Out-of-sight, Out-of-mind? Distance Decay in Use and Non-use Value of Water Quality*

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Abstract

Accurately measuring the welfare benefits of environmental quality improvements is central to regulatory benefit–cost analysis. A common practice in applied valuation is to infer the spatial extent of benefits from observed use behavior, implicitly assuming that willingness to pay declines sharply with distance. We show that this practice systematically understates welfare when households derive both use and non-use value from environmental quality. Using national cellphone-based mobility data, we first document how visitation to surface water features declines with distance. We then combine these revealed preference data with microdata from multiple stated preference surveys to separately identify use and non-use willingness to pay and their respective distance decay patterns. We find that while use values are larger for households located near a water quality improvement, they decay rapidly with distance, whereas non-use values decline much more slowly. As a result, a substantial share of aggregate welfare arises from households who do not visit affected sites. These findings imply that standard spatial aggregation rules used in regulatory analysis can substantially understate the benefits of water quality improvements.

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1 Introduction

Over the past 50 years, more than $1 trillion has been invested under the Clean Water Act to reduce pollution entering surface waters in the United States. Despite this substantial expenditure, the benefits derived from such investments remain uncertain (Keiser, Kling, and Shapiro, 2019). Economists have developed a range of methods to quantify the economic value of improved water quality, including stated preference surveys (e.g., Vossler et al. (2023); Johnston, Moeltner, et al. (2023)), assessments of human health impacts (e.g., Ebenstein (2012); Alsan and Goldin (2019)), and recreation demand models (e.g., Phaneuf and Smith (2005); Dundas and Haefen (2020)). A common feature of these approaches is that willingness to pay for environmental quality is assumed to decline with physical distance from the affected resource, making spatial aggregation central to benefit–cost analysis.

Much of the existing understanding of the relationship between distance and WTP for water quality improvements comes from recreation demand studies. These studies typically use travel cost methods to estimate use values derived from direct interaction with water resources, such as fishing, swimming, or boating. However, far less is known about how distance affects non-use values–such as existence, bequest, or option values–which are not tied to direct use. While revealed preference data can effectively capture use values, they provide no information on non-use values. Meanwhile, stated preference methods can elicit total WTP, including both use and non-use components. Still, they typically do not disentangle these values, as respondents themselves are unable to separate their use and non-use WTP reliably. As a result, little is known about how non-use values vary over space, despite their potentially large contribution to aggregate welfare.

This gap has important implications for applied policy analysis. In practice, regulatory agencies often rely on observed behavior to define the spatial extent of benefits, implicitly assuming that welfare declines sharply beyond the range of typical use. For example, the US Environmental Protection Agency (EPA) developed a meta-analysis-based benefit transfer function to estimate benefits of water quality improvements for proposed regulations as part of the Ben-

SPLASH integrated assessment model (Corona et al., 2020).[1] While the use of a meta-analysis to perform benefits transfer allows for relatively inexpensive and quick estimation of benefits from a proposed regulation,[2] its use of study-level data limits the analyst's ability to model heterogeneity in individuals' willingness-to-pay (WTP). Attempts to incorporate distance into the meta-analysis in BenSPLASH have yielded uncertain results, mainly because doing so requires a study-level aggregated distance measure (Johnston, Besedin, and Holland, 2019a). In the absence of empirically grounded evidence on how willingness to pay — particularly non-use willingness to pay — decays with distance, analysts must impose assumptions about the "extent of the market" for environmental improvements. As we show in this paper, such assumptions can lead to systematic understatement of welfare when non-use values are spatially diffuse.

This paper addresses a central gap regarding how willingness to pay for environmental quality varies over space when households derive both use and non-use value. We show that relying on observed visitation behavior to define the spatial extent of benefits, an approach commonly embedded in regulatory analysis, can systematically misrepresent welfare when non-use values are present. We begin by presenting reduced-form evidence on the relationship between distance and visitation to water-based recreation sites using national cell phone mobility data from Advan. These data provide detailed insights into visitation patterns, which serve as a revealed preference measure of use values. However, non-use values are not identified from visitation data alone. To address this, we combine the revealed preference data with microdata from several recent stated preference (SP) surveys on water quality improvements. Using a unified structural framework that decomposes total willingness to pay into use and non-use components, we estimate distinct distance decay patterns for each and quantify their implications for aggregate welfare.

Our mobility data report anonymized trip counts from home census block groups (CBGs) to recreational points of interest (POIs). With these data, we capture recreational visitation across the US between 2019 and 2023 to nearly 70,000 water-based recreation sites, identified by

[1] We provide a detailed description of benefits estimation in BenSPLASH in Appendix A.
[2] This is relative to conducting a primary stated preference survey for the proposed regulation, for example.

intersecting Advan's park POIs with water features from the National Hydrography Dataset (Zhang et al., 2024). Consistent with prior work, the majority of observed trips to water-based recreation sites originate from individuals who live relatively close to the POI. However, the rate at which visitation declines with distance varies substantially across both origin and destination characteristics. In particular, visitation decays more slowly for larger sites, lake-rich areas, and less urban locations, indicating that households are willing to travel farther to access certain types of recreational opportunities. Since an individual's non-use value is independent of their choice to recreate at any given site, we cannot use the mobility data to learn about non-use values.

Therefore, we turn to stated preference data, building on the frameworks proposed by Day et al. (2019) and Kim and Lupi (2023). We model household utility as the sum of a use component, which depends on recreation site choice, and a non-use component, which is independent of site choice but potentially influenced by spatial proximity. A central empirical challenge in this analysis is the requirement for data that cover both revealed and stated preferences. Such integrated datasets are rarely available. To overcome this, we combine the cell phone mobility data with household-level SP survey data that quantify WTP for water quality improvements. The mobility data inform how recreational benefits vary with distance and site characteristics, while the SP data capture households' total valuation of water quality changes, including non-use values that are not revealed through observed travel behavior. Together, these data allow us to disentangle use and non-use components of WTP in a way that is consistent with observed visitation patterns.

Our SP data come from two recent surveys, including those of Johnston, Moeltner, et al. (2023) and Moore et al. (2026). These surveys present respondents with policy scenarios involving improvements in water quality, asking them to vote for or against each policy relative to a baseline scenario, accounting for associated costs. Together, these surveys span regional and national contexts and differ in spatial scope and policy framing, providing complementary variation that supports identification of both use and non-use values across a wide range of water quality improvements.

We estimate expected use values from the cellphone-based recreation demand model using a random utility framework and infer non-use values by leveraging variation in water quality scenarios and respondent locations from the SP surveys. As a validation step, we reproduce prior estimates of household WTP for water quality improvements in each survey's respective original study using our estimated model.

We then use the model to simulate distance decay curves separately for use and non-use values. We find that use values are highest for households located close to improved water bodies and decline sharply with distance, while non-use WTP decays much more slowly with distance than use WTP. Although use WTP dominates at short distances, most household–watershed distance pairs lie beyond the range where use values are economically meaningful. As a result, non-use values account for an increasing share of total WTP as we aggregate benefits over larger spatial extents. This pattern holds across regional and national survey contexts.

Our results also have direct implications for the EPA's BenSPASH framework, which aggregates recreational benefits within a fixed radius of improved water bodies. The performance of this spatial cutoff depends on the context. Our model results from the NCEE's national survey indicate that limiting benefits to a 100-mile radius captures only 10% of the total benefits. However, when we estimate the model with survey data with a regional scope from Johnston, Moeltner, et al. (2023), we find that a 100-mile radius captures 70% of use values and 28% of non-use values. These results suggest that the original justification for the 100-mile radius, that it captured most recreation-based trips to water features, holds in some situations, yet always omits significant benefits. Current benefit-cost analyses that apply a uniform spatial boundary systematically undercount the societal benefits of water quality improvements.

Our paper contributes to the literature in three ways. The first contribution is to combine national-scale revealed preference data with detailed household-level stated preference surveys. This contributes to a literature on combined approaches to demand estimation (e.g., Cameron (1992), Phaneuf, Taylor, and Braden (2013), and Day et al. (2019)). We merge cellphone mobility data from Advan (formerly SafeGraph), which captures millions of anonymized trips from home CBGs to recreational POIs, with microdata from three recent stated prefer-

ence surveys focused on water quality improvements. This integrated dataset allows us to link observed recreation behavior with stated preferences over hypothetical policy scenarios, providing a uniquely comprehensive basis for estimating both use and non-use values. Our revealed preference data span 2019 to 2023 and cover nearly 70,000 water-based recreation sites across the contiguous United States, identified by intersecting Advan POIs with surface water features from the National Hydrography Dataset Plus Version 2 (NHD Plus v2)(Zhang et al., 2024).

Our second contribution is to provide the first national-scale estimates of distance decay in both use and non-use WTP for water quality improvements. Previous work has estimated distance decay for users and/or non-users or relied on strong assumptions to decompose use and non-use values (e.g., Hanley, Schläpfer, and Spurgeon (2003), Bateman et al. (2005), Herriges, Kling, and Phaneuf (2004), Olsen, Jensen, and Panduro (2020), Huang et al. (2016), and Smith et al. (2022)). Critically, the distinction between users and non-users is not the same as use and non-use values. Users may still have non-use value for an environmental good. Using a structural model that integrates revealed and stated preference data, we decompose total WTP into its use and non-use components and estimate how each varies with distance from a water body. Preliminary results from the stated preference surveys indicate that use values decay sharply with distance, consistent with existing recreation demand studies, while non-use values remain relatively constant over distance.

Our third contribution is to provide practical guidance for improving the spatial accuracy of benefit transfer models (e.g., Griffiths et al. (2012), Newbold et al. (2018), and Corona et al. (2020)). By explicitly modeling the spatial extent of non-use values and quantifying their minimal distance decay, we offer an empirically grounded basis for expanding the geographic scope of benefit aggregation. Our results support a differentiated approach in which recreational use values are aggregated within 100 miles, while non-use values are aggregated over broader regional or national scales. Incorporating these refinements into regulatory impact analyses would provide more comprehensive and accurate estimates of the economic benefits associated with water quality improvements, informing better policy design and resource allocation

decisions.

We first explore the reduced-form evidence of distance decay in national cell-phone based mobility data in Section 2. We then introduce and estimate the structural model allowing us to decompose use and non-use values in Section 3. We present the results from that model in Section 4 and then conclude in Section 5.

2 Descriptive Evidence of Distance Decay

In this section, we present descriptive evidence on how visitation to water-based recreation sites declines with distance, using national-scale cellphone mobility data. The primary goal is to document the presence and shape of distance decay in revealed recreational behavior and to assess whether commonly used assumptions about the spatial extent of recreation markets, most notably the EPA's 100-mile cutoff in the BenSPaSH model, are consistent with observed visitation patterns. These reduced-form results provide empirical grounding for the specification of the use-value component of our structural recreation demand model and inform the subsequent decomposition of use and non-use values.

We begin by constructing a national dataset that links residential locations to observed visits to water-based recreation sites, yielding a revealed-preference measure of recreation use. We first present summary statistics to characterize the spatial distribution of visits and travel distances in the data. We then outline our empirical approach for measuring distance decay in visitation, focusing on how visitation rates change as a function of travel distance. This reduced-form analysis allows us to directly evaluate the extent to which recreational demand attenuates with distance and to benchmark observed patterns against assumptions embedded in policy-relevant valuation frameworks.

Throughout the section, we emphasize national visitation patterns to match the geographic scope at which the EPA's BenSPaSH model is applied. This alignment ensures that the descriptive evidence is directly relevant for policy analysis and benefit–cost applications. To further assess the generality of the results and facilitate comparison with the stated-preference literature, we

replicate the distance-decay analysis for the specific regions examined in Johnston, Moeltner, et al. (2023). The regional analyses, reported in Appendix B, reveal distance-decay patterns that are qualitatively consistent with the national evidence, reinforcing the robustness of the observed decline in visitation with distance.

2.1 Data

Advan Mobility Data We use large-scale mobility data from Advan to measure visits to water-based recreational sites across the contiguous United States. Advan collects anonymized GPS-based mobility data from approximately 45 million mobile devices, providing high-resolution foot traffic data aggregated at CBG level. The data are derived from smartphone GPS signals shared through multiple mobile applications on both iOS and Android platforms. For each POI, Advan provides aggregated visitor counts by home CBG and reports the average time spent at each site. It is important to note that the dataset represents a subset of visitors who use smartphones and have opted to share their location data, which may underrepresent certain demographic groups, including older individuals and lower-income populations.

Our analysis focuses on the period from 2018 to 2022. We restrict the sample to POIs categorized as nature parks and similar recreational facilities within the 48 contiguous U.S. states, excluding Alaska, Hawaii, Puerto Rico, and other territories where recreation visits frequently involve air travel. To identify water-based recreation sites, we match Advan POIs to water features from the NHD Plus Version 2. Specifically, we apply a 20-meter buffer around river flowlines, shorelines, and water bodies, as well as a 50-meter buffer around the recreational visit polygons provided by Advan. These buffered areas are merged to define a comprehensive set of water-based recreation sites (Zhang et al., 2024).

Visitor home locations are identified by Advan using six weeks of nighttime location data (between 6 pm and 7 am), assigning home CBGs based on observed patterns. To protect user privacy, Advan suppresses data when fewer than two visitors are observed from a CBG, and reports exactly four visitors if the count falls between two and four. Our data represent monthly visits from each origin CBG to each destination site, providing the basis for estimating

recreation demand as a function of travel distance and site attributes. To ensure consistency with the spatial resolution of the national survey data used in later sections, we aggregate these visits to the ZIP code–Hydrology Unit Code (HUC8) level for the main analysis.[3]

Supplemental Data In addition to the cellphone-based mobility data, we incorporate several supplemental datasets that enhance the accuracy and scope of our analysis of distance decay in willingness to pay for water quality improvements. These additional datasets include driving distances derived from road network data, measures of water quality, site characteristics, and demographic data. Together, these datasets enable us to refine both our revealed preference and stated preference models and account for heterogeneity in behavior and preferences across populations and locations.

