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A revealed preference approach to the measurement of congestion in travel cost models

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Abstract

Travel cost models are regularly used to determine the value of recreational sites or particular site characteristics, yet congestion, a key site attribute, is often excluded from such analyses. One reason for this omission is that congestion is determined in equilibrium by the process of individuals sorting across sites and thus presents significant endogeneity problems. This paper illustrates this source of endogeneity, describes how previous research has dealt with it using stated preference techniques, and describes an instrumental variables approach to address it in a revealed preference context. We demonstrate that failing to address the endogeneity of congestion leads one to dramatically understate its costs. We apply our technique to the valuation of a large recreational fishing site in Wisconsin (Lake Winnebago) which, if eliminated, would induce significant re-sorting of anglers amongst remaining sites. Ignoring congestion leads to an understatement of the lake's value by more than 50%.

Keywords: Congestion; Random utility model; Site valuation; Travel cost; Discrete choice; Instrumental variables; Quantile regression

1. Introduction

Random utility models (RUMs) of recreation demand exploit the information in the trade-offs individuals make between travel time and site attributes in order to value the latter. The same models can be used to value bundles of attributes (i.e., entire sites). Consider the case of recreational fishing. Applications typically include data on site attributes such as expected fish catch, urban and industrial development, water quality, and amenities like paved boat ramps and fishing piers. The RUM has become a staple of the legal and policy communities because it provides a convenient tool for attaching values to non-marketed commodities (e.g., water quality) that might be the subject of litigation or environmental policy debates, or for determining the cost to anglers if a fishing site were to be lost to pollution.

One important attribute that is conspicuously absent from nearly every such study (and particularly those based on revealed preference techniques) is congestion. Measures of congestion describe the number of other individuals encountered during the recreation experience.[1] For activities like hunting, hiking, camping, fishing,

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[1]There are a number of papers that deal specifically with the question of how to define congestion. We describe these in Section 2.

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and beach use, congestion is likely to be an important attribute of that experience. When congestion is not included in the estimation of a RUM, three important things occur. (i) The role of congestion as an effective rationing device is ignored. This can have implications for the proper design of policy. (ii) Congestion becomes an omitted variable that will lead to biased estimates of the value of other attributes with which it is correlated. (iii) The ability to accurately value entire sites is compromised, especially when those sites are large and their closure induces significant resorting over remaining sites.

This analysis addresses congestion empirically using revealed preference techniques. It does so by relying on a previously unexploited source of variation in the data—the isolation of alternative sites in exogenous attribute space. Without exploiting this source of variation, controlling for congestion is a difficult task. Variables describing the equilibrium behavior of other individuals in the site-choice problem are typically endogenous. Without properly accounting for that source of endogeneity, there is a natural tendency to understate the cost of congestion and to even mistakenly recover estimates of benefits from larger crowds (i.e., agglomeration effects). In this study, we describe the source of this endogeneity, cast it as a simple instrumental variables problem in a familiar regression context, and demonstrate how it can be solved in an application to Wisconsin recreational fishing. We then use our estimates to demonstrate how ignoring congestion can lead to significant biases in measuring the value of a large site.

It is important to note that, while we illustrate our technique for dealing with congestion in the context of the RUM multi-site model, this is certainly not the only technique available for valuing site attributes. Other approaches include those based on incomplete demand systems and Kuhn–Tucker methodologies, both of which introduces the extensive margin (i.e., how many trips to take) in addition to simply modeling site choice conditional on taking a trip. With suitable adaptations, the technique described here for measuring congestion costs could be applied to these approaches as well, allowing the researcher to examine the effect of congestion on both the intensive and extensive margins.

After a brief review of the literature on the role of congestion in travel cost models in Section 2, we describe our model of site selection with congestion in Section 3. In Section 4, we describe the data set we use in an application of our technique. In Section 5, we discuss an econometric complication that arises when we model different congestion effects depending upon whether they occur on a weekday versus a weekend. Section 6 reports model estimates. Section 7 illustrates the role of congestion in a site valuation exercise, and Section 8 shows how it impacts the benefits of a fish stocking program. Section 9 concludes.

2. Previous literature

It has long been recognized that congestion costs could be an important determinant of behavior in models of site selection. We categorize papers on the topic into three groups—one theoretical and two that are primarily empirical. The set of theoretical papers describe important issues that will motivate our modeling exercise. Anderson and Bonsor [1] were among the first to discuss the implications of congestion for measuring willingness to pay, while Fisher and Krutilla [12] note that optimal management of a recreation site requires a charge that incorporates both marginal congestion and environmental costs. Cesario [9] introduces the primary issue we address in our empirical application—that one cannot recover unbiased estimates of the value of a recreation site without accounting for equilibrium re-sorting. The removal of a recreational site adversely affects the welfare of users of other sites as displaced recreators re-sort across the remaining sites. Conversely, there is a tendency to understate the value of new site construction if congestion costs are ignored. In a more recent paper, Jakus and Shaw [14] discuss ways to measure congestion, emphasizing the value individuals expect at the time they make their site decision rather than, for example, an ex post realization of congestion. A similar point is made by Schuhmann and Schwabe [22], who also highlight the timing of congestion costs. This could entail, for example, differentiating between the expected number of other recreators on a weekday versus a weekend visit. Michael and Rieling [19] discuss the role of heterogeneous preferences for congestion in inducing recreators to sort over days of the week.

Empirical work on congestion in site valuation can generally be divided into studies based on stated versus revealed preference data. Cichetti and Smith [11] measure the effect of "wilderness encounters" (i.e., congestion in the hiking context) on stated willingness to pay with an application to the Spanish Peaks Primitive Area in Montana. McConnell [18] employs stated preference techniques to estimate the role of congestion in the demand for beach recreation and uses the results to characterize net surplus maximizing projects. Boxall et al. [8] similarly use a stated preference model to value congestion in four separate components of a back-country canoeing trip, emphasizing that the estimate of distaste for congestion may be very different depending upon the specific activity under consideration.

In this analysis, we adopt a revealed preference approach to measuring the costs of congestion. Consider briefly, however, how stated preference data solve the endogeneity problems associated with congestion. Congestion is determined by the optimizing decisions of recreators; measuring it falls into the general class of problems associated with endogenous sorting models. [3] In such models, congestion is likely to be correlated with unobservables that also drive the behavior of the decision-maker in question, making it an endogenous attribute. Stated preference models avoid this problem by hypothetically varying congestion while holding constant the unobservables that drive sorting behavior. The downsides of this solution are: (i) that stated preference models value hypothetical changes about which respondents may not reveal their true preferences, and (ii) respondents may not actually be able to "hold all else constant" when hypothetically varying the congestion variable—i.e., stated (dis)taste for congestion may reflect preferences for or against unobserved attributes typically associated with congestion.

There have been few attempts to value congestion with revealed preference data. Boxall et al. [7] conduct such an analysis, using fitted values of anticipated congestion from a first-stage estimation procedure to control for the endogeneity of that variable in the utility function. That procedure is based on survey data describing anticipated congestion (i.e., asking retrospectively what the recreator anticipated at the time the trip was planned), observed site attributes, and a number of recreator characteristics—all combined in an ordered logit model to predict the level of anticipated congestion. The effect of anticipated congestion on utility is then identified by interactions between recreator characteristics (e.g., wilderness recreation experience) and site attributes that are effectively introduced by the ordered logit functional form,[2] but which are not allowed to enter directly into the utility specification. In many contexts (such as the one we study here), justifying such an exclusion restriction proves difficult.[3] Our research describes instead an instrumental variables strategy based on the structure of the "game" played between recreators. That strategy depends only on having rich data describing recreation site attributes.

