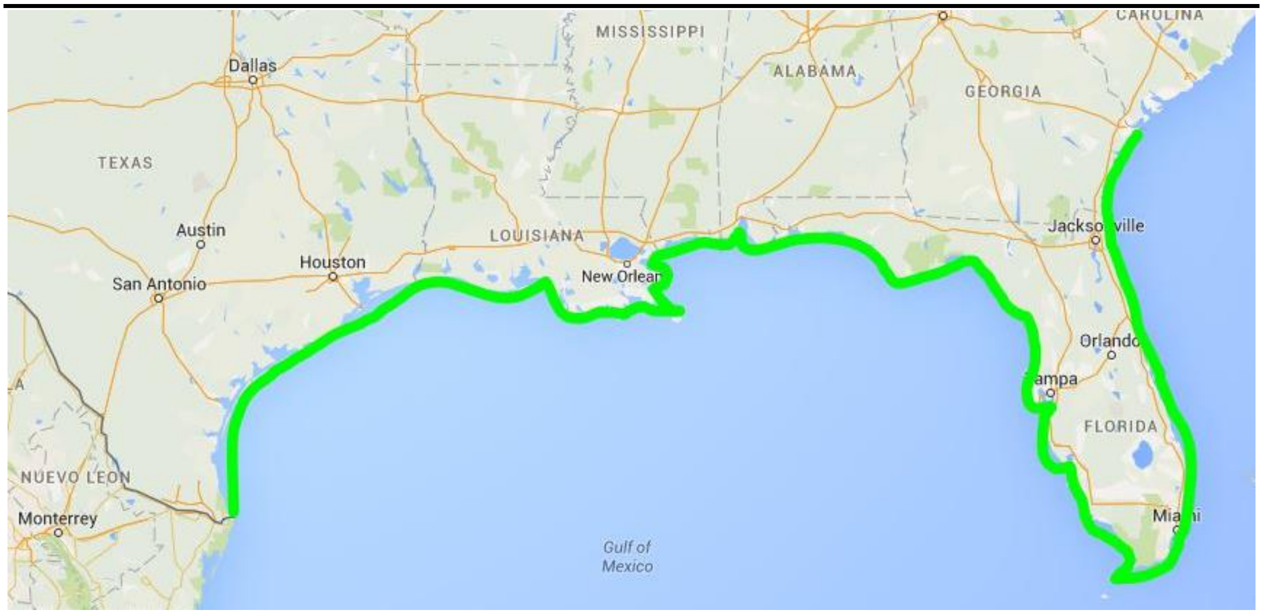


Figure 2 – Sampling Region for Recreational Trips



Note: Survey respondents reported recreational trips to shoreline areas highlighted in green.

Table 1

Summary Statistics for Recreational Trips

Total Trips	27,717
Total Trips Used in Estimation[1]	93%
Mean Trip Duration	2.2
Mean Recreation Days	1.5
% Multi-Day Trips	17%
Mean Party Size	2.7
% w/ One-Way Driving Distance < 5 Miles	30%
% w/ One-Way Driving Distance < 10 Miles	46%
% w/ One-Way Driving Distance < 100 Miles	84%
% w/ One-Way Driving Distance < 500 Miles	92%
% w/ One-Way Driving Distance < 1000 Miles	94%

Note: Constructed w/ sampling weights.

[1] Trips were primarily dropped because of uncertainty with regard to whether the primary purpose of the trip was recreation or the destination of the trip.

Table 2
First-Stage Parameter Estimates

	(1) Annual Model	(2) Jan / Feb / Mar	(3) Apr / May / Jun	(4) Jul / Aug / Sep	(5) Oct / Nov / Dec
Travel Cost	-1.0243***	-0.7521***	-1.1972***	-1.1766***	-1.0322***
	(11.8)	(19.7)	(8.17)	(22.3)	(18.3)
Dissimilarity	0.2116***	0.1981***	0.3195***	0.2199***	0.2266***
Coefficient	(14.8)	(6.85)	(15.5)	(6.19)	(10.9)
N	41,716	23,635	16,607	26,799	19,289
Log-Like	-33,427	-12,300	-27,178	-14,002	-11,507

t-statistics based on standard errors clustered by site in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 3
Simulation Results across Assumed Per Trip WTP to Avoid Congestion