To construct realistic measures of travel costs in the revealed preference portion of the analysis, we calculate driving distances between each CBG and water-based recreation sites using the Open Source Routing Machine (OSRM). OSRM provides detailed routing over road networks, allowing us to compute the shortest driving distance and estimated driving time for each origin-destination pair. This method accounts for the structure of the road network and avoids the inaccuracies inherent in straight-line distance measures, which often fail to reflect true accessibility. Distances are initially calculated at the CBG–site level and subsequently aggregated to the ZIP code–HUC8 level by averaging across relevant origin–destination pairs for the main analysis. These driving distance measures are used to calculate travel costs in the recreation demand model and are a critical component in estimating how distance influences site choice and recreation behavior.

We also incorporate data on water quality at recreation sites to capture the role of environmental quality in influencing both use and non-use values. Water quality measures include variables such as dissolved oxygen, turbidity, nutrient levels, and biological condition indices. These data are drawn from the National Hydrography Dataset (NHD) and the modeled water quality scenarios developed in the stated preference studies, including Johnston et al. (2023). These

[3]To implement this aggregation, we spatially match census block groups and ZIP codes and allocate visits from each CBG to ZIP codes based on the share of the CBG's land area that overlaps with each ZIP code.

measures are aggregated to appropriate spatial units, such as HUC8 watersheds, and provide a consistent basis for evaluating the environmental improvements presented in the stated preference surveys as well as the observed recreation behavior in the revealed preference data.

In addition to water quality, we include detailed site characteristics that are known to affect recreation demand. These characteristics include the type of water feature, such as lakes, rivers, or estuaries, as well as site-specific attributes such as available amenities, recreational facilities, site size, and accessibility. This information is used to control for differences in the attractiveness of recreation sites, allowing us to isolate the effect of distance on recreation site choice from other factors that influence visitation behavior.

2.2 Summary Statistics

Table 1 reports summary statistics for the cellphone-based mobility data used in the analysis. The unit of observation is a ZIP code–HUC8 pair, capturing aggregated recreation trips from residential ZIP codes to water-based recreation sites within each HUC8 watershed. The final sample consists of approximately 17.6 million ZIP–HUC8 observations, spanning 4,649 ZIP codes and 1,538 HUC8 watersheds nationwide.

On average, each ZIP–HUC8 pair records 27 visits, though visitation is highly skewed, with a large standard deviation reflecting substantial heterogeneity in recreational demand across space. The mean trip duration is 17.2 hours, capturing both short visits and multi-day recreational trips. Average travel distance is 932 miles, indicating that while most recreation occurs locally, a nontrivial share of trips involve long-distance travel. Each observation is constructed from an average of roughly 2,600 mobile devices in each ZIP Code, providing dense coverage across residential locations. Travel costs are constructed using the method of English et al. (2018), which calculates a weighted average of driving and flight costs based on trip distance and prevailing cost parameters. The resulting measure averages $424 per trip, with considerable dispersion across origins.

The table also summarizes key HUC8-level characteristics used to explain variation in visitation

Table 1: Summary Statistics

	Mean	Std. Dev.	Min	Max
Cell Phone Visits & Travel Costs				
Visits	27.00	506.47	0.00	177,513
Duration (hours)	17.16	12.42	0.06	64.35
Distance (miles)	931.80	704.31	1.24	3,541.70
Number of Devices	2,578.23	2,271.38	9	31,195.83
Travel Cost ($)	424.17	237.94	1.14	1,905.20
HUC8 Characteristics				
Share of Urban Sites	0.67	0.31	0	1
Distance to Nearest Highway (miles)	36.56	37.87	1.02	278.90
Site Area (km^2)	21.25	147.71	0.00	2,147.48
Share of Lake Sites	0.47	0.30	0	1
Observations		17,557,170		
Zip Code		4,649		
HUC 8		1,538		

Notes: Table 1 reports summary statistics for recreation trip observations used in the analysis. Reported values are means, standard deviations, minimum, and maximum.

patterns. On average, 67 percent of recreation sites within a HUC8 are classified as urban, and approximately 47 percent are lake-based. Watersheds are located an average of 36.6 miles from the nearest highway, capturing differences in accessibility across space. Site area varies substantially, with an average of 21.3 square kilometers and a highly right-skewed distribution, reflecting the presence of both small access points and large recreational water bodies.

Overall, the summary statistics highlight pronounced heterogeneity in visitation intensity, travel behavior, and site characteristics. The wide spatial distribution of trips and large variation in site attributes underscore the importance of explicitly modeling distance decay and spatial heterogeneity when estimating recreational use values from large-scale mobility data.

2.3 Empirical Strategy

We estimate a reduced-form model of visitation from home census block groups (CBGs) to water-based recreation sites as a function of distance and other covariates. The dependent variable is the total number of monthly visits from origin ZIP code i to destination water

feature j during time period t. The primary independent variable of interest is the driving distance between the origin and destination, measured using Open Source Routing Machine (OSRM) data.[4] The model also includes controls for water feature characteristics, origin CBG demographics, and time effects. The estimating equation is as follows:

$$\log V_{ijt} = \beta X_{ijt} + \zeta_i + \gamma_j + T_t + \varepsilon_{ijt},$$

where V_{ijt} is the number of visits from ZIP code i to site j in week t, X_{ijt} is a vector of explanatory variables including distance and site attributes, and ε_{ijt} is an idiosyncratic error term. The model includes fixed effects for each water feature γ_{jt} and origin ZIP code ζ_i, controlling for unobserved, time-invariant characteristics of both origins and destinations that influence visitation levels. Year and month-of-year fixed effects T_t are also included to account for seasonal variation and broader trends in recreation behavior. In additional specifications, we allow for water feature by year fixed effects to control for annual variation in site quality, including changes in water quality conditions.

We explore several different specifications of the distance variable. We evaluate different functional forms for the distance decay relationship, including log-linear, log-log, polynomial, categorical bins, and cubic B-splines. These alternative specifications allow us to assess the robustness of our findings and provide guidance for how distance should be incorporated into the structural model presented in Section 3.

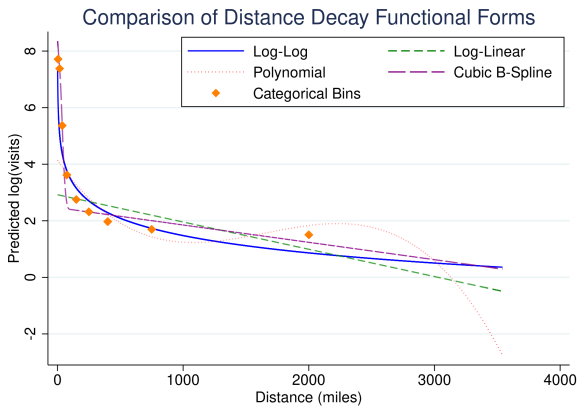
2.4 Results

Figure 1 summarizes our reduced-form analysis of how visitation responds to distance from a recreation site. We compare five commonly used functional forms to model distance decay: log-

[4]We intentionally model travel burden using physical distance rather than monetized travel cost. Our objective in Section 2 is to characterize how recreational participation and willingness to pay decay with distance from the resource, which directly corresponds to the distance-based aggregation rules used in policy applications such as EPA's BenSPLASH model. Monetizing travel cost would require additional assumptions about the value of time, vehicle operating costs, and trip purpose that vary across households and locations and are not identified in our data. Using distance allows us to isolate spatial decay in demand without introducing auxiliary assumptions that are orthogonal to the policy question of market extent.

log, log-linear, polynomial, categorical bins, and cubic B-spline. The figure displays predicted log of visits using data from NCEE survey. Across all specifications, we find strong and consistent evidence of distance decay. Visitation rates decline sharply with distance, especially within the first 50 miles, and taper at a slower rate beyond 100 miles. The steep initial drop followed by a long tail suggests a nonlinear relationship, best captured by flexible functional forms such as the log-log or cubic B-spline models.

Figure 1: Distance Decay in National Recreational Visits



Note: Figure 1 compares alternative functional forms used to estimate the distance decay in predicted log(visits) for NCEE household samples. Each curve represents a different modeling approach, including log-log, log-linear, polynomial, and cubic B-spline specifications. Orange diamonds represent average predicted values from categorical distance bins and serve as a nonparametric benchmark.

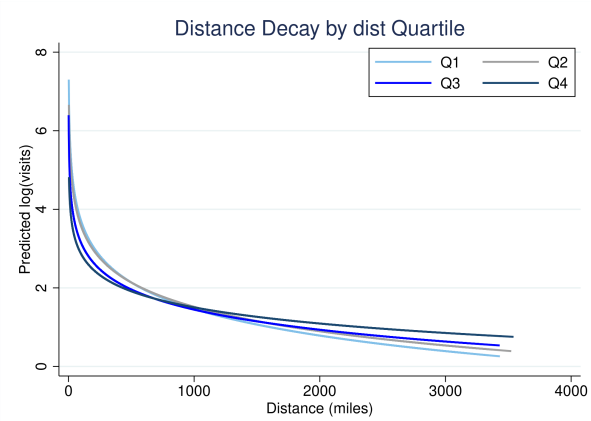
The various specifications differ in smoothness and curvature. The log-log and cubic B-spline models offer the best visual fit to observed visitation patterns, capturing both the steep decay in near-distance trips and the long tail of infrequent, long-distance visits. In contrast, the polynomial specification tends to understate short-distance decay and overpredict in mid-distance ranges. Categorical bins serve as a useful nonparametric benchmark, revealing that predicted visits remain positive even beyond 1000 miles, though the rate of decline slows significantly after 500 miles. These differences underscore the importance of model choice when interpreting distance elasticities and aggregating benefits.

These patterns have implications for the EPA's current practice in the BenSPLASH model, which assumes that recreational benefits are realized only by households within 100 miles of an im-

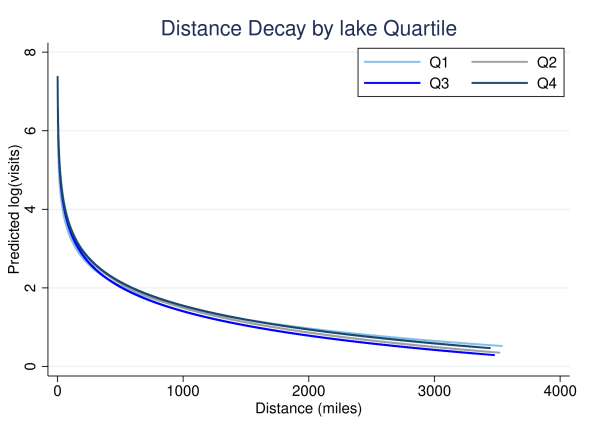
proved water body. Our results support this approximation in broad terms: the majority of predicted visits are concentrated within 100 miles. However, we also observe non-trivial visitation beyond that threshold, particularly for certain site types or among specific demographic groups. This suggests that the 100-mile cutoff may miss meaningful recreational activity in destination-like settings.

Figure 2: Distance Decay by HUC8 Type

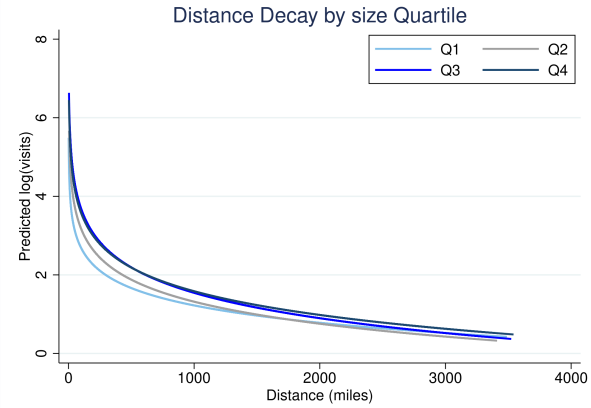
(a) Distance Quartiles



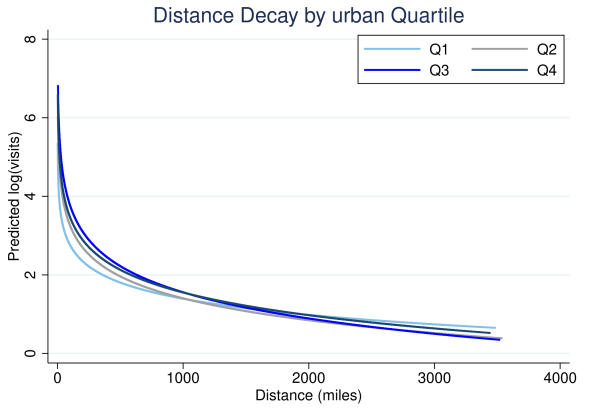
(b) Lake Quartiles



(c) Site Area Quartiles



(d) Urban Quartile

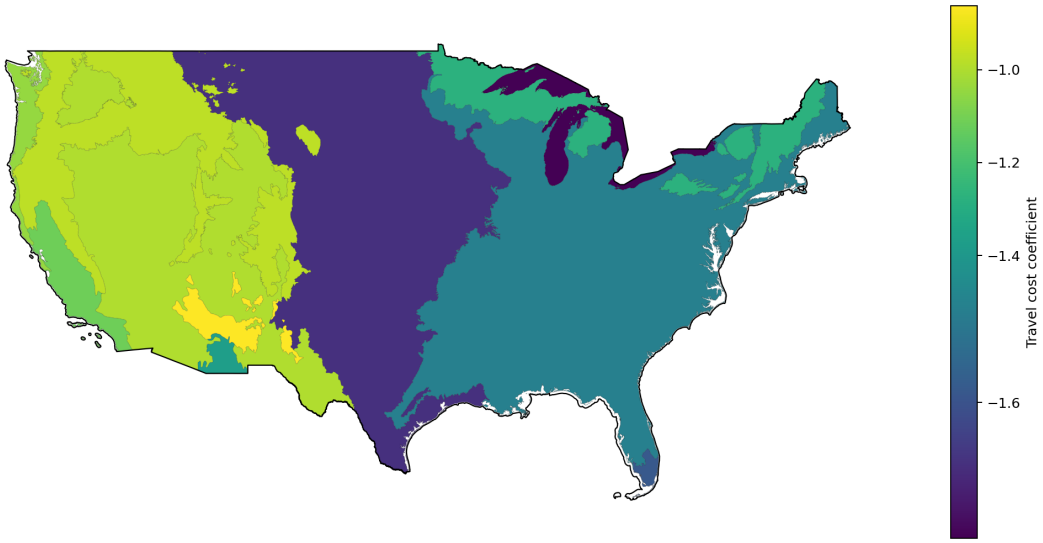


Note: Figure 2 illustrates estimated distance-decay relationships in predicted log(visits) for NCEE household samples by quartiles in terms of distance to nearest highway, number of lake-based sites, average site area, and number of urban sites in each HUC8. Each curve represents log-log specifications.