In addition to the role of congestion in models of site selection, this analysis also touches on a number of other literatures. Our application to the recreational fishing behavior of Wisconsin anglers builds upon a long line of research using RUMs and travel costs to value site attributes. Bockstael et al. [4] provides one of the earliest published applications of the RUM to recreation demand in their valuation of catch improvements for Florida sportfishing. Subsequent research has considered the sensitivity of the RUM to a number of data handling and modeling decisions such as the definition of sites, the definition of the choice set, and the assumed error structure. During the last decade researchers have relaxed some of the strict assumptions on the error structure. Nested logit specifications, which allow for correlations among the unobservables for groups of alternatives, and random parameters specifications, which allow individual preferences for site characteristics to be heterogeneous, have become the norm. Murdock [20,21] incorporates the random parameters logit into a specification that introduces unobserved site attributes into a travel cost analysis of Wisconsin recreational fishing. We make use of the same data here.

Finally, for reasons that will be made clear in Section 5, applying our empirical strategy will require the use of instrumental variables techniques adapted to estimation in a quantile regression framework. Recent work has produced a number of approaches to this problem [10,13,17]. An alternative method based on recent work by Han Hong and Thomas MaCurdy proves to be particularly well-suited to our application.

[2]Consider the logit probability expression as it is used in a RUM. Utility may be a linear function of two variables, X and Y, without any interactions. The logit probability of observing any particular choice will, however, be a non-linear function of X and Y that includes interactions between these variables. The same idea applies to the ordered logit used by Boxall et al. [7].

[3]I.e., the question being whether preferences for site attributes should not be allowed to vary with recreator characteristics while the relationship between anticipated congestion and observed site attributes should be allowed to vary with those characteristics. There may be applications in which there are recreator characteristics that naturally satisfy this restriction.

3. Model

Our model of congestion in a RUM framework is akin to describing a Nash bargaining model in which individuals make choices given their expectations about the decisions that will be made by other individuals. In equilibrium, those expectations are confirmed by other individuals' actual behavior. We therefore begin with the decision of an individual angler i. The angler simultaneously chooses a site ($s = 1, 2, \ldots, S$) and a time period (t = weekday, weekend). The combination of sites and time periods leads to a total of $j = 1, 2, \ldots, J$ alternatives where $J = t \times S$. For the sake of simplicity, we model each fishing trip as an independent event, ignoring the fact that we see the same angler make multiple trips over the course of the summer. We do not model the choice of how many fishing trips are taken by an individual angler, nor the angler's participation decision more generally (i.e., whether to fish at all or to pursue some outside recreation alternative). While these complications could be incorporated into the framework outlined below, they are not the focus of the current paper and are, therefore, omitted. The implications of these assumptions are discussed throughout the remainder of the text when appropriate.

The utility obtained from choosing site-period combination j is given by

$$U_{ij} = \delta_j + X_j'\Gamma(Z_i) + \Phi(Z_i)\sigma_j + \Theta(Z_i)TC_{i,j} + \varepsilon_{i,j}, \quad (1)$$

where

$$\delta_j = X_j'\beta + \alpha\sigma_j + \xi_j, \quad (2)$$

$$\Gamma(Z_i) = Z_i'\gamma \quad \Phi(Z_i) = Z_i'\phi \quad \Theta(Z_i) = \theta_0 + Z_i'\theta_1 \quad (3)$$

Z_i is a vector of observable attributes of angler i; X_j is a vector of observable attributes of alternative j, including a dummy for the choice representing a weekday trip[4]; $TC_{i,j}$ is the travel cost incurred by angler i in choosing j[5]; ξ_j, is a (scalar) unobservable attribute of choice j (common to all anglers); ε_{ij}, is an idiosyncratic source of utility for angler i at choice j; and σ_j is the expected share of all anglers choosing j.

δ_j represents the baseline utility from site j, which is what an individual with all elements of Z_i set equal to zero would receive, except for the common component of the marginal utility of travel costs, $\theta_0\, TC_{i,j}$. The sign of α determines whether utility exhibits congestion (−) or agglomeration (+) effects. Agglomeration effects are common in models of urbanization and industrial "clustering". We expect congestion effects to be more relevant for our application.

Individuals are ascribed rational expectations about the behavior of their fellow anglers. This means that the vector of expected shares will be constant across individuals and equal to the actual share. Practically, this assumption is consistent with the idea that anglers have repeatedly played the sorting game with one another and have achieved a Nash equilibrium.

We set up the problem as a heterogeneous parameters discrete choice model, allowing preferences for several observable attributes (including congestion and travel cost) to vary with observable individual attributes Z_i. A random parameters logit model, which allows for additional heterogeneity in the taste parameters based on unobserved individual attributes, could also be incorporated into our modeling framework. (See Murdock [21] for a random-parameters model without congestion.)

3.1. Equilibrium

Each angler maximizes his or her utility over the choice of alternative j given expectations about the behavior of other anglers. In equilibrium, those expectations are validated. We assume that the idiosyncratic unobservable component of utility, $\varepsilon_{i,j}$, is distributed i.i.d. extreme value. This means that we can write the

[4]Other than the weekday dummy variable, X_j includes observed site characteristics that are fixed over time periods and are the same for all anglers.

[5]We measure travel cost by the angler's imputed opportunity cost of time multiplied by the roundtrip travel time, plus 15¢ per mile. Murdock (2002) describes this imputation in more detail. Travel cost is assumed not to vary depending upon whether the trip is taken on a weekday or weekend.

probability of angler i choosing alternative j as[6]

$$P(U_{ij} \geqslant U_{il} \;\; \forall \;\; l \neq j | X, Z_i, TC_i) = \frac{\text{EXP}\left\{\delta_j + X_j \Gamma(Z_i) + \Phi(Z_i)\sigma_j + \Theta(Z_i) TC_{ij}\right\}}{\sum_{l=1}^{J} \text{EXP}\left\{\delta_l + X_l \Gamma(Z_i) + \Phi(Z_i)\sigma_l + \Theta(Z_i) TC_{il}\right\}}. \tag{4}$$

We can predict the share of anglers who will end up choosing each site in each period by simply taking the average of the probabilities that each angler chooses each site:

$$\sigma_j = \frac{1}{N} \sum_i P(U_{ij} \geqslant U_{il} \;\; \forall \;\; l \neq j | X, Z_i, TC_i) \quad \forall \; j. \tag{5}$$

It is a straightforward application of Brower's fixed-point theorem to show that there exists a vector of σ_j's that satisfy the contraction mapping implied by (5). Whether the equilibrium is unique or not is a more complicated question that depends upon the degree of effective variation in the observed choice attributes.[7] Proving uniqueness in the case of agglomeration effects is difficult, and depends upon the idiosyncratic features of the data.[8] In the case of congestion effects, however, one can show that the equilibrium is generically unique. Bayer and Timmins [2] demonstrates this and other features of this class of equilibrium models.

3.2. Estimation

While important for counterfactual simulations, uniqueness is not necessary to estimate the parameters of Eq. (1) by maximum likelihood [3].[9] In particular, we can write the likelihood of observing a vector of site choices:

$$L(\delta, \gamma, \phi, \theta | Z, X, TC, Y) = \prod_{i \in N} \prod_{j=1}^{J} \left[P\left(U_{ij} \geqslant U_{il} \;\; \forall \;\; l \neq j | X, Z_i, TC_i\right)\right]^{Y_{ij}}, \tag{6}$$

where N represents the set of all anglers' trips, and Y_{ij} equals 1 if angler i chooses j ($=0$ otherwise). Maximizing Eq. (6) with respect to the vector (δ, γ, ϕ, θ) gives us estimates of baseline utility for each site (δ_j), along with parameters describing how utility for various site attributes varies with observable angler attributes.

Given the large number of potential alternatives from which individuals can choose (1138 in the current application), recovering the full set of δ_j's by searching over the likelihood function can be computationally prohibitive. We therefore employ the contraction mapping technique outlined by Berry [5] and used in Berry et al. [6]. The idea of this technique is to choose values for (γ, ϕ, θ), and then find the vector of δ_j's that make the predicted share of individuals choosing each alternative exactly equal the actual share. This is easily done by way of a contraction mapping. As the likelihood maximization procedure searches over alternative values of (γ, ϕ, θ) the contraction mapping procedure repeatedly updates the corresponding vector of δ_j's so that predicted shares equal actual shares. Details of this procedure are described in Appendix B. Note that neither β nor α is estimated at this stage. These parameters are part of the baseline utility, δ_j.

