ESTIMATING DEMAND FOR ENVIRONMENTAL GOODS AND SERVICES, NOW AND LATER

BY

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DISSERTATION

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Abstract

This dissertation presents three papers that estimate the demand for environmental goods and services. Chapter 1 begins with a brief overview of the practice of nonmarket valuation, with discussion of previous applications and the methods that I advance in the subsequent chapters. I also provide a common nomenclature for continuity in understanding, the underlying intuition and motivation, and discussion of the results throughout.

In chapter 2, I examine the behavioral response of winter recreationists to marginal changes in mountain snowpack. I make three primary contributions in this chapter: 1) I develop a new method to estimate elasticities for climate amenities by matching the spatial and temporal variation in the level of the amenity with the frequency of related market transactions; 2) I derive state-specific snowpack elasticities for all major markets across the United States and find significant heterogeneity in the behavioral response across states; and 3) I estimate year-to-year variation in the recreation revenue from snowpack under current and future climate scenarios. I predict that resort markets could face reductions in local snow-related revenue of -40% to -80%, almost twice as large as previous estimates suggest.

In chapter 3, I extend the analysis from the previous chapter to estimate utility functions for winter recreationists in the United States. I make two primary contributions in this chapter: 1) I estimate the marginal willingness to pay (MWTP) for mountain snowpack at the national and regional

levels; and 2) I construct a matrix of substitution elasticities between resort markets. Both contributions invoke random utility maximization to estimate structural parameters in the utility functions of alpine skiers. For the first contribution (1), I maintain trip-level data to estimate marginal utilities and subsequent MWTP. I address price endogeneity concerns using an instrumental variables approach. For the second contribution (2), I aggregate the trip-level data to market-level and calculate daily market shares. This allows me to recover substitution patterns that provide insight into how skiers move across markets based on marginal changes in mountain snowpack. Each of these are important for understanding consumer welfare in the alpine skiing market and the implications under a changing climate.

In chapter 4, I examine preferences for surface water quality and quantify some overlooked benefits of nutrient reductions in the Mississippi River Basin. Improvements in local surface water quality in the Mississippi River Basin (MRB) can contribute to the regional environmental goals of reducing hypoxia in the Gulf of Mexico. To inform estimates of the benefits of water quality policy, I use a choice experiment survey in a typical sub-watershed of the MRB to estimate willingness to pay for local environmental improvements and helping to reduce hypoxia far downstream. I find that residents place large values on reduced local algal blooms, improved local fish populations and diversity, and meeting local commitments to help with the regional environmental problem.

I conclude my analysis in chapter 5 by providing a clear summary of my findings and why they are important. I discuss some of the possible implications for the benefits that I quantify and list a few examples of how they can be used when generating climate and environmental policy.

To all my mentors, past, present, and future, and to Lauren my love, who I will always look up to: Thank you.

Examine each question in terms of what is ethically and aesthetically right, as well as what is economically expedient. A thing is right when it tends to preserve the integrity, stability, and beauty of the biotic community. It is wrong when it tends otherwise.—Aldo Leopold, The Land Ethic

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CHAPTER 1

INTRODUCTION

This dissertation presents three papers that estimate the demand for environmental goods and services—nonmarket valuation. Why is this an important enough topic to write three papers on? The motivation can be traced back to the idea that one person's actions can have unsolicited effects on another person, often times without compensation. In many instances, the natural environment becomes the channel through which these unsolicited effects, or externalities, are distributed. Externalities need not be strictly good or bad. If one person receives unsolicited benefits (a good externality) from another person's actions, we might be interested in quantifying that benefit to provide compensation to the person doing the action. We might be particularly interested if the scenario involves unsolicited damages (a bad externality). More generally, however, it is less important whether the externalities are good or bad. If we can quantify, in some meaningful way, the size and scope (how many people are affected and where) we can begin to explore if there is too much, too little, or just enough of the original action. The process of quantifying these benefits and damages, particularly when they are distributed to others through the natural environment, is the practice of nonmarket valuation. In the following chapters, I estimate the benefits of mountain snowpack to outdoor recreation and tourism opportunities. I also estimate the benefits of clean rivers and lakes, and the benefits that people would receive from reduced pollution in the Gulf of Mexico.

The quality or quantity of environmental goods and services can differ across locations (spatial variation) and throughout time (temporal variation). Similarly, the values people place on these goods and services can also vary spatially and temporally. Variation in these values is called preference heterogeneity. Preferences are a utility theoretic derivation of the value people place on these goods and services. This is cryptic economic speak for simply estimating values in a way that is tractable. In economics, we elicit these preference in several ways. For example, we can simply ask a person how much they value the sunshine or clean air. This is an example of a person's stated preference for an environmental good or service. Alternatively, we can use information about their observed behavior to say something about their preferences. We do this by measuring how they respond in the market (such as buying something in a store) when we observe a change in the environment (such as an increase in air pollution). This is an example of a person's revealed preference for an environmental good or service.