Figure 2 extends the descriptive analysis by examining heterogeneity in distance-decay patterns across HUC8 characteristics. Panel (a) shows that distance decay varies systematically with

proximity to major transportation networks, with substantially steeper decay in HUC8s located farther from highways. Panel (b) reveals comparatively modest differences across quartiles defined by the number of lake-based sites, suggesting that lake abundance primarily affects the overall level of recreational demand rather than households' marginal sensitivity to distance. Panel (c) indicates that HUC8s with larger average site area exhibit more gradual distance decay, consistent with larger sites attracting visitors from a wider geographic area. Panel (d) stratifies HUC8s by urbanization and shows that less urban regions experience steeper decay, whereas more urban areas draw visitors from a broader spatial extent. Taken together, these results highlight that physical access, site characteristics, and regional context play distinct and important roles in shaping the spatial reach of recreational demand.

Figure 3: Spatial Heterogeneity in Distance Decay across U.S. Ecoregions



Note: Figure 3 maps estimated travel cost coefficients from reduced-form regressions that allow distance decay in recreational visitation to vary by Level I ecoregion. Darker colors indicate steeper distance decay (greater sensitivity to travel distance), while lighter colors indicate flatter decay. Estimates are obtained from specifications that interact log of travel distance with ecoregion indicators and include ZIP code, HUC8, and month fixed effects. The map is restricted to the contiguous United States and the District of Columbia.

Finally, Figure 3 summarizes heterogeneity in distance decay at a broader ecological scale by mapping estimated log-distance coefficients across Level I ecoregions. The updated map reveals pronounced spatial variation: decay is steepest in the Great Lakes and parts of the interior United States, moderate along much of the East Coast, and flattest in the western and mountain regions. Importantly, the steeper decay estimated for the Great Lakes does not imply weaker long-distance appeal. Rather, it reflects the combination of exceptionally dense local supplies of water resources and large nearby population centers, which generate high volumes of short-distance trips and provide abundant close substitutes. In such settings, the marginal utility of traveling farther declines rapidly because households can access comparable amenities within short distances. By contrast, many western regions contain fewer substitutable water bodies and more destination-oriented sites, so recreation demand is less sensitive to travel distance and supports longer-distance travel. These patterns are consistent with differences in both the availability of substitutes and the structure of recreation markets across space, suggesting that distance decay is not uniform and that applying a single market-extent assumption may induce region-specific bias in benefit estimates.

Taken together, these reduced-form results provide strong empirical motivation for a structural modeling approach that allows distance decay to vary across contexts and disentangles different sources of value. They suggest that both use values and their spatial extent depend systematically on site attributes and regional characteristics. In Section 3, we build on these insights by developing a joint revealed- and stated-preference model that explicitly incorporates heterogeneous distance decay and allows us to separately identify use and non-use values of water quality improvements.

3 Structural Model of Use and Non-use Value

The evidence presented in Section 2 describes the relationship between distance and visitation to water-based recreation sites, confirming the presence of distance decay in recreational behavior. However, the reduced-form analysis is limited to observed use values and, by construction, does not provide insights into non-use values or the total economic value of water

quality improvements. To address these limitations, we develop a structural model that combines revealed preference (RP) and stated preference (SP) data, allowing us to decompose individual willingness to pay (WTP) into use and non-use components and estimate how each varies with distance. This model provides a theoretically consistent framework for estimating how both types of values vary with distance and offers a foundation for more accurate benefit assessments and policy evaluations.

Our approach builds on the framework of Kim and Lupi (2023) and Day et al. (2019), specifying a joint model that leverages RP data to estimate use values based on observed recreation behavior and SP data to recover non-use values embedded in survey responses. In the model, individuals decide whether to vote for or against a policy scenario. The scenarios represent water quality at water features throughout the study region, as well as the associated monetary costs required to achieve that water quality.[5] An individuals' utility for a particular scenario comes from three objects: use utility, non-use utility, and the numeraire.[6] Individuals derive use utility after deciding which water feature to visit (or not to visit any water feature) each period.[7] This choice is affected by the water quality at each site and the associated travel costs. These travel costs are the mechanism through which distance from an individual to a water feature affects "use" willingness-to-pay for water quality improvements: the further away someone lives, the higher the travel costs are, making them less likely to visit a water feature, and thus less likely to benefit from improvements in water quality at that location. Distance therefore affects use values exclusively through access costs and participation decisions, rather than through preferences over environmental quality itself.

Meanwhile, non-use utility captures any benefit that individuals receive from a water feature

[5]Typically, there is a baseline or business-as-usual case that comes at zero cost, compared against a proposed policy that improves water quality, but comes at a cost.

[6]In our framework, "use" refers to utility derived from direct participation in water-based recreational activities that require access to the water resource, such as fishing, swimming, boating, or shoreline recreation, as revealed by observed visitation behavior. Activities that do not require the water body as an input — for example, visiting a shopping center or restaurant located near a water feature — are not classified as use, even if individuals incidentally enjoy proximity to water during those activities. Under weak complementarity, such incidental or passive benefits accrue regardless of participation and are therefore captured as non-use value. This definition follows the standard treatment in the recreation demand and non-use valuation literature and ensures that use values are identified solely through revealed participation decisions, while all remaining welfare effects that persist in the absence of participation are attributed to non-use.

[7]We include not visiting any water feature as an "outside option" in the model.

that is independent of their decision to visit that water feature. This non-use value includes both commonly described option and existence values (Smith, 1987). Consistent with weak complementarity, these values are independent of direct recreational participation and are therefore not revealed by observed visitation behavior. In the model, an individuals' non-use utility under a given policy is the distance-weighted sum of utility across all water features. Importantly, they get this non-use utility from a site even if they do not visit it. Distance weighting allows people to place a higher (or lower) non-use value on water features that are closer to them, reflecting, for example, differences in salience, information, option value, or perceived relevance.

3.1 Model Framework

We specify preferences to separately capture utility derived from recreational use of surface water resources and utility derived independently of direct interaction with those resources. This distinction follows the standard weak complementarity framework, in which environmental quality affects welfare both through its interaction with use decisions and through a non-use component that generates utility even when recreational participation is zero.

The utility of individual i conditional on visiting water feature j in period t in state of the world s is expressed as

$$u_{ijts} = v_{ijts}^{\text{use}} + v_{its}^{\text{nonuse}} + v_{ijts}^{o} + \varepsilon_{ijts}, \tag{1}$$

where v_{ijts}^{use} captures the utility from visiting the site, v_{its}^{nonuse} captures non-use utility, v_{ijts}^{o} represents the numeraire, and ε_{ijts} is an idiosyncratic error term. Non-use utility enters additively and does not vary across site choices within a period, reflecting benefits that are independent of the decision to visit any particular site. The states of the world, s, refer to the baseline and policy scenarios presented in the SP surveys, which differ in water quality and associated costs. We model numeraire utility as being linear in income net of travel costs and policy costs,

$$v_{ijts}^{o} = \gamma(y_{it} - p_{ij} - c_s), \tag{2}$$

where y_{it} is income, p_{ij} is the travel cost to site j, c_s is the cost of the policy, and γ is the marginal utility of income.

Use utility varies across the specific water features j and is defined as

$$v_{ijts}^{\text{use}} = \alpha_{jt} + q_{js}'\beta. \tag{3}$$

where α_{jt} is an alternative-period-specific constant capturing average site attractiveness in a given period across individuals, q_{js} is a vector representing water quality at site j under scenario s, and β is the marginal utility of water quality.

We specify non-use utility as a distance-weighted sum over utility from every water feature,

$$v_{its}^{\text{nonuse}} = \sum_j (d_{ij}+1)^{\lambda}(a_{ijt} + q_{js}'b), \tag{4}$$

where d_{ij} is the distance between individual i and site j, λ captures the rate of distance decay in non-use values, a_{ijt} represents site attributes, and b reflects the marginal non-use utility of water quality. Note that $\lambda < 0$ implies that households non-use value is decreasing as a water feature gets further away. We interpret this distance-weighted aggregation as a reduced-form representation of how the salience and perceived relevance of environmental quality decline with distance, rather than as a literal description of information or attention processes.

The probability that household i chooses to visit site j in period t under scenario s is

$$\begin{aligned}
Pr_{ijts} &= Pr(u_{ijts} - u_{ikts} > 0) \quad \forall\, k \neq j \\
&= Pr\left[(v_{ijts}^{\text{use}} + v_{its}^{\text{nonuse}} + v_{ijts}^{o}) - (v_{ikts}^{\text{use}} + v_{its}^{\text{nonuse}} + v_{ikts}^{o}) > \varepsilon_{ikts} - \varepsilon_{ijts}\right] \quad \forall\, k \neq j \\
&= Pr\left[(v_{ijts}^{\text{use}} - \gamma p_{ij}) - (v_{ikts}^{\text{use}} - \gamma p_{ik}) > \sigma^{RP}(\varepsilon_{ikt}^{RP} - \varepsilon_{ijt}^{RP})\right] \quad \forall\, k \neq j,
\end{aligned}$$

where we have decomposed the error term into an individual-site-time portion and individual-time-scenario portion, $\varepsilon_{ijts} = \sigma^{RP}\varepsilon_{ijt}^{RP} + \sigma^{SP}\varepsilon_{its}^{SP}$.

We use these site visit probabilities, along with observed visitation behavior, to estimate the

parameters governing individual use utility. Importantly, non-use utility is constant across site choices and therefore cancels out of all revealed preference comparisons. As a result, no amount of variation in visitation behavior can identify non-use values from revealed preference data alone, regardless of data richness or sample size. This non-identification is structural rather than empirical. This cancellation is the fundamental reason why we must use stated preference research designs to learn about non-use values.

Assuming that ε_{ijt}^{RP} is distributed type 1 extreme value with scale parameter σ^{RP}, we have a closed form solution for Pr_{ijts},

$$Pr_{ijts} = \frac{\exp\left((v_{ijts}^{\text{use}} - \gamma p_{ij})/\sigma^{RP}\right)}{1 + \sum_k \exp\left((v_{ikts}^{\text{use}} - \gamma p_{ik})/\sigma^{RP}\right)}. \tag{5}$$

We are then able to calculate the expected value of use utility net of travel costs over the idiosyncratic site shocks as

$$EV_{its}^{RP} = \log\left(\sum_{j=0}^{J} \exp\left((\alpha_{jt} + q_{js}'\beta - \gamma p_{ij})/\sigma^{RP}\right)\right) + \kappa^{RP}, \tag{6}$$

where κ^{RP} is Euler's constant. We index the outside option of no water-based recreation visit as choosing option $j = 0$.

Individual's decide how to vote on a proposed policy based on their expected utility under that policy. The typical setup in modern stated preference studies is to have scenario $s = 0$ as the business-as-usual case, with $q_{j0} = q_j$ and $c_0 = 0$, and scenario $s = 1$ generating an improvement in water quality $q_{ij1} = q_j + \Delta q_{ij}$ at some cost $c_{i1} > 0$. Utility under each scenario s is

$$u_{is} = \tilde{v}_{is} + \tilde{\varepsilon}_{is}^{SP}$$

where $\tilde{\varepsilon}_{is}^{SP} = \sum_t \varepsilon_{its}^{SP}$ and $\tilde{v}_{is}$ is the deterministic portion of utility,

$$\tilde{v}_{is} = \frac{1}{\sigma^{SP}} \sum_t \left(v_{its}^{\text{nonuse}} + EV_{its}^{RP} + \gamma(y_i - c_s)\right) + \kappa, \tag{7}$$

with a constant of integration, κ. Thus, the probability that individual i votes in favor of scenario $s = 1$ is

$$Pr(u_{i1} > u_{i0}) = Pr\left(\Delta\tilde{v}_i > \Delta\tilde{\varepsilon}_i^{SP}\right)$$

where $\Delta\tilde{v}_i = \tilde{v}_{i1} - \tilde{v}_{i0}$ and $\Delta\tilde{\varepsilon}_i^{SP} = \tilde{\varepsilon}_{i1}^{SP} - \tilde{\varepsilon}_{i0}^{SP}$. Kim and Lupi (2023) derive the distribution of $\Delta\tilde{\varepsilon}_i^{SP}$ under the assumption that the underlying shocks, ε_{ijts}^{SP}, are distributed type 1 extreme value. This distribution, along with the calculated deterministic utility differences, $\Delta\tilde{v}_i$, and individual's actual votes in response to the proposed policy allow us to estimate the rest of the parameters of the utility function, including those governing non-use values.