Note the role of the congestion variable, σ_j, at this stage of the estimation procedure. Specifically, one might worry about the potential endogeneity of the share of other anglers choosing a particular site in a particular

[6]Clarifying notation, when a subscript is omitted from a variable (e.g., j is omitted from X in the conditioning arguments of Eq. (4)), we refer to a vector taken over that index variable. X therefore refers to the matrix of site attributes X_j for all sites $j = 1, 2, \ldots, J$.

[7]"Effective variation" in the choice set implies both that choices are different in observable dimensions, and that individuals care about those differences—i.e., significant differences in attributes over which individuals are indifferent will do nothing to help achieve uniqueness in the sorting equilibrium.

[8]Consider a model with two alternative sites where the only attribute individuals care about is the number of other individuals who choose the same site. There will be two equilibria—one in which all individuals congregate in the first site, and the other in which they all congregate in the second.

[9]This is important, because we do not know a priori whether preferences exhibit congestion or agglomeration effects, and we require an estimation technique that is valid under both.

time period. The decisions of other anglers, which together determine σ_j, are affected by the same unobservable site attributes that determine the decision of the angler in question. As will be shown below, this is an important concern, but one that is avoided at this stage of the estimation problem. While it will likely be the case that σ_j is correlated with unobservable site attributes, ξ_j, we control for these unobservable attributes non-parametrically with δ_j at this stage of the procedure. This source of endogeneity becomes an issue when we turn to decomposing the estimates of δ_j in order to learn about the determinants of baseline utility.

Consider this decomposition, which reflects the parameterization in Eq. (2):

$$\delta_j = X_j'\beta + \alpha\sigma_j + \xi_j. \tag{7}$$

This is simply a linear estimation problem with ξ_j serving as the regression error. Equilibrium sorting, however, implies a mechanical correlation between σ_j and ξ_j, $\mathrm{COV}[\sigma_j, \xi_j] > 0$. Locations with desirable unobservable attributes will attract more visitors and will have higher baseline utility. Without additional information, the model is unable to tell these two forces apart and will tend to overstate the value of σ_j. There is a natural tendency in estimating (7) by OLS to recover an upward biased estimate of α, and to therefore either understate the costs of congestion or even find benefits from agglomeration.

While not presented in this exact framework, the fundamental difficulty faced by all papers seeking to estimate congestion costs is the same. Consider how the previous literature on site-choice has dealt with this problem. In Section 2, we broke the literature down into two groups of papers—those that rely on stated preference versus those that use revealed preference evidence. The papers that use stated preference evidence essentially avoid this endogeneity problem by hypothetically varying σ_j while holding ξ_j constant—i.e., by asking ‘‘what would you be willing to pay to have less congestion holding everything else about the choice problem (including unobservables) the same?’’—i.e., assuming $\mathrm{COV}[\sigma_j, \xi_j] = 0$ within the confines of the stated preference experiment.

The only paper we cite that instead uses revealed preference data solves the problem by employing fitted values of σ_j taken from the predictions of an ordered logit model. To be precise, Boxall et al. [7] base anticipated congestion predictions on information about site attributes that is also used in the site selection model (X_j) as well as on individual attributes (Z_i). However, individual attributes do not vary with the chosen alternative, so it is only through their interactions with the X_j variables (which arise implicitly from the ordered logit functional form used to predict anticipated congestion) and the assumption that such interactions do not directly enter utility that the α parameter in Eq. (7) is identified.[10]

3.3. *An instrumental variables approach*

In response to this identification problem, we propose an instrumental variables estimator for Eq. (7). A valid instrument in this case would be some variable that is correlated with σ_j, uncorrelated with ξ_j, and that can reasonably be excluded as a determinant of δ_j. We propose such an instrument based on the underlying equilibrium model of sorting across alternatives. In particular, combinations of the exogenous attributes of alternatives other than j can provide valid instruments for the share of anglers choosing j. Intuitively, this is because anglers look across available alternatives for the combination of site attributes that will maximize utility. Having a great many alternatives with desirable attributes will, for example, reduce the share of anglers making a particular choice j, Ceteris paribus. In the decomposition of δ_j, however, the attributes of alternatives other than j can logically be excluded—Eq. (7) is a structural equation that describes a component of the utility function. There is no reason why the attributes of choices other than j should enter into the expression for the utility derived from choosing j, *except in the way they impact the share of other anglers also choosing j*. Finally, in order to constitute valid instruments, the attributes of choices other than j must be uncorrelated with ξ_j. Given that we assume that X_j is uncorrelated with ξ_j (i.e., the standard assumption in any kind of hedonic exercise), it is not difficult to further assume that X_{-j} is also uncorrelated with ξ_j.

Bayer and Timmins [3] justifies a particular function of the exogenous attributes of the entire choice set as an instrument for σ_j in Eq. (7). In particular, they argue for using the predicted share of anglers choosing j

[10]This approach will prove particularly useful (e.g., in contrast to the solution proposed below) if the choice set is small (so that there is little effective variation in X_j) and if there are individual attributes that affect perceptions about congestion but not the actual site choice.

based only on exogenous attributes of all possible choices[11]:

$$\tilde{\sigma}_j = \frac{1}{N}\sum_i \frac{\mathrm{EXP}\left\{X_j'\hat{\Gamma}(Z_i) + X_j'\hat{\beta} + \hat{\Theta}(Z_i)TC_{ij}\right\}}{\sum_{l=1}^{J}\mathrm{EXP}\left\{X_l'\hat{\Gamma}(Z_i) + X_l'\hat{\beta} + \hat{\Theta}(Z_i)TC_{il}\right\}}. \tag{8}$$

If exogenous attributes are important determinants of site choice (relative to endogenously determined congestion effects), this instrument will have good power. As sites become similar in exogenous dimensions, the instrument will become increasingly weak.

The obvious problem with using the instrument described in (8) lies in the fact that it requires that we already have in hand some estimate of (γ, β, θ_0, θ_1), while identifying these parameters is the goal of the IV strategy. Bayer and Timmins [3] describe a procedure whereby an initial guess at (γ, β, θ_0, θ_1) can be found by estimating (6) and (7) while simply ignoring the endogeneity of σ_j in the latter equation. With these estimates, the instruments in (8) are calculated and used in an IV estimation of Eq. (7) that accounts for the endogeneity of σ_j. This procedure is discussed in more detail in the appendix. Bayer and Timmins [3] also provides Monte Carlo evidence on the performance of this instrumental variables strategy in a variety of empirical contexts.

4. Data

This section describes the data on angler characteristics, travel cost, and fishing site characteristics that we use in our application. Murdock [20] provides additional details about the data and data collection process.

The 1998 Wisconsin fishing and outdoor recreation (WFOR) survey is our primary source of data. A random digit dial telephone survey recruited anglers willing to complete a fishing diary each month for June–September. Of the anglers completing the telephone interview, 81.0% agreed to participate in the diary portion of the survey. Our analysis focuses on the 512 anglers that reported taking a single day fishing trip. A comparison between all anglers contacted during the telephone survey and the final sample reveals that they are very similar. These anglers report 3581 single day fishing trips (1750 weekend and 1831 weekday) that are used for estimation.

The WFOR survey provides sampling weights that describe the number of anglers in the general population represented by each of the respondents. These weights are used in the following estimations and counterfactual simulations.

Fishing sites are defined using the water body name and quadrangle.[12] Fig. 1 shows a map of Wisconsin with the quadrangles marked. Each inland lake visited by an angler constitutes a separate fishing site. In quadrangles containing multiple inland lakes, each unique inland lake forms a separate fishing site. Lake Michigan, Green Bay, Lake Winnebago, and all rivers and streams are divided into quadrangles because of their large size or long length. According to this definition, there are 569 different locations visited by the sample on single day trips.