Assumed Per Trip WTP to Avoid Doubling of Congestion Levels	$0	$5	$10	$15	$20	$25
Revenue Raised	$424	$455	$471	$483	$493	$502
Compensating Variation (CV)	-$556	-$566	-$538	-$511	-$486	-$462
Decomposition						
Pure Price Effect	-$556	-$556	-$556	-$556	-$556	-$556
Taxed Site Congestion Effect	$0	$99	$159	$204	$242	$273
Non-Taxed Site Congestion Effect	$0	-$108	-$141	-$159	-$171	-$179
Avg. Fee Per Trip	$9.65	$9.83	$9.91	$9.98	$10.02	$10.07
Gulf Beach Trips w/o Fee	57	57	57	57	57	57
Gulf Beach Trips w/ Fee	44	46	48	49	49	50
% Change	-22.4%	-18.4%	-16.1%	-14.5%	-13.1%	-12.0%
Non-Gulf Beach Trips w/o Fee	99	99	99	99	99	99
Non-Gulf Beach Trips w/ Fee	106	104	103	102	102	102
% Change	6.9%	4.6%	3.6%	3.0%	2.5%	2.1%
Gulf Beach User Days w/o Fee	107	107	107	107	107	107
Gulf Beach User Days w/ Fee	71	76	78	80	81	83
% Change	-33.6%	-29.4%	-27.0%	-25.3%	-23.9%	-22.8%
Non-Gulf Beach User Days w/o Fee	177	177	177	177	177	177
Non-Gulf Beach User Days w/ Fee	196	191	189	188	187	186
% Change	10.8%	8.1%	6.9%	6.2%	5.6%	5.1%
Efficiency Measures						
Revenue Raised + CV	-$132	-$112	-$67	-$28	$8	$39
$\frac{1}{2}\triangle Trips_G \times$ *Avg. Fee*	-$61	-$51	-$45	-$41	-$37	-$34
Price Elasticity of Trip Demand						
Gulf Beach Trips	1.78	1.43	1.25	1.11	1.00	0.91
Total Beach Trips	0.29	0.29	0.27	0.26	0.24	0.23

This table reports simulated results for a $5/day fee for residents of Florida, Alabama, and Mississippi and $10/day fee for others. All estimates except avg. fee per trip are reported in millions. Monetary estimates are in 2012 $s. Price elasticity of demand for trips to Gulf sites approximated by the percentage change in average price divided by the percentage change in trips to the Gulf.

Table 4
Distributional Impacts by Race and Trip Origin

Assumed Per Trip WTP to Avoid Doubling of Congestion Levels	$0	$5	$10	$15	$20	$25
White (75% of sample)						
Percent of Total Trips w/ Fee	83%	83%	83%	83%	83%	83%
Percent Reduction in Trips	21%	17%	15%	13%	12%	11%
Percent of Total CV	79%	78%	77%	76%	76%	76%
Percent of Total Fees Paid	80%	79%	79%	79%	79%	79%
Non-White (25% of sample)						
Percent of Total Trips w/ Fee	17%	17%	17%	17%	17%	17%
Percent Reduction in Trips	28%	24%	21%	20%	18%	17%
Percent of Total CV	21%	22%	23%	24%	24%	24%
Percent of Total Fees Paid	20%	21%	21%	21%	21%	21%
Locals (9% of sample)						
Percent of Total Trips w/ Fee	90%	89%	89%	89%	89%	88%
Percent Reduction in Trips	14%	10%	7%	6%	4%	3%
Percent of Total CV	56%	54%	51%	49%	46%	44%
Percent of Total Fees Paid	67%	66%	66%	65%	65%	65%
Non-Locals (91% of sample)						
Percent of Total Trips w/ Fee	10%	11%	11%	11%	11%	12%
Percent Reduction in Trips	59%	55%	52%	51%	49%	48%
Percent of Total CV	44%	46%	49%	51%	54%	56%
Percent of Total Fees Paid	33%	34%	34%	35%	35%	35%

All estimates except are reported in millions. Monetary estimates are in 2012 $s.

Table 5
Distributional Impacts by Income

Assumed Per Trip WTP to Avoid Doubling of Congestion Levels	$0	$5	$10	$15	$20	$25
Lowest 20% of Income						
Percent of Total Trips w/ Fee	14%	14%	14%	14%	14%	14%
Percent Reduction in Trips	37%	32%	30%	28%	26%	25%
Percent of Total CV	24%	24%	24%	25%	25%	26%
Percent of Total Fees Paid	21%	21%	22%	22%	22%	22%
2nd Lowest 20% of Income						
Percent of Total Trips w/ Fee	24%	24%	24%	24%	24%	24%
Percent Reduction in Trips	27%	22%	19%	17%	16%	14%
Percent of Total CV	27%	27%	27%	27%	27%	27%
Percent of Total Fees Paid	27%	27%	27%	27%	27%	27%
Middle 20% of Income						
Percent of Total Trips w/ Fee	21%	21%	21%	21%	21%	21%
Percent Reduction in Trips	21%	17%	15%	13%	12%	11%
Percent of Total CV	20%	20%	19%	19%	19%	19%
Percent of Total Fees Paid	21%	21%	21%	21%	21%	21%
2nd Highest 20% of Income						
Percent of Total Trips w/ Fee	19%	19%	19%	19%	19%	19%
Percent Reduction in Trips	17%	14%	12%	10%	9%	8%
Percent of Total CV	16%	16%	16%	16%	15%	15%
Percent of Total Fees Paid	17%	17%	16%	16%	16%	16%
Highest 20% of Income						
Percent of Total Trips w/ Fee	23%	22%	22%	22%	22%	22%
Percent Reduction in Trips	10%	8%	6%	5%	4%	3%
Percent of Total CV	13%	14%	14%	14%	14%	13%
Percent of Total Fees Paid	15%	15%	14%	14%	14%	14%

All estimates are reported in millions. Monetary estimates are in 2012 $s.