We can write the change in deterministic utility as $\Delta\tilde{v}_i = \Delta E_i^{\text{NU}} + \Delta E_i^{RP}$, for

$$\Delta E_i^{\text{RP}} = \frac{1}{\sigma^{SP}} \sum_{t=1}^{T} \left[\ln S_{it}^{(1)} - \ln S_{it}^{(0)} \right], \tag{8}$$

$$\Delta E_i^{\text{NU}} = \frac{1}{\sigma^{SP}} \sum_{t=1}^{T} \sum_{j=1}^{J} (1 + d_{ij})^{\lambda}\, b\, \Delta q_{ij} \tag{9}$$

where

$$S_{it}^{(0)} = \sum_{j=0}^{J} \exp\left((\alpha_{jt} + q_j'\beta - \gamma p_{ij}) / \sigma^{RP} \right) \tag{10}$$

$$S_{it}^{(1)} = \sum_{j=0}^{J} \exp\left((\alpha_{jt} + (q_j + \Delta q_{ij})'\beta - \gamma(c_i + p_{ij})) / \sigma^{RP} \right), \tag{11}$$

Note that we have included the per-choice-occasion policy cost, c_{it}, as part of ΔE_i^{RP}. The household pays this cost in the policy scenario regardless of whether they visit a water-based recreation site. Therefore, it is important to include the outside option $j = 0$ as part of the sum.

3.2 Data

We estimate the model using cell-phone-based mobility data described in Section 2 and micro-data from two recent stated preference surveys focused on household WTP for water-quality improvements. These surveys provide the necessary information to estimate total WTP and, in combination with mobility data, to decompose it into use and non-use WTP. Here, we provide a brief overview of each stated preference study, with additional details in Appendix C.1.

Johnston et al. The first stated preference dataset comes from Johnston, Moeltner, et al. (2023), who surveyed households in New England on their WTP for improvements in river water quality. The survey includes three distinct water quality indices: a water safety index based on fecal coliform concentrations, an aquatic life index based on chloride concentrations, and an overall water quality index that incorporates both indices along with dissolved inorganic nitrogen. They normalize each index to a scale of 0 to 100. Using the FrAMES water quality model (Wollheim et al., 2008), Johnston et al. simulate water quality conditions at the river segment level under a business-as-usual scenario and 41 alternative policy scenarios. These scenarios represent combinations of riparian buffer expansion, wastewater treatment upgrades, stormwater retention improvements, and reductions in road salt application. They present respondents with referendum-style voting tasks in which they choose whether to support a proposed policy relative to the baseline, with annual costs ranging from $30 to $1,200. The survey was fielded in May and June of 2021, yielding 1,239 completed responses. In addition to the publicly posted replication data for the study, the authors provided us with each respondent's home zip code and the underlying modeled water quality data. For integration into our model, we aggregate their river-segment data to the HUC-12 watershed level, calculating weighted averages of each water quality index for each watershed, with river-segment length as the weighting factor. We use these aggregated measures to characterize baseline conditions and policy-induced changes in water quality throughout the region.

NCEE The second stated preference data come from a nationally representative survey conducted by the US EPA's National Center for Environmental Economics. A working paper with

their initial results will be available soon. They use two measures of water quality at the HUC-2 level, a "Recreation Score" based on the EPA water quality index and an "Aquatic Life" score based on their observed-to-expected metric (Hill et al., 2020). They present respondents with six policy scenarios. These policy scenarios vary in the magnitude, location, and spatial scale of water quality improvements, as well as the cost to the respondent. We disaggregate their HUC-2 water quality measures to the HUC-8 level. They collected data from nearly 6000 respondents in the Fall of 2024.

3.3 Estimation and Identification

We estimate the structural model in two stages. The first stage focuses on revealed preference behavior, using the Advan mobility data to estimate the marginal utility of income and the origin-destination-time-specific utilities for each origin CBG, destination HUC, and month combination. Using cell phone data allows us to estimate these origin-site-time-specific utilities with high-dimensional fixed effects, which would be underpowered using sample sizes typically collected in stated preference surveys.

We then port estimated parameters from the first stage into a maximum likelihood algorithm disciplined by individuals' responses to stated preference surveys on water quality to estimate the remaining parameters governing individual utility. Importantly, these survey responses allow us to identify non-use utility parameters.

3.3.1 Revealed Preference Estimation

We model recreational behavior using a discrete-choice framework that follows the approach of Berry (1994), employing the two-step estimation technique outlined by Murdock (2006). This framework allows us to estimate recreation demand and recover the mean utility households derive from visiting water-based recreation sites. In the first step, we use a random utility model (RUM) to estimate site-specific alternative-specific constants (ASCs), which reflect the mean utility of each site across all visitors. In the second step, we regress these ASCs on site attributes, including water quality measures, to estimate the marginal utility of environmental

quality improvements.

In the RUM, visitors from different census block groups (CBGs) make discrete choices among all recreation sites in their choice sets, plus an outside option that represents non-participation in recreation activities. We define a market as the set of all recreation site choices made by visitors from a particular CBG within a quarter. The model assumes static preferences, that is, visitors make decisions in each time period without considering future changes in travel costs or site characteristics.

A key challenge in modeling recreation demand at this spatial and temporal scale is the prevalence of zero market shares. It is common for some sites to record no observed visits from specific CBGs during certain periods. This issue is well documented in the industrial organization literature on discrete-choice demand models (Earle and Kim, 2025; Gandhi, Lu, and Shi, 2023; Ackerberg and Rysman, 2005; Quan and Williams, 2018). Traditional demand models typically assume strictly positive market shares, making them less suited for datasets with frequent zeros (Berry, Linton, and Pakes, 2004). Additionally, small sample sizes and survey-based data can introduce sampling error, potentially distorting demand estimates and exacerbating measurement error.

Zero shares in our setting can arise from two sources. First, some sites may truly be unvisited, raising concerns about selection bias if unvisited sites differ systematically from visited sites in terms of accessibility, quality, or other unobserved characteristics. Second, visits may occur but be unrecorded due to sampling limitations in the cellphone data, introducing measurement error and potentially biasing estimates of demand and travel behavior. In addition to sampling variability, the Advan data apply privacy-preserving censoring rules at the CBG–destination level: visit counts below two are suppressed, and counts between two and four are top-coded at four. This procedure can introduce substantial noise in raw trip counts, particularly for low-frequency destinations or low-density origin areas.

To address these concerns, we take a two-pronged approach. First, we construct the choice set for each CBG based on all sites visited over the entire study period, which limits the influence

of sparsely observed or censored destinations. Second, we apply an empirical Bayes posterior mean estimation procedure, following Li (2019), to address sampling error and sparsity in observed visit counts. Although this estimator is designed primarily to correct for sampling variability, it also partially mitigates distortions introduced by privacy-related censoring by shrinking suppressed or top-coded cell-level counts toward posterior means implied by aggregate choice patterns. As a result, our revealed preference estimates are driven by stable cross-sectional and spatial patterns in participation rather than by potentially noisy cell-level visit counts.

For each market, defined as a CBG-year-quarter, we construct an empirical Bayes prior using a set of similar markets. Similarity is determined by the 50 closest CBGs in terms of travel distance. The market shares of the same recreational site from these similar markets serve as the prior distribution. We fit this observed distribution using a Beta-Binomial model and apply a Bayesian approach to estimate the posterior distribution. The posterior mean, which shrinks observed zero shares toward positive expected values, provides adjusted market shares that reduce bias arising from sampling error and zero observations. This method enables flexible adjustments while maintaining the heterogeneity of site choices across markets. We provide additional details in Appendix D.2.

Once we have estimated adjusted market shares, we proceed with the two-step estimation of the recreation demand model. The probability that visitors from CBG c select recreational site j in year-quarter t can be measured by the market share of recreational site j in the market of c's during year-quarter t, given by:

$$\text{share}_{cjt} = \frac{\exp(CBG_c + Site_j + \boldsymbol{W}_{jt} + Time_t + \gamma^{cell} p_{cjt})}{1 + \sum_{k=1}^{J} \exp(CBG_c + Site_k + \boldsymbol{W}_{kt} + Time_t + \gamma^{cell} p_{ckt})}, \tag{12}$$

where share_{cjt} is adjusted market shares using posterior means, CBG_c are origin CBG fixed effects that capture time-invariant characteristics of residents in CBG c, such as demographic or socioeconomic factors, that affect overall recreation demand. $Site_j$ are site fixed effects that capture time-invariant attributes of recreational site j, $Time_t$ are time fixed effects absorbing

seasonality, $\boldsymbol{W}_{jt}$ controls for the impact of weather conditions, and p_{cjt} is travel costs from CBG c to site j. Note that we have divided through by σ^{RP} (see Equation 5), thus the coefficients here are all estimated relative to σ^{RP}. The probability that a visitor from CBG c selects the outside option o at time t is given by:

$$\text{share}_{c0t} = \frac{1}{1 + \sum_{k=1}^{J} \exp(CBG_c + Site_k + \boldsymbol{W}_{kt} + Time_t + \gamma^{cell} p_{ckt})}. \tag{13}$$

Taking the log-ratio of a recreational site's market share relative to the outside option, we obtain:

$$\log(\text{share}_{cjt}) - \log(\text{share}_{c0t}) = CBG_c + Site_j + \boldsymbol{W}_{jt} + Time_t + \gamma^{cell} p_{ckt}. \tag{14}$$

This transformation expresses the relative market share of each recreational site j compared to the outside option in the market of c's during year-quarter t, allowing us to estimate the objects on the left-hand-side of equation (14) which determine individual use utility for a given site using linear regression.

Since we want to use these estimates in combination with the stated preference data, we must correct for the difference in the scale of the error terms between the stated preference data and the cell phone data (Adamowicz, Louviere, and Williams, 1994). Let σ^{RPcell} be the scale on the error term ε^{RP}_{cjts} in the cell phone data, and $\sigma^{RPsurvey}$ be the scale in the stated preference data. Since the overall scale of utility is not identified, we must normalize one of the parameters governing use utility—we choose to normalize $\gamma = 1$.[8] This normalization is useful since we use the same travel cost data in both stages of estimation, and means that our estimated coefficient on travel cost from Equation (14) is $\hat{\gamma}^{cell} = \frac{1}{\hat{\sigma}^{RPcell}}$.

Additionally, let $\delta_{cjt} = \alpha_{cjt} + q_j'\beta$ be alternative specific constants (ASCs), "constant" here over scenarios s, which include the utility individuals derive from water quality and other site-time specific characteristics of a water-based recreation site. We take the fixed effects estimated via Equation (14) and divide by $\hat{\gamma}^{cell}$ to rescale the units to be relative to a dollar in travel

[8] A common alternative is to think of σ^{RP} as normalized to 1. Our approach is mathematically equivalent, but makes it easier to describe the correction for differences in scale between cell phone and survey data.

costs,

$$\hat{\delta}_{cjt} = \left(\widehat{CBG}_c + \widehat{Site}_j + \widehat{\boldsymbol{W}}_{jt} + \widehat{Time}_t\right)/\hat{\gamma}^{cell}. \tag{15}$$

Unfortunately, we do not have exogenous variation in water quality to decompose the ASCs with linear regression as is commonly done in recreation demand models (e.g., Earle and Kim, 2025). Therefore, we must rely on the experimental variation in water quality created in the stated preference surveys to identify marginal use utility of water quality. The estimates $\{\hat{\gamma}^{cell}, \hat{\delta}_{cjt}\}$ serve as key inputs for the second stage of estimating the structural model.

3.3.2 Stated Preference Estimation

The second stage of estimation combines the RP outputs with SP data to estimate parameters governing marginal non-use utility of water quality, non-use distance decay, and the marginal utility of income. Additional details on this process are in Appendix E. The remaining parameters are $\theta = \{\beta, \gamma^{survey}, b, \lambda, \sigma^{SP}\}$, which we estimate via maximum likelihood.

As before, we normalize $\gamma = 1$ and estimate a new coefficient on travel costs, $\gamma^{survey} = \frac{1}{\sigma^{RPsurvey}}$, which reflects the variance of the revealed preference component within the stated preference routine. Estimating separate γ^{cell} and γ^{survey} parameters allows us to correct for differences in scale between our two data sources.

They are identified by the experimental variation in water quality and program costs generated in the stated preference survey setup. In both the New England and Midwest surveys, households respond repeated choice experiments where the set of water features with improvements is changing along with the costs of the program. Thus, generating variation in the distance between respondents and the improving water features. Since use utility is driven by actual visitation behavior in the first stage, we identify nonuse utility parameters via excess votes for policies relative to cost and expected use utility.

Given data on water quality, distances, travel costs, policy costs $\{p_{ij}, c_{is}, q_{js}, d_{ij}\}$, estimates

from the first stage $\{\hat{\gamma}^{cell}, \hat{\delta}_{cjt}\}$, we are able to calculate the probability an individual votes in favor of a policy conditional on the parameters, $Pr_i^{s=1}(\theta) = F_{t,df}\left(\Delta\tilde{v}_i(\theta)/sd\right)$. Here, $\Delta\tilde{v}_i(\theta) = \tilde{v}_{i1}(\theta) - \tilde{v}_{i0}(\theta)$ is the difference in utility between scenarios, where $\tilde{v}_{is}$ is defined in Equation (7).[9] $F_{t,df}(\cdot)$ is the Student's T cumulative distribution function with $df = 5T + 4$, where T is the number of time periods and $sd = \pi\left((15T + 12)/(5T^2 + 2T)\right)^{-1/2}$. Kim and Lupi (2023) derive this distribution of $\Delta\tilde{\varepsilon}_{is}^{SP}$ assuming that the underlying ε_{its}^{SP} are distributed type 1 extreme value.

Therefore, the log-likelihood function $\mathscr{L}(\theta)$ of observing respondents' actual votes Y_i conditional on parameters θ is

$$\mathscr{L}(\theta) = \sum_i Y_i \log Pr_i^{s=1}(\theta) + (1 - Y_i)\log\left(1 - Pr_i^{s=1}(\theta)\right). \tag{16}$$

We use a gradient-based maximization algorithm to maximize this log-likelihood function. Derivations of the gradients are in Appendix E.1, along with an optimized process by which we calculate the log-likelihood value for a given parameter guess. We place bounds on the parameters—that β, b, and σ^{SP} are positive (and less than a large number) and that λ is negative (and greater than a large, negative number). We randomly select a starting value from within those bounds, and repeat the optimization process using many starting values to ensure that we do not find a local maximum of the likelihood function.