The fish catch measures vary across fishing sites but not across anglers. The detailed data available for this study allows catch to be identified separately for a variety of different fish species. Fish catch rates are constructed by combining information from the Wisconsin Department of Natural Resources (WDNR) and the WFOR survey. The WDNR provides information on the surface area, depth, and fish abundance (‘abundant’, ‘common’, ‘present’, and ‘not present’) for virtually all inland lakes. Since the bulk of the data were collected in the 1950s and 1960s, however, they are dated. Moreover, they exclude Lake Michigan, Green Bay, streams, and rivers. The WFOR fish catch data are detailed and comprehensive—for

[11]If one were concerned that individuals had sorted geographically in response to ξ_j (e.g., retirees choosing to settle close to the best fishing sites), travel cost would be endogenous and should then be excluded from the formation of the instrument at this stage. If this is not a concern, however, including travel cost has the potential to greatly increase the instruments' power.

[12]According to the US Geological Survey, Wisconsin contains 1154 quadrangles and each is roughly 7 mile long and 5 m wide.

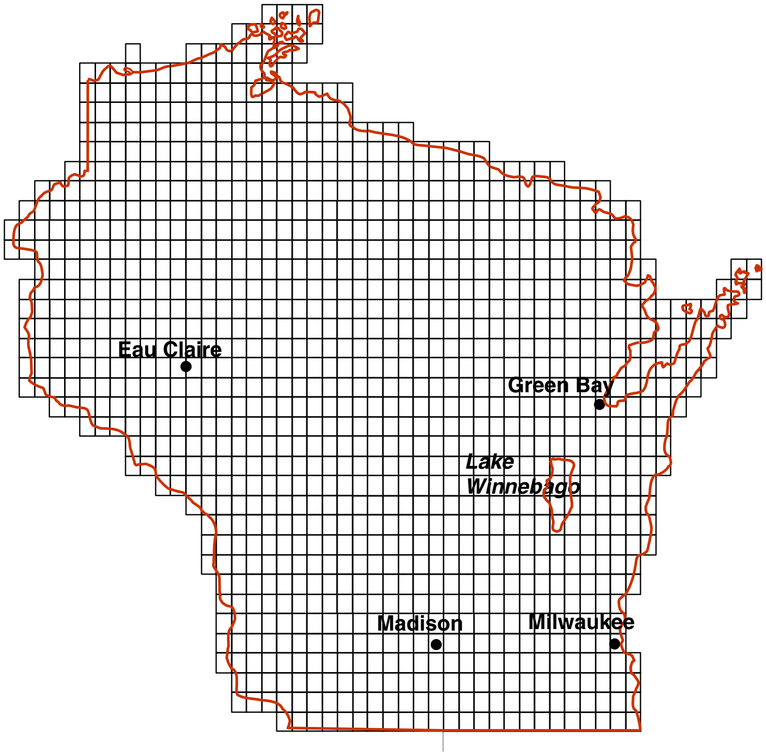

Fig. 1. Map of Wisconsin showing quadrangles used in defining fishing sites.

each day spent fishing, survey participants recorded the number and species of fish they personally caught and the time spent fishing.

A weighted least squares (WLS) procedure is used to combine both sources of data in order to obtain a catch rate for each species at each site. A separate WLS regression is estimated for each site and species. Each regression includes all sites of similar type within 50 miles. Weighting allows sites with more observed fishing trips, located nearer the origin site, and with more physical similarities to have more influence in the regression. Because the only right-hand-side variable is the WDNR measure of fish abundance, which is missing for some species and all locations that are not inland lakes, many of the WLS regressions include only a constant term and hence produce a simple weighted average of the WFOR survey data. The predicted value for each species at each site serves as the expected catch.

Table 1 summarizes expected fish catch along with other site characteristics. In general, motor trolling is not permitted in Wisconsin's waters except where expressly allowed.[13] Shoreland development may affect choice to the extent that some anglers value a natural and quiet setting. Inspection of the Delorme Atlas and Gazetteer map indicates sites that have at least a portion of their shoreland designated as urban. Map inspection also reveals which fishing sites are contained within a national, state, or county forest (or park), or within a wildlife area.

Our data also describe a variety of site amenities, including access to boat launches (both paved and unpaved), parking lots, picnic areas, docks, fishing piers, camp sites, and restrooms. Many of these attributes are highly correlated with one another in the sample, making it impossible to include all of them in our estimation. Table 2 describes a number of the most important correlations. While there are relatively high correlations between many site amenities, correlations are low between the expected catches of many fish species.

[13]Motor trolling involves trailing a lure or bait from a moving vessel (motor boat or sail boat).

Table 1
Data summary

Variable	Description	Mean	SD
(a) Site attributes			
Urban	Dummy = 1 if urban area on shoreline	0.18	0.38
Wildlife	Dummy = 1 if site inside a wildlife area or refuge	0.06	0.23
Forest	Dummy = 1 if site inside a county, state or national forest	0.18	0.38
Launch	Dummy = 1 if site has a boat launch	0.82	0.38
Nlaunch	Number of boat launches available at site	1.58	2.26
Paved	Dummy = 1 if offers at least one paved boat launch	0.73	0.45
Parking	Dummy = 1 if parking lot is available	0.79	0.45
Picnic	Dummy = 1 if picnic area is available	0.52	0.50
Dock	Dummy = 1 if boating dock is available	0.49	0.50
Pier	Dummy = 1 if fishing pier is available	0.36	0.48
Restroom	Dummy = 1 if restroom available	0.58	0.49
River	Dummy = 1 if a river fishing location	0.31	0.46
Small lake	Dummy = 1 if inland lake surface area <50 acres	0.17	0.38
Trout	Catch rate brook, brown, and rainbow trout	0.09	0.17
Smallmouth	Catch rate smallmouth bass	0.20	0.20
Walleye	Catch rate walleye	0.13	0.15
Northern	Catch rate northern pike	0.08	0.06
Musky	Catch rate muskellunge	0.01	0.02
Salmon	Catch rate coho and chinook salmon	0.01	0.05
Panfish	Catch rate yellow perch, bluegill, crappie, sunfish	1.58	0.89

Variable	Description	Weekdays ($n = 1831$)		Weekends ($n = 1750$)	
		Mean	SD	Mean	SD
(b) Angler attributes					
Kids	Dummy = 1 if children under age 14 in household	0.31	0.46	0.39	0.49
Unemployed	Dummy = 1 if angler not employed full or part time	0.24	0.43	0.12	0.33
Boat owner	Dummy = 1 if angler in a household that owns a boat	0.59	0.49	0.59	0.49
Travel cost	Round-trip travel time × opportunity cost of time + 15¢ per mile	17.55	18.99	20.19	20.63

5. Practical issues in estimation

The estimation procedure, as described in Section 3, uses the non-zero share of anglers choosing to visit each site in each period in the recovery of the vector of alternative-specific fixed effects, δ_j. These fixed effects play a very important role in the estimation, as they allow for the inclusion of alternative-specific unobservable attributes, ξ_j. Given the limited number of site attributes described in the data, including such unobservables is critically important.[14] By virtue of the way in which the data were collected, we are assured of seeing non-zero shares for all sites across the combined weekday and weekend periods. This is not the case, however, when we consider either period by itself.

Table 3 shows how the share of trips is spread over the 569 sites when considering only weekday or weekend trips. In total, 21.6% of all sites are not visited on a weekend, while 33.0% are not visited on a weekday. This poses a practical problem for the recovery of period-specific baseline utilities—the data tell us only that these are unattractive choices (i.e., so unattractive as to not induce a single visitor in the sample). The data give no indication, however, of exactly how unattractive these sites are.

We address this problem by first introducing a numerical "patch" that allows the contraction mapping described in Section 3 to function properly. This simply amounts to adding a small increment (e.g., $\psi = 10^{-3}$) to the total number of visits to each site in each period before calculating shares. This means that no shares

[14]See Murdock [21] for evidence on the biases introduced by ignoring unobserved site attributes.