Supplemental Materials

Derivation of Equation (3)

We can write the effects at each site symmetrically like so:

(S1) $$\frac{dx_1}{dF_1} = \frac{\partial g_1}{\partial p_1} + \frac{\partial g_1}{\partial c_1}\frac{dx_1}{dF_1}/L_1 + \frac{\partial g_1}{\partial c_2}\frac{dx_2}{dF_1}/L_2$$

(S2) $$\frac{dx_2}{dF_1} = \frac{\partial g_2}{\partial p_1} + \frac{\partial g_2}{\partial c_1}\frac{dx_1}{dF_1}/L_1 + \frac{\partial g_2}{\partial c_2}\frac{dx_2}{dF_1}/L_2$$

Re-arranging (S1):

(S3) $$\frac{dx_1}{dF_1} = \frac{\frac{\partial g_1}{\partial p_1} + \frac{\partial g_1}{\partial c_2}\frac{dx_2}{dF_1}/L_2}{1 - \frac{\partial g_1}{\partial c_1}/L_1}$$

Substituting into (S2):

(S4) $$\frac{dx_2}{dF_1} = \frac{\partial g_2}{\partial p_1} + \frac{\partial g_2}{\partial c_1}\left[\frac{\frac{\partial g_1}{\partial p_1} + \frac{\partial g_1}{\partial c_2}\frac{dx_2}{dF_1}/L_2}{L_1 - \frac{\partial g_1}{\partial c_1}}\right] + \frac{\partial g_2}{\partial c_2}\frac{dx_2}{dF_1}/L_2$$

$$\frac{dx_2}{dF_1} = \frac{\partial g_2}{\partial p_1} + \frac{\frac{\partial g_2}{\partial c_1}\frac{\partial g_1}{\partial p_1}}{L_1 - \frac{\partial g_1}{\partial c_1}} + \left[\frac{\frac{\partial g_2}{\partial c_1}\frac{\partial g_1}{\partial c_2} + \frac{\partial g_2}{\partial c_2}}{L_1 - \frac{\partial g_1}{\partial c_1}}\right]\frac{dx_2}{dF_1}/L_2$$

(S5)
$$\left[1-\frac{\frac{\frac{\partial g_2}{\partial c_1}\frac{\partial g_1}{\partial c_2}}{L_2}}{L_1-\frac{\partial g_1}{\partial c_1}}-\frac{\partial g_2}{\partial c_2}/L_2\right]\frac{dx_2}{dF_1}=\frac{\partial g_2}{\partial p_1}+\frac{\frac{\partial g_2}{\partial c_1}\frac{\partial g_1}{\partial p_1}}{L_1-\frac{\partial g_1}{\partial c_1}}$$

(S6)
$$\left[\left(L_1-\frac{\partial g_1}{\partial c_1}\right)\left(1-\frac{\partial g_2}{\partial c_2}/L_2\right)-\frac{\frac{\partial g_2}{\partial c_1}\frac{\partial g_1}{\partial c_2}}{L_2}\right]\frac{dx_2}{dF_1}=\left(L_1-\frac{\partial g_1}{\partial c_1}\right)\frac{\partial g_2}{\partial p_1}+\frac{\partial g_2}{\partial c_1}\frac{\partial g_1}{\partial p_1}$$

Finally, change in per-mile demand at site two from a fee at site one is:

(S7)
$$\frac{dx_2/dF_1}{L_2}=\frac{\left(L_1-\frac{\partial g_1}{\partial c_1}\right)\frac{\partial g_2}{\partial p_1}+\frac{\partial g_2}{\partial c_1}\frac{\partial g_1}{\partial p_1}}{\left(L_1-\frac{\partial g_1}{\partial c_1}\right)\left(L_2-\frac{\partial g_2}{\partial c_2}\right)-\frac{\partial g_2}{\partial c_1}\frac{\partial g_1}{\partial c_2}}$$

Or alternatively:

(S7')
$$\frac{dx_2}{dF_1}=\frac{\left(1-\frac{\partial g_1}{\partial c_1}/L_1\right)\frac{\partial g_2}{\partial p_1}+\frac{\partial g_2}{\partial c_1}\frac{\partial g_1}{\partial p_1}/L_1}{\left(1-\frac{\partial g_1}{\partial c_1}/L_1\right)\left(1-\frac{\partial g_2}{\partial c_2}/L_2\right)-\left(\frac{\partial g_2}{\partial c_1}/L_2\right)\left(\frac{\partial g_1}{\partial c_2}/L_1\right)}$$

The first term in the denominator is positive, but the second term is negative. Similarly in the numerator, the first term is positive, but the second is negative. Therefore, it is not possible to sign dx_2/dF_1 in general.