We calculate standard errors from the inverse of the observed information matrix, which we approximate by numerically differentiating the gradient of the log-likelihood to form the Hessian at the estimated parameters. The variance-covariance matrix is the inverse Hessian, and the standard errors are the square roots of its diagonal elements.

[9] Even though Equation (7) has income y_{it} and non-use individual-site-time specific constants a_{ijt}, these terms cancel out when taking the difference $\tilde{v}_{i1}(\theta) - \tilde{v}_{i0}(\theta)$. Thus, we do not need data on income to estimate the model, and we cannot identify the a_{ijt}'s.

3.4 Estimation Results and Model Validation

Table 2 contains both the first and second stage parameter estimates for each stated preference study analyzed. Recall β and b reflect the marginal use and non-use value of water quality. These values are not directly comparable across studies since each study uses a different measure of water quality. We generally find that the marginal use value of water quality is larger in magnitude than the marginal non-use value. Non-use distance decay is effectively zero for the Johnston paper.[10] However, we do have evidence of decay in non-use value in the NCEE study. Appendix D.3 provides visual summaries of the high-dimensional fixed effects that make up the $\hat{\delta}_{cjt}$ estimates.

Table 2: Main parameter estimates

	Johnston et al.	**NCEE**
β	0.15	2.01
	(—)	(0.45)
b	0.0000726	1999
	(—)	(1167)
λ	−1e-8	−1.12
	(—)	(0.04)
γ^{cell}	0.021	0.0046
	(0.0001)	(0.0001)
γ^{survey}	0.000024	0.0020
	(—)	(0.00014)
σ^{SP}	0.052	0.31
	(—)	(0.023)

Note: Numerical standard errors are in parentheses, which we are presently unable to calculate for the Johnston et al. study as the solutions sit on a boundary. Each study is estimated separately. γ^{cell} comes from the first stage revealed preference estimation, while the rest of the parameters from the second-stage maximum likelihood estimation.

The structural model allows us to compute household WTP for water quality improvements, decomposed into use and non-use components. Use WTP is derived from changes in recreation behavior and varies with distance due to changes in travel cost p_{ij},

[10] Standard errors are not reported for the Johnston study because the distance-decay parameter λ is estimated at the boundary of the parameter space. Alternatively, we could reparameterize to remove the boundary, i.e. we have some input parameter $\lambda_{input} = -\exp\lambda$ to enforce that λ is negative. We plan to implement this approach in a future version of the paper.

$$WTP_i^{\text{use}}(\Delta q) = \frac{1}{\gamma^{survey}} \sum_t \log \left[\frac{\sum_j \exp\left(\gamma^{survey}(\hat{\delta}_{ijt} - p_{ij}) + \Delta q_j' \beta\right)}{\sum_j \exp\left(\gamma^{survey}(\hat{\delta}_{ijt} - p_{ij})\right)} \right] \tag{17}$$

Non-use WTP reflects changes in water quality, weighted by distance:

$$WTP_i^{\text{nonuse}}(\Delta q) = \frac{1}{\gamma^{survey}} \sum_t \sum_j (d_{ij} + 1)^{\lambda} \Delta q_j b \tag{18}$$

We first assess the internal consistency of our model by comparing our simulated WTP estimates to those reported in the original studies. Johnston, Moeltner, et al. (2023) report a household WTP of $658 for the average scenario presented in their surveys.[11] Using our model's parameter estimates and Equations (17) and (18), we simulate an average WTP of $771, slightly above, but in line with their results. Importantly, our structural model allows us to decompose total WTP into use and non-use components. In our simulation with the Johnston data, 37% of total WTP is attributable to non-use values. Preliminary results from the NCEE study report a marginal WTP for a one-point improvement in the respondent's home region of $23. We simulate the same one-point improvement in each respondent's home HUC-2 with our estimated model and get an mean WTP of $10.20, of which 38% is non-use value.

We can also benchmark our results against those from Corona et al. (2020), who estimate WTP for a one-point improvement in water quality at the HUC-4 level to be $3.10.[12] We simulate marginal improvements across all HUC-4s present in each respective study and calculate the median marginal WTP across them. In the Johnston et al. study, the median WTP is $9.46, of which 57% is attributable to non-use values. The median WTP across HUC-4s in the NCEE study is $0.42, 52% of which is non-use. Note that we expect differences here since none of these three studies are valuing the same HUC4. This exercise simply confirms that our model generates reasonable estimates relative to the existing literature.

[11] We calculated this by summing the parameter means from Table 2 multiplied by the mean value for the corresponding variable from Table S3.

[12] This estimate is for one particular HUC-4, the Republican River Basin in Colorado, Kansas, and Nebraska.

4 Results

4.1 Distance decay in use and non-use WTP

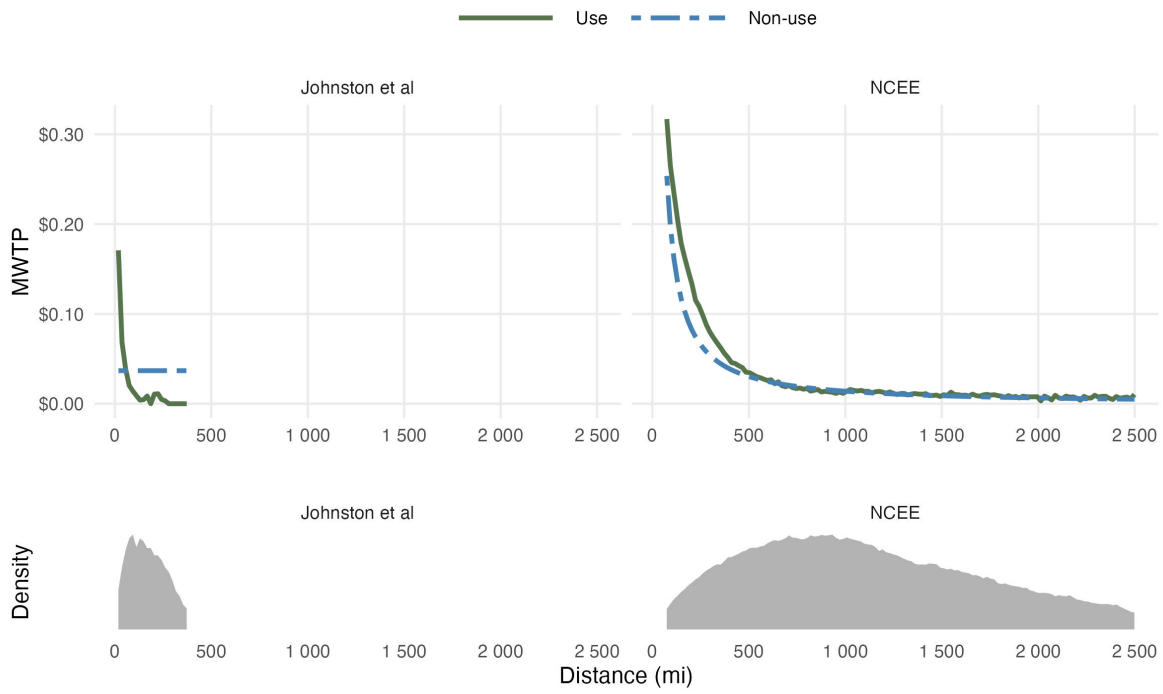
We begin by calculating distance-decay curves for marginal use and non-use value. For each study, we calculate individual WTP for a simulated 1-point improvement in water quality for a single watershed. We repeat this process across many watersheds and take the average WTP within 20-mile-wide distance bins between the individual and the watershed.[13] Thus, we measure marginal WTP by distance, weighted by the observed distribution of household-to-watershed distances in the respective survey. Figure 4a shows the results, with MWTP by distance curves for each study in the top panel. The bottom panel has the distribution of individual-to-watershed distances from which we calculate MWTP. Finally, we integrate the marginal WTP curves over the distribution of household-to-watershed distances to calculate cumulative WTP as we move further along in distance, shown in Figure 4b.

In the Johnston, Moeltner, et al. (2023) data, households near water features exhibit much higher use MWTP, but these use values decline sharply with distance. MWTP for a 1-point improvement in water quality for a watershed within 20 miles of the household is nearly 20 cents. In contrast, the same improvement 100 miles from the household is 1.5 cents. In comparison, non-use marginal WTP remains flat at 3.7 cents. These marginal distributions imply that nearly all of the use values accrue to households nearby. Figure 4b shows that \$17 of \$22 in use WTP, or 80%, accrues to households within 100 miles of the improving watershed. Meanwhile, only \$13 of \$45, or 28%, in non-use WTP accrues to households within 100 miles.

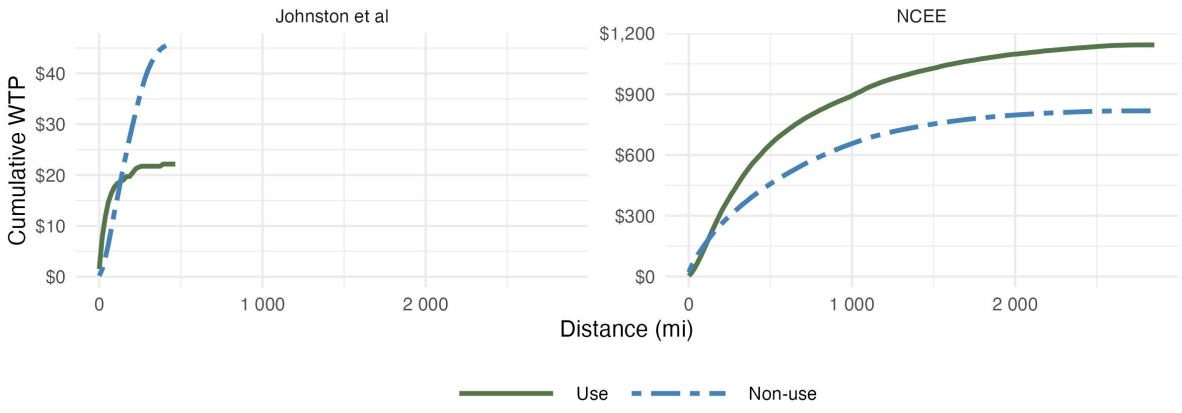
A limitation of the Johnston, Moeltner, et al. (2023) data in this setting is that they cover a relatively small region, limiting variation in distances between households and watersheds. 90% of the individual-watershed combinations are within 300 miles of each other. The national scale of the NCEE survey provides considerably more variation in distances, with only 6 percent of individual-watershed combinations being *less* than 300 miles.

[13] We use straight-line distance here, not driving distance.

Figure 4: Marginal and Cumulative WTP



(a) Marginal use and non-use WTP by distance.



(b) Cumulative use and non-use WTP by distance.

Note: We simulate WTP for a 1-point water quality improvement in a single watershed for all individual respondents, repeatedly for all watersheds in each study. We then take the average of these WTPs across individuals and simulations by distance between the individual and watershed with the water quality improvement. Cumulative WTP adds up marginal WTP for all households within the given distance. The density of households reflects the empirical distribution of household to watershed distances.

Our results with the NCEE data exhibit strong distance decay in both use and non-use values, and the decay for use values is slower than that in the Johnston, Moeltner, et al. (2023) data. While marginal use WTP dropped by a factor of 15 between 0 and 100 miles in the Johnston, Moeltner, et al. (2023) data, it only dropped by a factor of 2 in the NCEE data. Non-use value initially decays faster than use value, but is relatively flatter at larger distances. Both the slower decay in MWTP and the broader distribution of household-to-watershed distances in the NCEE data mean that a much smaller share of total WTP accrues to households within 100 miles.

4.2 Spatial Distribution of Use and Non-Use MWTP

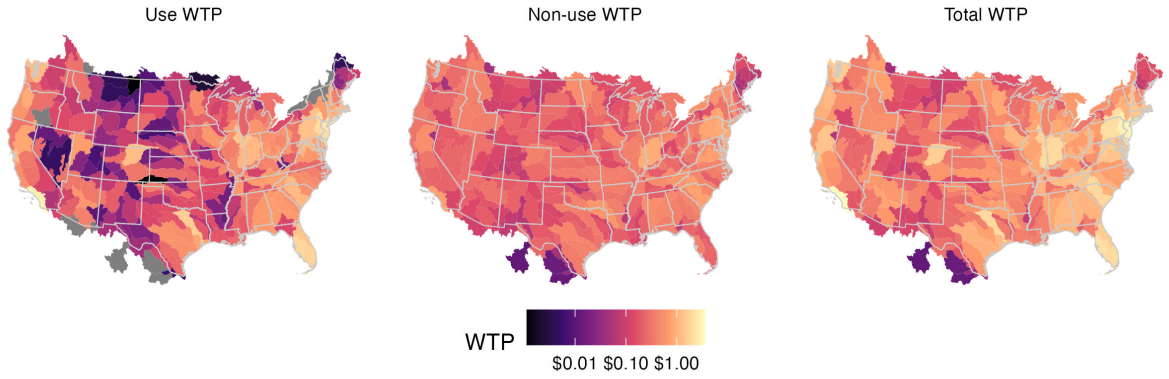
We also plot WTP across space using the same simulations as in the previous section. We simulate WTP for a 1-point improvement in water quality in a single watershed, then plot total WTP for that change across all survey respondents. Figure 5 shows total WTP for NCEE and Johnston, Moeltner, et al. (2023) data, broken out by use and non-use values. For both use and non-use values, the distribution of household distances relative to the watershed is an important driver of WTP. Note that in the Johnston, Moeltner, et al. (2023) data, we do not estimate any decay in non-use values and so non-use WTP is constant across watersheds.