Table 2

	Forest	Wildlife	Urban
(a) Correlations between site attributes urbanization			
Forest	1.00		
Wildlife	−0.11	1.00	
Urban	−0.21	−0.11	1.00

	Paved	Mtroll	Launch	Parking	Nlaunch
(b) Boating amenities					
Paved	1.00				
Mtroll	0.27	1.00			
Launch	0.75	0.19	1.00		
Parking	0.46	0.17	0.46	1.00	
Nlaunch	0.38	0.45	0.32	0.24	1.00

	Restroom	Pier	Picnic
(c) Other amenities			
Restroom	1.00		
Pier	0.29	1.00	
Picnic	0.63	0.30	1.00

	Trout	Smallmouth	Walleye	Northern	Musky	Salmon	Panfish
(d) Catch rates							
Trout	1.00						
Smallmouth	0.24	1.00					
Walleye	0.19	0.19	1.00				
Northern	0.16	−0.08	−0.10	1.00			
Musky	−0.15	−0.10	0.09	0.21	1.00		
Salmon	0.14	−0.02	−0.15	−0.24	−0.08	1.00	
Panfish	−0.58	−0.47	−0.40	0.10	0.27	−0.27	1.00

will equal zero, although some will be very small. For very small values of ψ, the effect of this patch is seen entirely in the recovered values for δ_j for those sites with actual shares equal to zero. In particular, the smaller the value of ψ that is chosen, the more negative the values of δ_j become for those sites. Because very small values of ψ have virtually no effect on the relative odds of any two choices with positive numbers of visitors, however, the impact on the remaining values of δ_j is negligible.[15] In Appendix A, Fig. A1 shows the estimated distribution of δ_j under the assumption that $\psi = (10^{-3}, 10^{-6}, 10^{-9}, 10^{-12})$. A series of bi-modal distributions emerges. The lower mode reflects values of δ_j determined by the assumption about ψ. For smaller values, that mode shifts further to the left. Key to our strategy, the upper portion of the distribution (i.e., that based on visited sites) does not change with alternative assumptions about ψ. In Fig. A1, all four distributions overlap perfectly over this range.

We require a second-stage estimator that is robust to the fact that the values of δ_j for unvisited sites are arbitrarily negative. Quantile estimation is flexible in that it does not depend upon the specific values in the lower tail of the δ_j distribution. As long as a majority of sites have positive numbers of visitors, the median regression is well-suited to this purpose.[16,17]

[15]It is easy to show with Monte Carlo evidence that as $\psi \rightarrow 0$, all the parameters besides δ_j, for the unvisited sites converge to stable values. The values of δ_j for the unvisited sites, however, $\rightarrow -\infty$.

[16]Koenker and Bassett [15] provide the original theory for quantile regression techniques. Koenker and Hallock [16] provide a convenient summary.

[17]Alternatively, one could have simply dropped unvisited sites from the analysis for the time period (weekday or weekend) in which they were not visited. While this would not have had any impact on the estimated values of the first-stage parameters, it would introduce a

Table 3
Distribution of visitor shares by period[a]

	Percentile				
	10	20	30	40	50
Weekdays	0.00	0.00	0.00	2.61×10^{-4}	5.21×10^{-4}
Weekends	0.00	0.00	2.68×10^{-4}	4.91×10^{-4}	7.44×10^{-4}

[a]Each row of this table shows the percentage of sites with fewer than a certain share of the total number of trips taken within a particular period. 33% of the sites have no trips taken on a weekday, while 21.6% of sites have no trips taken on a weekend.

Adapting the median regression to deal with endogenous regressors is not as simple as in the case of mean regression. It has, however, been the focus of recent work in econometric theory [10,13,17]. This is important in our context because of the presence of the endogenous regressors σ_j. We use a simple smoothed GMM estimation approach based upon a technique described in working papers by Hong and MaCurdy. In essence, assuming specifications for the quantiles of structural error distributions conditional upon exogenous or pre-determined instruments, the estimator formulates these conditional quantiles into moment conditions capable of being estimated within a conventional nonlinear instrumental variables or generalized method of moments framework. This apparatus matches the sample analog of the conditional quantiles against their population values, employing a smoothing procedure familiar in various problems found in non-parametric inference and simulation estimation. The analysis applies standard arguments to demonstrate consistency and asymptotic normality of the resulting smoothed GMM quantile estimator. Simulation exercises reveal that this procedure accurately produces estimators and test statistics generated by conventional quantile estimation approaches.

To apply this GMM quantile procedure, let δ_j denote baseline utility from alternative j, and let (X_j, σ_j) denote our vector of exogenous attributes and endogenously determined shares. We are interested in obtaining information about the distribution of δ_j conditional upon (X_j, σ_j). We will use $Q_\rho(X_j, \sigma_j)$ to represent the ρth percentile of this conditional distribution, where $\rho \in (0, 100)$. Our smoothed GMM quantile estimator makes use of the following moment conditions, which underlie the construction of most quantile estimation procedures:

$$P\left(\delta_j < Q_\rho(X_j, \sigma_j) | X_j, \sigma_j\right) = \rho. \tag{9}$$

This relation implies the condition:

$$E\left[1\left(\delta_j < Q_\rho(X_j, \sigma_j)\right) - \rho(X_j, \sigma_j)\right] = 0, \tag{10}$$

where $1(\bullet)$ represents the indicator function which takes value 1 when the condition expressed in parentheses is true, and 0 otherwise. The indicator function inside the moment condition is neither continuous nor differentiable. To incorporate this moment condition into the standard framework of nonlinear method of moments estimation, Hong and MaCurdy propose using the modified smooth version of this condition:

$$E\left[\lim_{N\to\infty} \Phi\left(\frac{\delta_j - Q_\rho(X_j, \sigma_j)}{s_N}\right) - (1-\rho)\right] = 0, \tag{11}$$

where N represents the sample size (1138) and Φ is a continuously differentiable distribution function with bounded symmetric density function φ. The following analysis uses the cumulative standard normal distribution function, but other distributions (e.g., logit) could be used as well. The quantity s_N is a bandwidth parameter that converges to 0 as $N \to \infty$ at a rate slower than that of $N^{1/2}$. Formally, one may choose $s_N = N^{-d}$, where $0 < d < 1/2$ (a condition required for the proof of asymptotic normality). We choose $s_N = 0.25$, which is implied by $d = 0.2$. Since Φ is a bounded function, one can exchange expectation and limit

(*footnote continued*)
selection bias here in the second stage. The numerical patch and quantile estimator we propose here solves this selection problem with minimal distributional assumptions.

Table 4
First-stage parameter estimates

Angler attribute	Site attribute	Estimate	t-statistic
Boat owner	Paved	0.809	7.34
Boat owner	Wildlife	0.230	1.57
Boat owner	Forest	0.042	0.65
Boat owner	Urban	−0.670	−8.42
Kids	Restroom	0.309	4.70
Boat owner	River	−0.254	−3.29
Boat owner	Small lake	−0.520	−3.52
Kids	Panfish	0.088	2.99
Boat owner	Share (× 100)	0.227	2.98
	Travel cost	−0.117	−101.33

Maximum likelihood estimation of Eq. (6)

in (11) to obtain the smoothed moment condition in (9). The estimation below relies on the fact that our instrument vector $\left(X_j, \tilde{\sigma}_j\right)$ will be conditionally independent of the error terms defined by $\left(1\left[\delta_j > Q_\rho(X_j, \sigma_j)\right] - \rho\right)$ in forming a valid set of moment conditions. Standard errors are those reported by the GMM estimation procedure in any statistical package.

Appendix B provides a concise overview of the entire estimation procedure.

6. Estimation results

Our estimation results are reported in two stages, reflecting the two-part estimation procedure described above. Table 4 reports estimates of the first-stage (i.e., maximum likelihood) parameter estimates, describing how preferences for certain components of X_j, σ_j, and TC_{ij} vary with angler attributes (e.g., presence of children in household and boat ownership). Given the flexibility introduced by the second stage of the estimation procedure (in particular, the inclusion of the unobserved attribute ξ_j), we do not attempt to estimate all possible first-stage interactions. Particularly important is the interaction between boat ownership and our proxy for variables we might expect to be important to boat owners. As a proxy for these factors, we use an indicator for a paved boat launch at the site, which is highly correlated with there being no restrictions on motor trolling and there being multiple launches and a parking lot. The interaction between this indicator and boat ownership is positive and significant. Sites designated as wildlife areas and managed forests are (insignificantly) more attractive to boat owners, while urban sites, small lakes and rivers are (significantly) less attractive. Anglers with children in the household under the age of 14 derive more utility from site amenities (proxied for by the presence of restrooms) and from higher rates of panfish catch.[18] Relative to non-boat owners, boat owners are less negatively affected by congestion, possibly because they are not constrained to fish from a crowded shoreline. Finally, note that travel cost enters negatively and is very precisely estimated. We will use the disutility of travel cost to convert changes in utility associated with the elimination of a large site into comparable units in the following section.