4.3 Implications for the BenSPLASH model

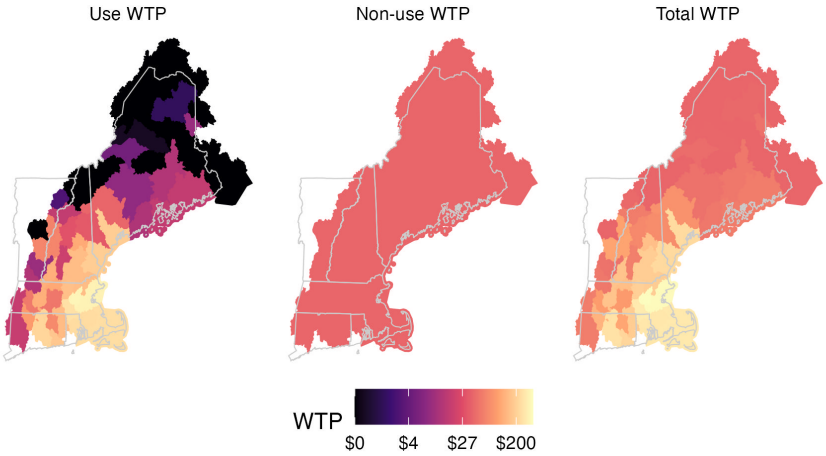
The EPA's BenSPASH model estimates the economic benefits of water quality improvements by aggregating WTP within a fixed 100-mile radius of the improved water bodies. This spatial boundary was initially justified by empirical evidence indicating that most recreation trips – and thus most use-related benefits – occur within relatively short distances from a household's home location. By limiting aggregation to this radius, BenSPASH is thought to capture the majority of use values while maintaining a manageable spatial framework for benefit transfer applications.

Our results suggest that the 100-mile assumption generally results in the omission of significant water-quality benefits. However, the qualitative description of the most impacted benefits differs

Figure 5: Use and non-use WTP across space



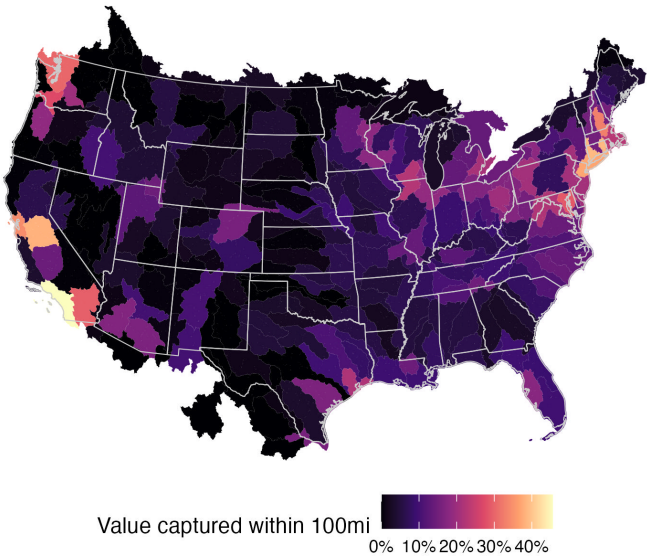
(a) WTP by HUC-4 using NCEE data



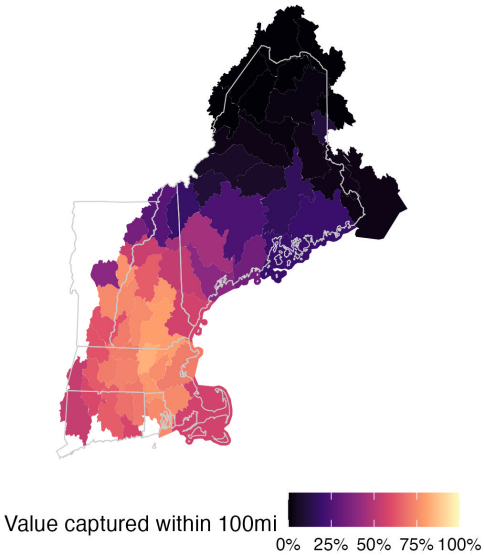
(b) WTP by HUC8 using Johnston, Moeltner, et al. (2023) data

Note: We calculate individual use and non-use WTP for a 1-point water quality improvement in a single HUC, then sum up across households in each respective survey. The color scale is on a log scale for ease of visualization. Panel (a) shows results using NCEE data, where we calculate WTP for 1-point improvements at the HUC-8 level and then sum up across all HUC-8's in a HUC-4. Panel (b) shows results using Johnston, Moeltner, et al. (2023) data, where we calculate WTP for 1-point improvements at the HUC-12 level and then sum up across all HUC-12's in a HUC-8.

Figure 6: Percent of total WTP within 100mi



(a) Percent of WTP within 100mi using NCEE data



(b) Percent of WTP within 100mi using Johnston, Moeltner, et al. (2023) data

Note: We calculate total individual WTP (both use and non-use) for a 1-point water quality improvement in a single HUC. We then take the ratio of the sum of WTP for individuals living within 100 miles to the sum of WTP for all households.

between our Johnston, Moeltner, et al. (2023) and NCEE results. As described previously, the cumulative WTP plots in Figure 4b show that in the Johnston, Moeltner, et al. (2023) data, most use values accrue to households nearby, while most non-use value comes from households further away. The 100-mile radius captures 45% of total WTP in the Johnston, Moeltner, et al. (2023) data. However, it captures only 15% of total WTP in the NCEE data due to slower decay and a broader distribution over distances.

We can also investigate the implications of using a 100-mile radius across space. Figure 6 shows the percentage of total WTP from households living within 100mi of the improving watershed. The radius-based approach undervalues water quality improvements across all watersheds; however, the bias is particularly severe in watersheds far from population centers.

5 Conclusion

We provide new evidence on the spatial dimensions of willingness to pay (WTP) for water quality improvements, with particular attention to the distinction between use and non-use values and their respective distance decay patterns. By combining large-scale revealed preference data from cellphone-based mobility records with stated preference survey microdata, we develop a structural model that decomposes household WTP into use and non-use components. This model allows us to estimate the rate at which WTP declines with distance, providing critical insights for the spatial aggregation of benefits in environmental policy evaluation.

Our main findings indicate a sharp distance decay in use values for water quality. Households living within 100 miles of a water feature derive the majority of recreational use benefits, but these values diminish quickly as distance increases. In contrast, non-use values exhibit minimal decay over distance, remaining relatively constant even at distances exceeding 500 miles from the improved site. This distinction has important implications for benefit transfer and the aggregation of economic values in regulatory analysis.

We demonstrate that the current spatial aggregation approach used in the EPA's BenSPLASH model captures a larger portion of use values by applying a 100-mile radius around improved

water bodies. However, this same boundary captures only a small fraction of non-use values. These results suggest that spatial assumptions in existing benefit transfer models may lead to incomplete accounting of the societal value of water quality improvements, particularly when non-use values represent a significant portion of total WTP.

Despite these contributions, our study has several limitations. First, while our structural model allows us to estimate distance decay patterns for both use and non-use values, the functional forms we adopt impose certain restrictions that may not capture the full complexity of household preferences. Alternative specifications, such as spatially varying decay functions or hierarchical models that account for heterogeneity across different population groups, may yield additional insights. Second, the reliance on cellphone mobility data to measure recreation behavior introduces potential sampling biases. Our data may underrepresent certain demographic groups, such as low-income households or older populations, which could affect the generalizability of our revealed preference estimates. Third, the non-use values we estimate are based on stated preference surveys from specific regions of the United States. While these surveys offer valuable microdata for modeling purposes, their geographic scope may limit the extent to which our findings generalize to other areas or environmental contexts.

Future research can extend this analysis in several directions. One promising avenue is to integrate additional stated preference datasets covering a wider range of geographic areas and water quality scenarios. This would allow for a more comprehensive assessment of non-use values and their spatial distribution. Additionally, future work could explore heterogeneity in distance decay patterns across different demographic and socioeconomic groups, which may inform targeted policy interventions. Finally, the modeling framework developed here could be applied to other types of environmental goods and services, such as air quality improvements or biodiversity conservation, where distance decay and non-use values are also relevant.

In conclusion, this study advances our understanding of how distance affects household WTP for water quality improvements and highlights the importance of explicitly modeling both use and non-use values in benefit transfer applications. Our results provide actionable insights for refining the EPA's BenSPLASH model and other regulatory tools, ensuring that the full societal

benefits of water quality policies are more accurately represented in economic analyses.

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Appendix A Water quality benefits estimation with BenSPASH

Understanding distance decay is not only of theoretical and empirical interest but also critical for informing environmental policy evaluation and benefit-cost analysis. The U.S. Environmental Protection Agency (EPA) relies heavily on spatially explicit models to quantify the economic benefits of water quality improvements in regulatory impact assessments. One such model is the Benefits Spatial Analysis for Surface Water Quality model, or BenSPASH, which serves as the agency's primary tool for estimating household willingness to pay (WTP) for changes in water quality at the national scale (Corona et al., 2020).

BenSPASH builds on a benefit transfer meta-regression model (MRM) developed by Johnston, Besedin, and Holland (Johnston, Besedin, and Holland, 2019b), which aggregates findings from dozens of stated preference (SP) studies. The model estimates household WTP as a function of water quality changes, site attributes, and demographic characteristics. Because most SP studies used in the MRM draw respondents from regional or state-level samples, BenSPASH must make assumptions about the spatial extent of the market, specifically how far from an improved waterbody households are willing to pay for water quality improvements.

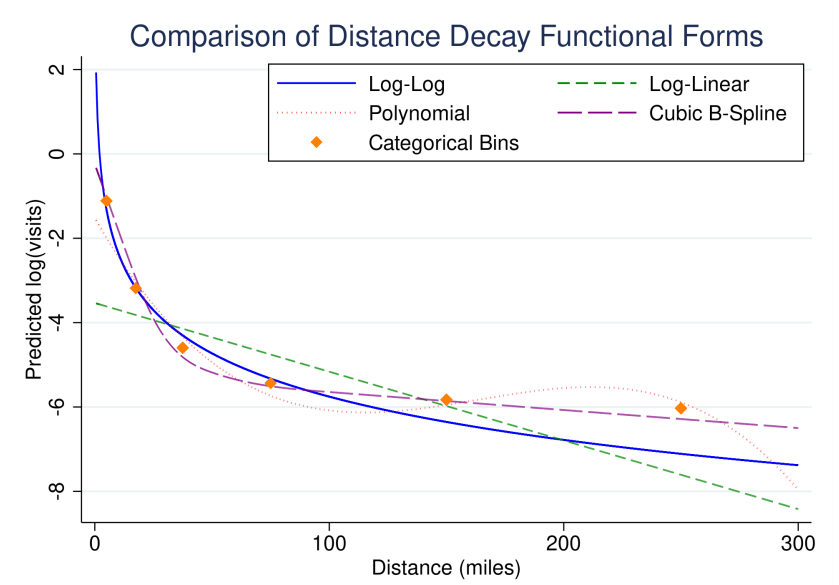
A key simplifying assumption in BenSPASH is that households derive positive WTP for improvements in water quality only if they live within a given miles of the affected waterbody. Analysts can choose the radius they want to use–common choices are 100 kilometers or 100 miles. This 100-mile buffer is based on assumptions regarding the likely spatial extent of recreation-related use values and a conservative treatment of non-use values. Households outside this buffer are assumed to have zero WTP for improvements, effectively imposing a hard cutoff in benefit aggregation. While this assumption may be reasonable for recreation-driven use values, its validity for non-use values-such as existence or bequest motives-is less clear.

Appendix B Evidence on Distance Decay in Regional Studies

Figure A1 summarizes our reduced-form analysis of how visitation responds to distance from a recreation site. We compare five commonly used functional forms to model distance decay: log-log, log-linear, polynomial, categorical bins, and cubic B-spline. The figure displays predicted log of visits using data from Johnston et al. (2023a). Across all specifications, we find strong and consistent evidence of distance decay. Visitation rates decline sharply with distance and taper at a slower rate beyond 100 miles. The steep initial drop followed by a long tail suggests a nonlinear relationship, best captured by flexible functional forms such as the log-log or cubic B-spline models.

The various specifications differ in smoothness and curvature. The log-log and cubic B-spline models offer the best visual fit to observed visitation patterns, capturing both the steep decay

Figure A1: Distance Decay



Note: Figure A1 compares alternative functional forms used to estimate the distance decay in predicted log(visits) for household samples in Johnston et al. (2023a). Each curve represents a different modeling approach, including log-log, log-linear, polynomial, and cubic B-spline specifications. Orange diamonds represent average predicted values from categorical distance bins and serve as a nonparametric benchmark.

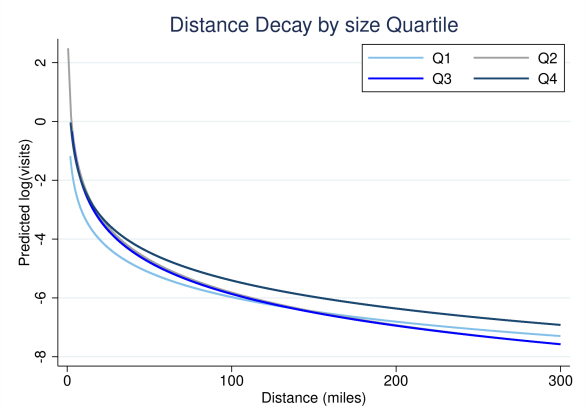
in near-distance trips and the long tail of infrequent, long-distance visits. In contrast, the polynomial specification tends to understate short-distance decay and overpredict in mid-distance ranges. Categorical bins serve as a useful nonparametric benchmark, revealing that predicted visits remain positive even beyond 200 miles, though the rate of decline slows significantly after 150 miles. This reinforces the importance of model choice when interpreting elasticity and decay rates.

These patterns have implications for the EPA's current practice in the BenSPLASH model, which assumes that recreational benefits are realized only by households within 100 miles of an improved water body. Our results support this approximation in broad terms: the majority of predicted visits are concentrated within 100 miles. However, we also observe non-trivial visitation beyond that threshold, particularly for certain site types or among specific demographic groups. This suggests that the 100-mile cutoff may miss meaningful recreational activity in destination-like settings.

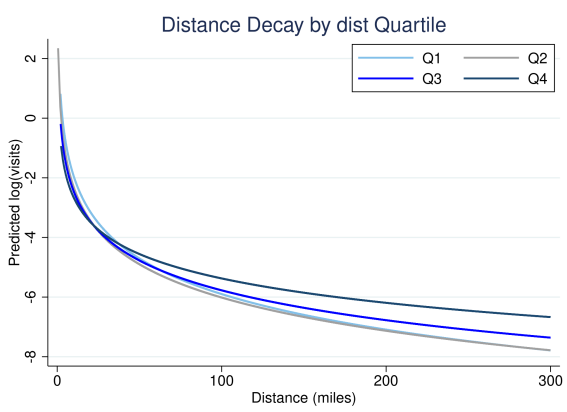
Figure A2 extends this analysis by documenting substantial heterogeneity in distance decay across different HUC12 site characteristics. Panels (a) show that larger water bodies (Q4 by size) attract visits from greater distances, with flatter decay curves than smaller sites (Q1).

Figure A2: Distance Decay by HUC12 Type

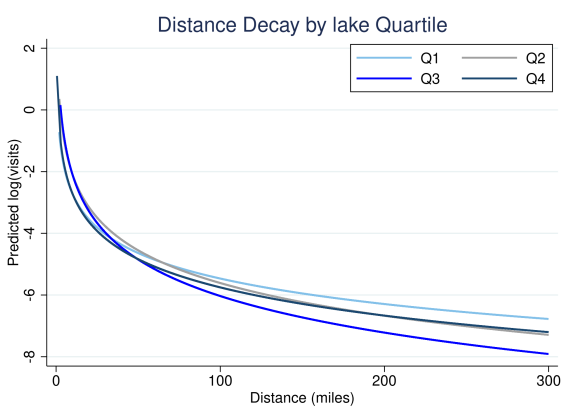
(a) Size



(b) Distance to Highway



(c) Number of lakes



Note: We compare alternative functional forms used to estimate the distance decay in predicted log(visits) for household samples in Johnston et al. (2023a). Each curve represents a different modeling approach, including log-log, log-linear, polynomial, and cubic B-spline specifications. Orange diamonds represent average predicted values from categorical distance bins and serve as a nonparametric benchmark.

Panels (b) stratify by proximity to urban hubs and show that more remote sites (Q4 by hub distance) have a shallower decay, indicating that households are willing to travel farther to reach these less accessible locations. Panels (c) reveal that lakes tend to draw longer-distance visitors than sites with less water coverage. These consistent patterns across both samples underscore that site attributes—such as size, remoteness, and lake presence—substantially shape the spatial extent of recreational use.

Taken together, these results provide complementary evidence to the national analysis. In these regions, we find distance-decay patterns that are qualitatively similar to those observed in the national data, reinforcing the conclusion that visitation declines gradually with distance and varies across site types and populations. These findings further suggest that decay should not be assumed uniform across populations or site types, and that using a one-size-fits-all cutoff (e.g., 100 miles) may underestimate the spatial scope of use values in specific contexts. These insights guide our structural modeling in Section 3, where we explicitly account for variation in decay rates across both households and recreation sites.

Appendix C Data Appendix

C.1 Stated Preference Survey Microdata

Here we give the details on how we transform survey microdata from other studies. As these are all published studies on their own, refer to the original papers for most details on survey implementation.

Johnston, Moeltner, et al., 2023 They survey households in New England on their WTP for water quality improvements—with their unit of analysis being river segments. They have three different measures of water quality: a water safety index, aquatic life index, and overall water quality index. The water safety index is based on fecal coliform concentrations. The aquatic life index is based on chloride concentrations. Then the overall water quality index is based on both of the previous measures in addition to dissolved inorganic nitrogen. All three are normalized to be an index between 0 and 100. These data were generated from FrAMES. They also bin these into seven categories to color-code the maps presented to survey respondents. They gave these categories written labels as well. They simulate water quality in 2025 under business as usual (BAU) and 41 alternative policy scenarios, which represent all combinations of levels for riparian buffer expansion, wastewater treatment upgrades, stormwater retention, and road salt application. The respondent was asked to vote for a given policy against the BAU scenario at an annual cost between 30 and 1,200 dollars. The authors have graciously supplied us with the zip code for each respondent in their survey and their underlying modeled water quality data.

In order to integrate these data into our model, we take their river segment data and aggregate it to the watershed level. This gives us baseline water quality and a proposed change in water quality for every watershed in New England. We then calculate the distance between each watershed centroid and CBG centroid in the data. Given these data, we are able to calculate the expected use value for each household associated with the BAU and policy change scenario using the estimated rec demand model. This is then fed into the estimation routine for the parameters of non-use utility.

NCEE National Stated Preference Survey The US EPA National Center for Environmental Economics conducted a survey of willingness to pay for water quality improvements. A working paper with the main results of their analysis will be available soon, providing complete details of their survey mechanism.

They present respondents with baseline Water Recreation and Aquatic Life scores for the entire continental US at the HUC-2 level. The Water Recreation score is from the EPA's water quality index (WQI), and the Aquatic Life score is from Observed to Expected (O/E)— both are on a 0 to 100-point scale. The proposed policies in the study are combinations of zero to seven-point improvements in either water quality metric, at an annual cost to the respondent for five years. The water quality improvements vary in their spatial scale, from one to three contiguous HUC-2s, and in their location. Thus, importantly, respondents are shown scenarios with improvements from anywhere in the country. This design generates considerably more variation in the distance between the respondent's home and a given water quality improvement than the other regional studies.

They collect a nationally representative sample of 5,686 surveys after filtering out bad responses. Each survey contains six policy scenarios, giving us over 34,000 choice scenarios. We disaggregate their HUC-2 water quality measures to the HUC-8 level. For now, we are using WQI rather than O/E to make the results comparable to those of the other studies.

Appendix D Modeling Recreation Choices for Use Value of Water Quality

D.1 Demand Model Assumption and Consideration

The definition of river visits presents a challenge, particularly for sites spanning multiple states. To address this, visits are defined based on the centroid of the park polygon, ensuring a consistent spatial reference. Another issue arises from mismatches between park definitions in cell phone data and survey data, which can lead to discrepancies in visit estimates. To mitigate this, visits are aggregated at the HUC12 level, allowing for better alignment with survey data while

capturing overall visitation patterns. This partial aggregation approach provides a reasonable approximation of a fully disaggregated model, as supported by prior studies, including Lupi and Feather (1998).

D.2 Handling Zero Market Shares

We discuss some of the key identification challenges inherent in modeling recreational site choices in the revealed preference section. A common challenge in modeling demand is the occurrence of zero market shares, where some product sales record no observed from specific markets during certain periods (Earle and Kim, 2025; Gandhi, Lu, and Shi, 2023; Ackerberg and Rysman, 2005; Quan and Williams, 2018). This issue is particularly prevalent in studies of retail markets using discrete-choice demand models, where infrequent purchases, niche product offerings, or limited consumer awareness can lead to observed zero sales. Berry, Linton, and Pakes (2004) highlights that traditional demand models often assume positive market shares for all products, making them less suited for datasets with frequent zero observations. Moreover, sampling errors in small datasets or survey-based approaches can further distort demand estimation, exacerbating the challenge of accurately capturing consumer preferences.

To overcome this challenge, previous researchers modified data by aggregation or selective trimming, sometimes unknowingly, leading to potential selection bias and distorted demand estimates that affect policy simulations (Dubé, Hortaçsu, and Joo, 2021). In our context, the presence of zero market shares raises concerns about potential bias from two scenarios: (1) the site is available but unvisited, (2) and visits occurred but were not captured in the sampled data. The first scenario can introduce selection bias, as unvisited sites may differ systematically from visited ones in terms of accessibility, attractiveness, or unobserved characteristics, leading to incorrect inferences about site preferences. The second scenario, where visits are missed due to sampling limitations, introduces measurement error, potentially underestimating actual demand and distorting the estimated effect of key variables.

To mitigate the first issue, we construct the choice set for each CBG based on all sites visited throughout the study period, ensuring a comprehensive representation of available options while excluding inaccessible recreational sites. For the second issue, we apply empirical Bayes posterior mean estimation, as proposed by Li (2019). This method refines the visit probability estimates and ensures compatibility of our recreation demand model with the estimation framework of Berry (1994), which requires strictly positive market shares. In practice, to maintain key heterogeneity across markets (CBG-year-quarter), we construct each market's empirical Bayes prior using a set of similar markets. Specifically, we define similar markets as the 50 closest in travel distance. The market shares for the same recreational site from these similar markets serve as the prior distribution. We then fit this observed distribution using a Beta-Binomial model, apply a Bayesian approach to estimate the posterior distribution, and predict

the adjusted market shares based on the posterior distribution. This method enables flexible adjustments by shrinking observed zero market shares toward expected positive values in comparable markets, reducing potential downward bias in recreation demand caused by sampling errors and providing a more accurate representation of true recreational behavior.

Formally, let K_{jc} be the random variable representing the number of visits to recreational site j from CBG c. The time subscripts t have been suppressed throughout this subsection for simplicity. Assume K_{jc} follows a binomial random distribution with N_c trials (the total number of observed visits from CBG c) and s^0_{jc} possibility (the market share of recreational site j in CBG c). We assume trip probability s^0_{jc} follows a Beta prior distribution with the two hyperparameters λ^1_{jc} and λ^2_{jc} that need to be estimated:

$$\begin{aligned} K_{jc} &\sim \text{Binomial}(N_c, s^0_{jc}), \\ s^0_{jc} &\sim \text{Beta}(\lambda^1_{jc}, \lambda^2_{jc}). \end{aligned} \tag{7}$$

To estimate the hyperparameters and construct the prior Beta distribution for the Bayesian approach, we use visitation data from similar markets $l \in P_c$, where P_c represents a set of markets with similar travel distances or demographic characteristics. The hyperparameters λ^1_{jc} and λ^2_{jc} are estimated by maximizing the log-likelihood over these similar markets:

$$f(K_{jl}, l \in P_c | \lambda^1_{jc}, \lambda^2_{jc}) = \prod_{l \in P_c} \binom{N_l}{K_{jl}} \frac{\Gamma(\lambda^1_{jc} + \lambda^2_{jc})\Gamma(\lambda^1_{jc} + K_{jl})\Gamma(N_l - K_{jl} + \lambda^2_{jc})}{\Gamma(\lambda^1_{jc})\Gamma(\lambda^2_{jc})\Gamma(N_l + \lambda^1_{jc} + \lambda^2_{jc})}. \tag{10}$$

The posterior distribution of the trip probability s_{jc} also follows a Beta distribution, with the posterior mean given by:

$$\hat{s}_{jc} = \frac{\lambda^1_{jc} + K_{jc}}{\lambda^1_{jc} + \lambda^2_{jc} + N_c}. \tag{8}$$

We use the strictly positive posterior means $\hat{s}_{jc}$ as the adjusted market shares. In large markets, the empirical Bayes posterior is very similar to the observed shares because the observed sales dominate the prior.

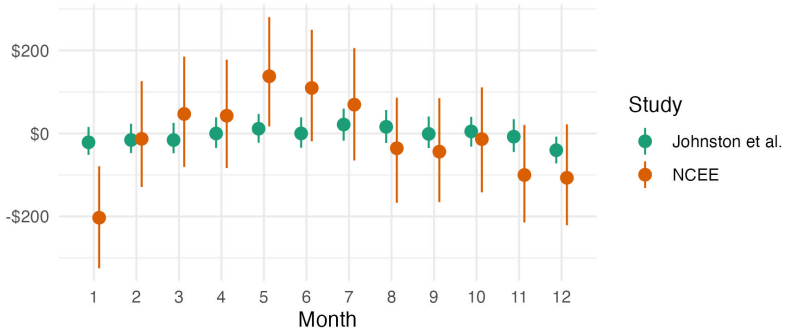
Recent Monte Carlo simulations further validate this approach. Using synthetic markets that replicate sparse visitation patterns, Cheng and Wan (2025) show that the empirical Bayes posterior-mean estimator yields the smallest bias and most stable recovery of true travel-cost parameters compared with conventional fixes such as dropping zeros, aggregating markets, or adding small constants. These findings reinforce the use of the EB correction as a consistent small-sample approximation compatible with the discrete-choice framework. In addition, the

empirical Bayes adjustment further stabilizes site fixed effects estimates for sites observed in few markets by shrinking sparse or zero market shares toward expected values based on similar CBGs, thereby improving identification precision and mitigating small-sample noise.

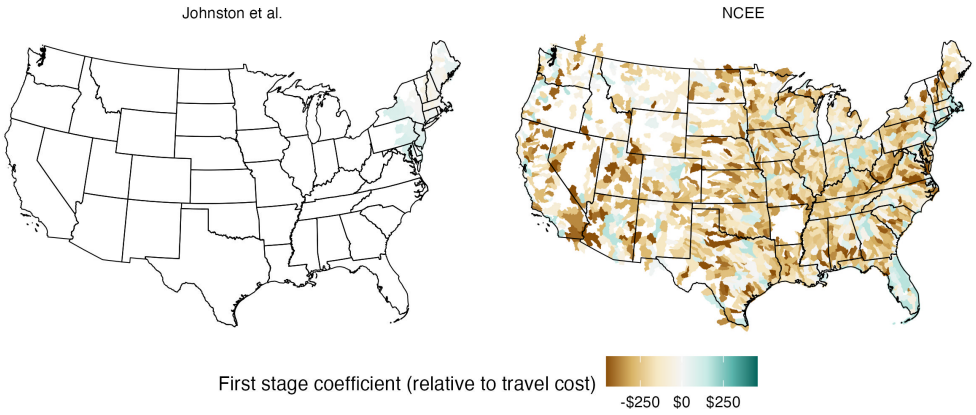
D.3 Summary of estimated high-dimensional fixed effects

Figure A3 summarizes our estimates from the first stage revealed preference model in Equation (14). The first panel, A3a, shows the median and range from the 25th to 75th percentile of the monthly destination HUC fixed effects across studies. Summer months tend to have the highest coefficients. The second panel, A3b, shows the median value for destination HUC fixed effects for each study. The final panel, A3c, shows the origin zip code fixed effects.