Table 5 reports estimates from our second-stage IV median regression decomposition of δ_j. The most important parameter for our purposes is the utility effect of expected share (i.e., congestion), which is negative and significant.[19] Other second stage parameter estimates generally have the expected sign. Expected catch variables play an important role in determining the utility derived from a site. Of the non-catch attributes, paved boat ramps, an urban designation, and the presence of restrooms are all significant and enter positively into utility. Being a small lake, conversely, is negative and significant.

[18] Average panfish catch rates are higher than for any other species, and catching panfish requires less expertise and elaborate tackle. This makes them ideal for fishing with children.

[19] One might include at this stage non-linear congestion terms (e.g., SHARE and SHARE2) to allow for the possibility of, for example, an increasing marginal disutility of congestion. This sort of complication, however, increases the burden on our instrumenting strategy, requiring more variation in exogenous choice attributes. We omit this complication from the current exercise.

Table 5
Second-stage parameter estimates[a]

	Estimate	t-statistic
Constant	−9.249	−13.67
Paved	0.766	2.35
Wildlife	0.483	1.50
Forest	0.275	0.75
Urban	0.447	2.11
Restroom	0.446	2.04
River	0.642	0.70
Small lake	−1.301	−3.67
Trout	5.453	4.07
Smallmouth	2.209	1.03
Walleye	6.128	7.88
Northern	6.000	1.99
Musky	24.379	5.44
Salmon	13.136	4.52
Panfish	1.869	5.48
Share (× 100)	−4.642	−4.00
Weekday	−0.769	−3.38
P-value for χ^2 test of overidentifying restrictions	0.120	

IV Median regression, smoothed GMM ($s_N = 0.25$).
Dependent variable = δ_j recovered from ML estimation described in Table 4.
[a]Heteroskedastic-consistent standard errors. Instruments for SHARE (× 100) include predicted share based on exogenous attributes, predicted share squared, and predicted share interacted with exogenous attributes.

One might be concerned that the disutility of fishing near other anglers is greater on small lakes where activity is more concentrated. We test for this effect by including an interaction between SHARE and a dummy variable indicating that the site is a lake with surface area less than 50 acres. Parameter estimates change very little, and the interaction, while negative, enters utility insignificantly.

6.1. The role of "IV" in our IV quantile estimation

In order to demonstrate the value of the IV strategy, Table 6 reports estimates from a similar set of second-stage regressions that ignore the endogeneity of σ_j. Estimates reflect a significant baseline preference *for* increased congestion (i.e., the expected direction of bias, and extreme enough to produce an agglomeration effect). This has important implications for site valuation,[20] but also leads to biases in the marginal values we place on specific site attributes. For example, the marginal utility of restrooms falls from 0.446 to −0.048, while the marginal disutility of a small lake drops from −1.301 to −0.251.

6.2. The role of "quantile" in our IV quantile estimation

To illustrate the advantage of quantile over least squares estimation in this application, we report results using ordinary least squares. Table A1 reports estimates of the second-stage utility parameters for different values of the "patch" described in the previous section under a two-stage least squares estimation procedure. While the results are identical (and, hence, not separately reported) under the IV quantile approach for each value of ψ, we find that parameter estimates associated with various site attributes (including congestion) vary dramatically with ψ under 2SLS estimation. Importantly, congestion enters with a positive sign, even after instrumenting. This is a result of two features of the model: (i) unvisited sites offer very low expected congestion, and (ii) their baseline utility becomes increasingly negative with smaller and smaller values of ψ. Treating these artificially low values of δ_j as "real" data in the 2SLS procedure makes it seem that congestion is desirable, even when instruments are employed.

[20]In the extreme, the elimination of a popular site could possibly be deemed welfare-improving.

Table 6
Second-stage parameter estimates (no instruments for share)

	Estimate	t-statistic
Constant	−10.051	−15.05
Paved	0.862	3.37
Wildlife	−0.127	−0.44
Forest	0.369	1.28
Urban	−0.502	−2.49
Restroom	−0.048	−0.22
River	2.254	4.16
Small lake	−0.251	−0.85
Trout	5.289	13.66
Smallmouth	1.783	3.18
Walleye	3.369	6.58
Northern	4.379	3.71
Musky	19.980	1.72
Salmon	12.527	5.31
Panfish	2.123	7.40
Share (x 100)	5.853	4.80
Weekday	−0.642	−3.68

Median regression, dependent variable = δ_j recovered From ML.
Estimation described in Table 4.

7. Valuing a large site

We now examine the role of congestion costs in valuing a large site. We focus on large sites, because the exercise of removing such a site from the choice set will involve significant re-sorting of anglers among the remaining sites. The welfare effects of that re-sorting need to be accounted for in the value ascribed to the site. Ignoring them has the potential to lead to a serious downward bias. A good candidate for such an exercise is Lake Winnebago—one of Wisconsin's premier sites for fishing and other water activities. Next to Lake Michigan, it is Wisconsin's largest inland lake with over 135,000 acres of surface area and is known for good walleye and perch fishing.

The procedure for valuing Lake Winnebago proceeds as follows. We begin by determining each angler's expected utility under the status quo in each period. In doing so, we first employ the contraction mapping defined in Section 3 to solve for the equilibrium vector of shares under the status quo (σ_j^0):

$$\sigma_j^0 = \frac{1}{N}\sum_i \frac{\mathrm{EXP}\{\hat{V}_{ij}\}}{\sum_{l=1}^{J}\mathrm{EXP}\{\hat{V}_{il}\}}, \tag{12}$$

where

$$\hat{V}_{ij} = \underbrace{X_j'\hat{\beta} + \hat{\alpha}\sigma_j^0 + \hat{\xi}_j}_{\hat{\delta}_j^0} + X_j'\hat{\Gamma}(Z_i) + \hat{\Phi}(Z_i)\sigma_j^0 + \hat{\Theta}(Z_i)TC_{i,j}. \tag{13}$$

A "hat" over a parameter refers to an estimated value recovered in the previous section. By construction, this replicates the shares of anglers choosing each alternative observed in the data.[21] Based on these shares, we can calculate each angler's expected utility according to the familiar log-sum rule:

$$EU_i^0 = \ln\left(\sum_{j=1}^{J}\mathrm{EXP}\left\{\hat{\delta}_j^0 + X_j'\hat{\Gamma}(Z_i) + \hat{\Phi}(Z_i)\sigma_j^0 + \hat{\Theta}(Z_i)TC_{i,j}\right\}\right), \tag{14}$$

[21]Recall that the inclusion of the δ_j's ensures that the predicted share of anglers choosing each site will exactly equal the actual share.

where

$$\hat{\delta}_j^0 = X_j'\hat{\beta} + \hat{\alpha}\sigma_j^0 + \hat{\xi}_j. \tag{15}$$

This welfare measure weights the utility the individual would get from each choice by the probability that he or she chooses it.

Next, we eliminate the sites associated with Lake Winnebago from the choice set (on both weekdays and weekends) and re-calculate the equilibrium share of trips to each of the remaining alternatives according to (12) and (13).[22] This yields a new vector of equilibrium shares ($\sigma_j{}^1$) from which we can calculate new values of expected utility ($EU_i{}^1$).[23] Different types of individuals' expected utilities are not directly comparable, so we divide by the absolute value of the marginal disutility of round-trip travel cost (−0.117), so as to convert all measures into dollars.[24] This yields the following measure of foregone expected utility:

$$\Delta EU_i^{1-0} = \frac{(EU_i^1 - EU_i^0)}{|-0.117|}. \tag{16}$$

Welfare falls for every angler, by an average of \$1.83 per trip. Aggregating across all trips and sample weights, this translates into total welfare losses of \$7.5 million per season.