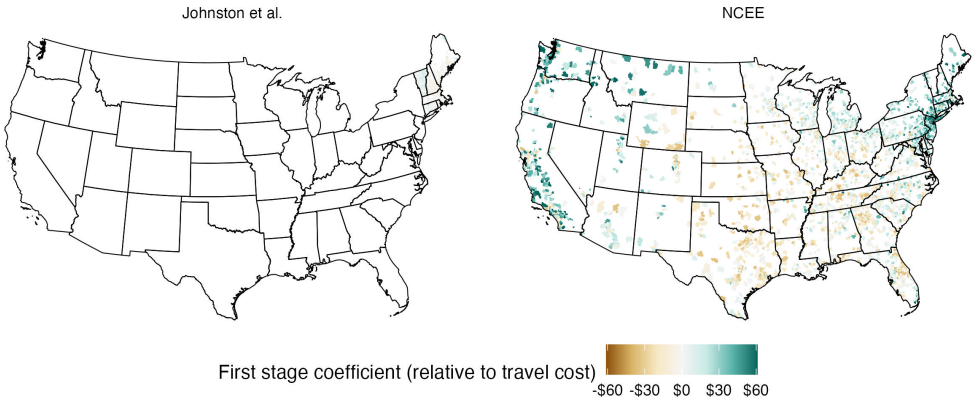
Figure A3: Distribution of Estimated high-dimensional fixed effects



(a) Monthly coefficients



(b) Destination watershed coefficients



(c) Origin zip code coefficients

Note: Summary of estimated fixed effects from the first stage. (a) Points represent the median HUC coefficient for each month for each study, range shows the 25th to 75th percentile. (b) Median value for each destination HUC-8 fixed effect taken across months. (c) Origin zip code fixed effects. All three normalize the estimated coefficients by the coefficient on travel costs, thus the values are interpreted as equivalent to a dollar in travel costs. We also winsorize the HUC and zip code coefficients at the 5th and 95th for the color scale.

Appendix E Stated Preference Estimation Details

E.1 Derivations of the gradient

Here we derive the gradient of the log-likelihood function.

Preliminaries

First, we reformulate the problem in a manner that is both conducive to taking derivatives and uses objects that are optimized for computational speed. For each respondent i, watershed j, occasion t:

$$A_{ijt} \equiv e^{\gamma(\hat{\delta}_{ijt} - p_{ij})} \tag{19}$$

$$B_{ij} \equiv e^{\beta \Delta q_{ij} - \gamma c_i}, \tag{20}$$

where p_{ij} are travel costs, Δq_{ij} is the change in water quality shown to respondent i, and c_i is the monthly (per-trip-occasion) policy cost. Recall that we defined $\hat{\delta}_{ijt}$ as being in terms of one dollar in travel costs, p_{ij} (see eq 15), which is why $\hat{\delta}_{ijt}$ is multiplied by γ.

Now, define

$$S_{it}^{(0)} = \sum_{j=0}^{J} A_{ijt} \qquad\qquad S_{it}^{(1)} = \sum_{j=0}^{J} A_{ijt} B_{ij}, \tag{21}$$

where $j = 0$ represents the outside option of making no water-based recreation trip. Note that we have estimated $\hat{\delta}_{ijt}$ relative to this outside option such that $\hat{\delta}_{i0t} = 0$. Since there are no travel costs and no change in water quality for the outside option ($p_{i0} = 0$ and $\Delta q_{i0} = 0$), we will have that $A_{i0t} = 1$ and $B_{i0} = e^{-\gamma c_i}$.

The RP and NU contributions to the SP index are

$$\Delta E_i^{\text{RP}} = \frac{1}{\sigma^{SP}} \sum_{t=1}^{T} \left[\ln S_{it}^{(1)} - \ln S_{it}^{(0)} \right], \tag{22}$$

$$\Delta E_i^{\text{NU}} = \frac{1}{\sigma^{SP}} \sum_{t=1}^{T} \sum_{j=1}^{J} (1 + d_{ij})^{\lambda} \, b \, \Delta q_{ij}, \tag{23}$$

$$\Delta v_i = \Delta E_i^{\text{RP}} + \Delta E_i^{\text{NU}}, \tag{24}$$

The stated-preference link uses a t-CDF with fixed df and scale sd:

$$z_i = \frac{\Delta v_i}{sd}, \qquad \pi_i \equiv Pr_i^{s=1}(\theta) = F_{t,df}(z_i), \qquad f_i = \frac{1}{sd} f_{t,df}(z_i). \tag{25}$$

The log-likelihood and objective are

$$\mathscr{L}(\theta) = \sum_i \Big[Y_i \ln \pi_i + (1 - Y_i) \ln(1 - \pi_i) \Big], \qquad \mathscr{J}(\theta) = -\mathscr{L}(\theta). \tag{26}$$

We will use the baseline and policy weights

$$\pi^{(0)}_{ijt} \equiv \frac{A_{ijt}}{S^{(0)}_{it}}, \qquad \pi^{(1)}_{ijt} \equiv \frac{A_{ijt} B_{ij}}{S^{(1)}_{it}}. \tag{27}$$

Derivative of the objective w.r.t. the SP index

By the chain rule,

$$\frac{\partial \mathscr{J}}{\partial \theta_k} = -\sum_i \frac{\partial \mathscr{L}}{\partial \theta_k} = -\sum_i \frac{\partial \mathscr{L}}{\partial \pi_i} \frac{\partial \pi_i}{\partial z_i} \frac{\partial z_i}{\partial \Delta v_i} \frac{\partial \Delta v_i}{\partial \theta_k}. \tag{28}$$

Compute each piece:

$$\frac{\partial \mathscr{L}}{\partial \pi_i} = \frac{y_i}{\pi_i} - \frac{1 - y_i}{1 - \pi_i}, \tag{29}$$

$$\frac{\partial \pi_i}{\partial z_i} = f_{t,df}(z_i), \tag{30}$$

$$\frac{\partial z_i}{\partial \Delta v_i} = \frac{1}{sd}. \tag{31}$$

Hence, with $f_i \equiv f_{t,df}(z_i)/sd$ and the score factor

$$S_i \equiv \left(\frac{y_i}{\pi_i} - \frac{1 - y_i}{1 - \pi_i} \right) f_i,$$

we get the universal form

$$\boxed{\frac{\partial \mathscr{J}}{\partial \theta_k} = -\sum_i S_i \, \frac{\partial \Delta v_i}{\partial \theta_k}, \qquad \theta_k \in \{\beta, \gamma, b, \lambda, \sigma\}.} \tag{32}$$

So it remains to derive $\partial \Delta v_i / \partial \theta_k$ for each parameter.

Derivative w.r.t. β

Start from

$$\Delta E^{\mathrm{RP}}_i = \frac{1}{\sigma^{SP}} \sum_t \big[\ln S^{(1)}_{it} - \ln S^{(0)}_{it} \big].$$

Use $\partial \ln S / \partial \beta = (\partial S / \partial \beta)/S$.

1) $\partial \ln S_{it}^{(0)}/\partial\beta = 0$. This is because we use a fixed $\hat{\delta}_{ijt}$ in this portion of the estimation.

2) $\partial \ln S_{it}^{(1)}/\partial\beta$**.** Because $S_{it}^{(1)} = \sum_j A_{ijt}B_{ij}$ and $B_{ij} = \exp\{\beta\Delta q_{ij} - \gamma c_i\}$,

$$\frac{\partial B_{ij}}{\partial\beta} = \Delta q_{ij} B_{ij}.$$

Therefore,

$$\frac{\partial}{\partial\beta}\ln S_{it}^{(1)} = \frac{\sum_j A_{ijt}B_{ij}(\Delta q_{ij})}{S_{it}^{(1)}} = \sum_j \pi_{ijt}^{(1)}(\Delta q_{ij}).$$

3) Assemble $\partial\Delta\nu_i/\partial\beta$**.**

$$\frac{\partial\Delta\nu_i}{\partial\beta} = \frac{1}{\sigma^{SP}}\sum_t\left(\frac{\partial}{\partial\beta}\ln S_{it}^{(1)} - \frac{\partial}{\partial\beta}\ln S_{it}^{(0)}\right) = \frac{1}{\sigma^{SP}}\sum_t\sum_{j=1}^{J}\pi_{ijt}^{(1)}\Delta q_{ij}.$$

This derivative does not need to include the outside option $j = 0$, since $\Delta q_{i0} = 0$.

Derivative w.r.t. γ

Use $\partial \ln S/\partial\gamma = (\partial S/\partial\gamma)/S$.

1) Ingredients. From $A_{ijt} = \exp\{\gamma(\hat{\delta}_{ijt} - p_{ij})\}$,

$$\frac{\partial A_{ijt}}{\partial\gamma} = A_{ijt}\left(\hat{\delta}_{ijt} - p_{ij}\right)$$

From $B_{ij} = \exp\{\beta\Delta q_{ij} - c_i)\}$,

$$\frac{\partial B_{ij}}{\partial\gamma} = B_{ij}(-c_i).$$

2) $\partial \ln S_{it}^{(0)}/\partial\gamma$**.**

$$\frac{\partial}{\partial\gamma}\ln S_{it}^{(0)} = \frac{1}{S_{it}^{(0)}}\sum_j A_{ijt}(\hat{\delta}_{ijt} - p_{ij}) = \sum_j \pi_{ijt}^{(0)}(\hat{\delta}_{ijt} - p_{ij}).$$

3) $\partial \ln S_{it}^{(1)} / \partial \gamma^p$**.**

$$\begin{aligned}\frac{\partial}{\partial \gamma} \ln S_{it}^{(1)} &= \frac{\sum_j [(\partial A_{ijt}/\partial \gamma) B_{ij} + A_{ijt}(\partial B_{ij}/\partial \gamma)]}{S_{it}^{(1)}} \\ &= \frac{\sum_j A_{ijt} B_{ij} \left(\hat{\delta}_{ijt} - p_{ij} - c_i\right)}{S_{it}^{(1)}} \\ &= \sum_j \pi_{ijt}^{(1)} \left(\hat{\delta}_{ijt} - p_{ij} - c_i\right).\end{aligned}$$

4) Assemble $\partial \Delta v_i / \partial \gamma$**.**

$$\frac{\partial \Delta v_i}{\partial \gamma} = \frac{1}{\sigma^{SP}} \sum_t \left(\sum_{j=0}^{J} \pi_{ijt}^{(1)} \left(\hat{\delta}_{ijt} - p_{ij} - c_i\right) - \sum_{j=1}^{J} \pi_{ijt}^{(0)} (\hat{\delta}_{ijt} - p_{ij}) \right).$$

The outside option does matter for the left hand term above since c_i is paid regardless of whether i takes any trips. For $j = 0$, the inside term simplifies to $-c_i e^{-\gamma c_i} / S_{it}^{(1)}$.

Derivative w.r.t. b

Only the NU term depends on b (linearly):

$$\Delta E_i^{\text{NU}} = \frac{T}{\sigma^{SP}} \sum_{j=1}^{J} (1 + d_{ij})^{\lambda} \, b \, \Delta q_{ij} \;\Rightarrow\; \frac{\partial \Delta v_i}{\partial b} = \frac{T}{\sigma^{SP}} \sum_{j=1}^{J} (1 + d_{ij})^{\lambda} \, \Delta q_{ij}.$$

Derivative w.r.t. λ

Only $(1 + d_{ij})^{\lambda}$ depends on λ, and

$$\frac{\partial}{\partial \lambda} (1 + d_{ij})^{\lambda} = (1 + d_{ij})^{\lambda} \ln(1 + d_{ij}).$$

Therefore,

$$\frac{\partial \Delta v_i}{\partial \lambda} = \frac{T}{\sigma^{SP}} \sum_{j=1}^{J} \ln(1 + d_{ij}) \, (1 + d_{ij})^{\lambda} \, b \, \Delta q_{ij}.$$

Derivative w.r.t. σ^{SP}

Write Δv_i as a constant (in σ^{SP}) divided by σ^{SP}:

$$\Delta v_i = \frac{1}{\sigma^{SP}} \underbrace{\left\{ \sum_t [\ln S_{it}^{(1)} - \ln S_{it}^{(0)}] + \sum_t \sum_{j=1}^{J} (1+d_{ij})^{\lambda} b \, \Delta q_{ij} \right\}}_{C_i \text{ does not depend on } \sigma^{SP}}.$$

Hence

$$\frac{\partial \Delta v_i}{\partial \sigma^{SP}} = -\frac{1}{(\sigma^{SP})^2} C_i = -\frac{\Delta v_i}{\sigma^{SP}}.$$

Final gradient

Plugging each $\partial \Delta v_i / \partial \theta_k$ into

$$\frac{\partial \mathscr{L}}{\partial \theta_k} = -\sum_i S_i \, \frac{\partial \Delta v_i}{\partial \theta_k},$$

with $S_i = \left(\frac{y_i}{\pi_i} - \frac{1-y_i}{1-\pi_i} \right) f_{t,df}(z_i)/sd$, gives the full gradient for $\theta_k \in \{\beta, \gamma, b, \lambda, \sigma^{SP}\}$.