In order to demonstrate the role of congestion effects in valuing a large site like Lake Winnebago, we next perform the same exercise but use parameter estimates derived from a model that ignores the role of congestion in utility. Tables 7 and 8 report first- and second-stage parameter estimates, respectively, for such a model. Without explicitly accounting for the disutility of congestion, we see that the model recovers smaller utilities for amenities associated with more crowded sites. The marginal utility of restrooms, for example, falls from 0.446 to 0.051 while that of urban designation falls from 0.447 to −0.105.

Without any role for congestion costs, there is no need to calculate the new equilibrium distribution of anglers without Lake Winnebago in the choice set—the welfare measure expressed in Eqs. (14) and (15) requires only that we know the attributes of the remaining sites. Using those equations, we calculate a comparable set of monetized foregone expected utilities. In line with our intuition, the costs of eliminating Lake Winnebago from the choice set are smaller in the model that ignores congestion costs. The average welfare loss per trip falls from \$1.83 with congestion to 86¢ without it. The total seasonal costs of eliminating Lake Winnebago fall from \$7.5 million to \$3.5 million. Ignoring the role of congestion costs yields an estimate of the value of Lake Winnebago that is less than 50% of its value when congestion costs are included.

We conclude by examining how welfare costs, both with and without congestion, are distributed across anglers depending upon their initial site choice. For anglers originally choosing Lake Winnebago, welfare loss per trip from eliminating Lake Winnebago rises from \$7.35 to \$9.66 (31%) when congestion costs are added. Most of this loss results from these anglers having to accept their second-best alternative. For anglers at the sites that receive the additional traffic because of re-sorting, however, the percentage of the loss attributable to congestion rises. Average cost per trip for anglers who had originally not chosen Lake Winnebago rises from 40¢ without congestion costs to \$1.27 when they are added (217.5%). These anglers make up the vast majority in the calculation of the overall welfare effect, implying that congestion costs play an important role.

[22]Eight of the quadrangles that divide Lake Winnebago are visited meaning that eliminating Lake Winnebago removes more than one site.

[23]Note that, because we do not model the participation decision, we do not allow anglers to opt out of taking a fishing trip at this stage. This will have the effect of biasing upward our estimate of the total cost of eliminating Lake Winnebago.

[24]We use the monetized value of the change in expected utility instead of a compensating variation in income to measure welfare, as the latter would require simulating actual choices of many anglers both before and after the elimination of Lake Winnebago (i.e., taking draws from the logit distribution for each angler for each alternative, and determining which alternative yields the highest utility). In order to achieve numerical precision, this requires a large number of simulations. By using expected utility, every angler contributes a positive (although possibly very small) probability of choosing every alternative. This probability has a closed-form representation, mitigating the computational cost.

Table 7
First-stage parameter estimates

Angler attribute	Site attribute	Estimate	t-statistic
Boat owner	Paved	0.794	7.53
Boat owner	Wildlife	0.227	1.55
Boat owner	Forest	0.042	0.65
Boat owner	Urban	−0.664	−8.53
Kids	Restroom	0.306	4.65
Boat owner	River	−0.252	−3.29
Boat owner	Small lake	−0.515	−3.59
Kids	Panfish	0.087	2.96
	Travel cost	−0.117	−101.50

Maximum likelihood estimation of Eq. (6)—no congestion effects.

Table 8
Second-stage parameter estimates—no congestion effects

	Estimate	t-statistic
Constant	−8.825	−8.52
Paved	0.617	1.68
Wildlife	−0.014	−0.02
Forest	0.370	0.96
Urban	−0.105	−0.27
Restroom	0.051	0.17
River	1.327	1.63
Small lake	−0.581	−1.35
Trout	5.163	4.67
Smallmouth	1.477	1.85
Walleye	5.010	4.38
Northern	3.904	1.40
Musky	20.418	2.94
Salmon	11.298	2.70
Panfish	1.906	4.33
Weekday	−0.558	−2.06

Median regression, dependent variable = δ_j recovered from ML.
Estimation described in Table 7.

8. Valuing a fish stocking program

Congestion effects can play an important role as well in the valuation of a site improvement. In particular, an improvement that encourages more visitors will be less valuable for the users of the improved site if congestion effects are important. If the improvement pulls users away from other congested sites, however, the inclusion of congestion effects may result in an even bigger equilibrium value.

We demonstrate this idea by simulating the effect of a policy that raises the expected catch of northern pike on Lake Winnebago to be equal to the average expected catch across all sites in the choice set (prior to the policy, expected catch on Lake Winnebago was approximately half of the mean). We then calculate equilibrium welfare effects in the same manner as in the previous section.

Ignoring congestion effects, anglers who had previously chosen Lake Winnebago benefit from the policy by 65.3¢ per trip. Increasing the expected catch of northern pike, however, raises the expected share of anglers fishing Lake Winnebago. Including congestion effects, the benefit per trip falls to 54.3¢. Because of the increased number of anglers choosing Lake Winnebago, there is an additional impact of the policy—reduced congestion at other sites. Anglers who did not originally fish Lake Winnebago receive an expected benefit of 4.8¢ per trip if congestion effects are ignored. That benefit rises to 6.2¢ when we include congestion effects.

Because there are so many more anglers who do not fish Lake Winnebago in the status quo, the overall expected benefit of the fish stocking program is actually bigger when we include congestion effects—i.e., \$388 thousand versus \$362 thousand when congestion effects are ignored.

9. Conclusions and caveats

Congestion is an important site attribute in models of recreation demand, but it is typically ignored, particularly in the revealed preference context. This is because properly controlling for congestion costs requires solving a difficult endogeneity problem. While stated preference models offer a potential solution based on answers to hypothetical questions, revealed preference approaches require a valid set of instruments. Implementing such an instrumental variables approach, we find evidence of significant congestion effects in Wisconsin recreational fishing. Failing to properly account for their endogeneity leads one to incorrectly recover agglomeration benefits and to mis-measure the value of other site attributes. This has practical implications for policy-makers. For example, we find that the value of a large site will be substantially understated (e.g., by more than one-half in the case of Lake Winnebago) if congestion costs are ignored. Congestion costs can also play an important role in valuing site improvements, although the direction of their impact is less obvious. These results highlight the need for further work on the equilibrium valuation of policy in travel cost models.

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Appendix A

Estimates under alternative assumptions about zero shares are shown in Table A1 (Fig. A1).

Table A1
Weekday second stage parameter estimates under alternative values of ψ IV median estimation and two-stage least squares ($n = 1138$)

	IV median		Two-stage least squares							
	All ψ		$\psi = 10^{-3}$		$\psi = 10^{-6}$		$\psi = 10^{-9}$		$\psi = 10^{-12}$	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Constant	−9.249	−13.67	−11.894	−7.40	−14.867	−6.40	−17.902	−5.86	−20.905	−5.51
Paved	0.766	2.35	1.333	2.60	1.771	2.39	2.215	2.27	2.656	2.19
Wildlife	0.483	1.50	0.149	0.17	0.546	0.44	0.938	0.58	1.333	0.66
Forest	0.275	0.75	−0.070	−0.13	−0.325	−0.42	−0.575	−0.57	−0.828	−0.66
Urban	0.447	2.11	0.018	0.03	0.196	0.24	0.367	0.34	0.541	0.40
Restroom	0.446	2.04	0.236	0.55	0.514	0.83	0.787	0.97	1.063	1.05
River	0.642	0.70	0.263	0.23	0.520	0.31	0.778	0.35	1.036	0.38
Small lake	−1.301	−3.67	−0.544	−0.90	−0.695	−0.80	−0.849	−0.74	−1.001	−0.70
Trout	5.453	4.07	3.751	2.45	3.713	1.68	3.714	1.27	3.695	1.02
Smallmouth	2.209	1.03	2.985	2.71	3.372	2.12	3.780	1.81	4.178	1.61
Walleye	6.128	7.88	3.897	2.11	3.147	1.18	2.456	0.70	1.736	0.40
Northern	6.000	1.99	5.807	1.51	7.526	1.35	9.283	1.27	11.021	1.21
Musky	24.379	5.44	18.742	1.96	15.594	1.13	12.728	0.70	9.721	0.43
Salmon	13.136	4.52	12.685	2.18	15.537	1.85	18.476	1.67	21.371	1.56
Panfish	1.869	5.48	1.246	2.04	1.383	1.57	1.533	1.32	1.677	1.16
Share ($\times$ 100)	−4.642	−4.00	3.834	1.43	8.250	2.13	12.565	2.46	16.931	2.67
Weekday	−0.769	−3.38	0.415	0.28	0.140	0.07	−0.105	−0.04	−0.365	−0.11

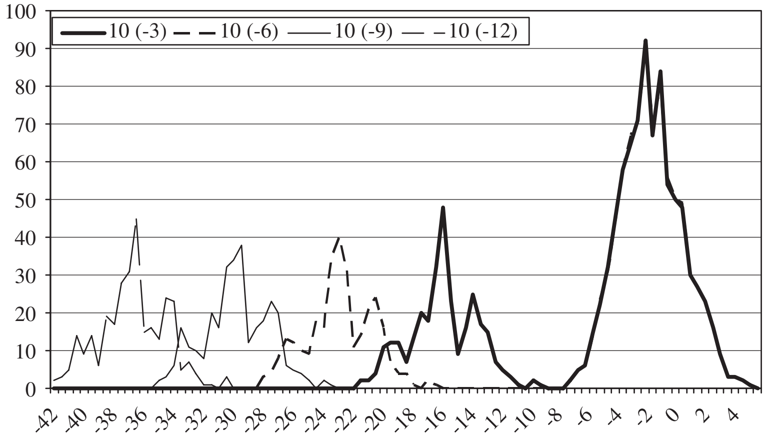

Fig. A1. Distribution of alternative fixed effects (δ_j), under alternative values of ψ.

Appendix B

The following discussion provides a step-by-step description of the estimation strategy in the context of a simple utility function that uses a single site attribute (CATCH_j) and a single angler attribute (AGE_i). The utility that angler i receives from choosing site j is given by

$$U_{i,j} = (\beta + \gamma\, AGE_i)CATCH_j + (\alpha + \phi\, AGE_i)\sigma_j + (\theta + \mu\, AGE_i)TC_{i,j} + \xi_j + \varepsilon_{i,j} \tag{B.1}$$

or alternatively,

$$\begin{aligned} U_{i,j} &= \delta_j + \gamma\, AGE_i \times CATCH_j + \phi\, AGE_i \times \sigma_j + (\theta + \mu\, AGE_i)TC_{i,j} + \varepsilon_{i,j} \\ \delta_j &= \beta\, CATCH_j + \alpha\sigma_j + \xi_j. \end{aligned} \tag{B.2}$$

Step ♯1: Contraction mapping to recover δ_j's given an initial guess (γ^q, ϕ^q, θ^q, μ^q).

The probability that individual i chooses location j, assuming that $\varepsilon_{i,j}$~i.i.d. Type I extreme value and given initial guesses for the parameters (γ^q, ϕ^q, θ^q, μ^q) and baseline utilities, $\{\delta_j^{m,q}\}_{j=1}^{J}$, is given by

$$P_{i,j}^{m,q} = \frac{\text{EXP}\left\{\delta_j^{m,q} + \gamma^q\, AGE_i \times CATCH_j + \phi^q\, AGE_i \times \sigma_j + (\theta^q + \mu^q\, AGE_i)TC_{i,j}\right\}}{\sum_{l=1}^{J} \text{EXP}\left\{\delta_l^{m,q} + \gamma^q\, AGE_i \times CATCH_l + \phi^q AGE_i \times \sigma_l + (\theta^q + \mu^q\, AGE_i)TC_{i,l}\right\}}, \tag{B.3}$$

where the first superscript (m) indicates the iteration with respect to calculating the baseline utilities, and the second superscript (q) indicates the iteration with respect to calculating the remaining parameters. It is straightforward to use (B.3) to predict the share of angler's who would choose each site:

$$\hat{\sigma}_j^{m,q} = \frac{1}{N}\sum_i P_{i,j}^{m,q}. \tag{B.4}$$

Berry [5] proves that the following iterative procedure will converge to the vector of δ_j's that equate observed to predicted shares, $\{\delta_j^{*,q}\}_{j=1}^{J}$, given the parameter vector (γ^q, ϕ^q, θ^q, μ^q):

$$\delta_j^{m+1,q} = \delta_j^{m,q} + (\ln \sigma_j - \ln \hat{\sigma}_j^{m,q}), \tag{B.5}$$

where σ_j denotes the actual share of anglers choosing site j in the data. Note that this procedure requires one of the baseline utilities to be normalized to some value (i.e., $\delta_1 = 0$).

Step ♯2: Nest step ♯1 inside a likelihood maximization algorithm.

Given the parameter vector (γ^q, ϕ^q, θ^q, μ^q) and the corresponding vector of baseline utilities that equate predicted to actual shares, $\{\delta_j^{*,q}\}_{j=1}^J$, we can calculate the likelihood of the observed data:

$$L(\delta^{*,q}, \gamma^q, \phi^q, \theta^q, \mu^q | AGE, CATCH, TC, \sigma) = \prod_{i \in N} \prod_{j=1}^{J} \left[P_{i,j}^{*,q} \right]^{Y_{i,j}}, \tag{B.6}$$

where $Y_{i,j} = 1$ if angler i chooses site j ($= 0$ otherwise). The researcher determines new values of (γ^{q+1}, ϕ^{q+1}, θ^{q+1}, μ^{q+1}) along with the corresponding values of $\{\delta_j^{*,q+1}\}_{j=1}^J$ so as to increase this likelihood expression. This procedure is repeated until the likelihood function is maximized at $\left(\gamma^*, \phi^*, \theta^*, \mu^*, \{\delta_j^*\}_{j=1}^J\right)$.

Step ♯3: Generate instruments.

Use the vector $\{\delta_j^*\}_{j=1}^J$ found in the final iteration of step ♯2 as the dependent variable in a median regression that ignores the fact that σ_j is endogenous. The intercept term κ absorbs the arbitrary normalization used in the contraction mapping (i.e., $\delta_I = 0$)[25]:

$$\delta_j^* = \kappa + \beta\, CATCH_j + \alpha \sigma_j + \xi_j. \tag{B.7}$$

Using the estimates from this median regression ($\hat{\kappa}, \hat{\beta}, \hat{\alpha}$) and from the preceding maximum likelihood estimation ($\gamma^*, \phi^*, \theta^*, \mu^*$), we can then calculate our instrument for the share of anglers choosing site j:

$$\tilde{\sigma}_j = \frac{1}{N} \sum_i \frac{\text{EXP}\left\{\hat{\kappa} + \hat{\beta}\, CATCH_j + \gamma^*\, AGE_i \times CATCH_j + (\theta^* + \mu^*\, AGE_i) TC_{i,j}\right\}}{\sum_{l=1}^{J} \text{EXP}\left\{\hat{\kappa} + \hat{\beta}\, CATCH_l + \gamma^*\, AGE_i \times CATCH_l + (\theta^* + \mu^*\, AGE_i) TC_{i,l}\right\}}. \tag{B.8}$$

Step #4: Quantile IV estimation.

We form the following moment conditions:

$$E\left[\Phi\left(\frac{\delta_j^* - \hat{\kappa} - \beta\, CATCH_j - \alpha\sigma_j}{s_N}\right) - 0.5\right] = 0 \quad \forall\ j, \tag{B.9}$$

where s_N is a sufficiently small smoothing parameter given the sample size N. Estimate the parameters (ψ, β, α) with the GMM procedure in any statistical package, using $CATCH_j$, $\tilde{\sigma}_j$, and a constant term as instruments. The resulting parameter estimates, along with $\left(\gamma^*, \phi^*, \theta^*, \mu^*, \{\delta_j^*\}_{j=1}^J\right)$, completely describe utility.

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[25] If there are no zero shares in the data (so that all of the δ_j's have empirical content), OLS can be used instead of median regression in this step.

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