Stated and revealed methods provide two ways of eliciting people's preferences. There are also two distinct ways to model preferences. The first is to estimate a reduced-form regression that simply establishes the relationship between some outcome of interest (say the amount of money spent on a given day) and the explanatory variables in the model (say the level of pollution on that day). The resulting coefficients from this regression inform us about how much (or little) these two things (money and air pollution) relate to one another. Alternatively, we can model the relationship between the two structurally. This approach assumes the researcher perfectly knows all of the variables that effect the outcome of interest, then estimate parameters that predict the outcome variable. A structural model typically has an outcome variable of interest between 0 and 1, and the parameters attached to each explanatory variable summarize its contribution to the overall model's prediction of an outcome equal to 1.

The following chapters use both stated and revealed preference methods to estimate the value people place on a few environmental goods and services. I also use both reduced-form and structural models to estimate these relationships. I build on existing methods to improve estimates of these values and to identify differences across location. I then use these values to say something about how people might be better or worse off in the future under alternative management or climate scenarios.

In chapter 2, I estimate the value of mountain snowpack to resort towns across the United States (US).[1] The value estimated in this chapter is the amount of money that is brought into local economies as a function of the amount of snow at the nearby resort. Identifying the relationship between local revenues and mountain snowpack helps identify to what extent people (in

[1]This chapter is co-authored with Peter Christensen.

aggregate) rely on the natural environment to provide recreation and tourism opportunities in their community. I use this relationship to say something more generally about how revenue in these resort communities might change under future climate. In the future, the level of snow at a resort is expected to be less than the current average with higher variability and more rapid runoff (Reclamation, 2013). Under these conditions, I estimate how economic activity (revenues) might be different than it is now. I estimate a revenue function for 26 states across the US that have operating ski resorts and active ski culture. I use the derived state-specific parameters in conjunction with state-specific climate projections to estimate reductions in revenue from winter outdoor recreation in each state under different climate.

The method I advance in this chapter is the use of high-frequency data on market transactions (short term property rentals) to estimate demand for snow at the nearby resort. This method allows market transactions to fluctuate at the same frequency as that of the environmental good. While this is not strictly a new approach to nonmarket valuation (see Dundas and von Haefen (2019) and Chan and Wichman (2018) for similar approaches in recreational fishing and bike rental markets), the additional features of data procurement via web crawlers and scrapers and the application to snow tourism has not before been carried out is such detail.

In chapter 3, I build on the analysis discussed in Chapter 2 by estimating utility functions for winter recreationists in the United States. I make two primary contributions in this chapter: 1) I estimate the marginal willingness to pay (MWTP) for mountain snowpack at the national and regional levels; and 2) I construct a matrix of substitution elasticities between US resort markets. Both contributions invoke random utility maximization (McFadden, 1973) to estimate structural parameters in the utility functions of alpine skiers.

For the first contribution (1), I maintain trip-level micro data to estimate marginal utilities and subsequent MWTP. I address price endogeneity concerns using an instrumental variables approach, and discuss this model and its results first. I also estimate a more flexible functional form in the utility function of skiers using a binned specification. This allows me to estimate the WTP in each snowpack bin, which is particularly useful for estimating welfare on a given day. I estimate the binned nonparametric approach for the national sample and regionally. For the second contribution (2), I aggregate the trip-level data to market-level and calculate daily market shares. This allows me to recover substitution patterns, providing insight into how skiers move across markets based on changes in mountain snowpack.

The method I advance in this paper is the application of a high-dimensional discrete choice model to estimate the marginal willingness to pay for mountain snowpack. Structural estimation can be computationally intensive and cumbersome. I use recent advancements in estimation algorithms (Fernández-Val and Weidner, 2016; Stammann, 2017) to estimate a trip-level demand model for outdoor winter recreation. I also apply market share estimation in the spirit of Berry, Levinsohn, and Pakes (1995) to recover new substitution parameters that map mountain snowpack to outdoor recreation decisions across the US.

In chapter 4, I estimate the value people place on the quality of surface water in their local river systems and the value they place on reducing nutrient transmission to the Gulf of Mexico.[2] I use a choice experiment to survey residents living within a watershed in central Illinois—The Upper Sangamon River Watershed. In addition to estimating the value people place on improvements to surface water quality, I investigate whether these values vary among the sampled respondents. More specifically, I am interested in identifying if the more rural residents of the watershed value these environmental changes differently than the more urban residents of the watershed. An environmental policy or program that affects both rural and urban populations might be inequitable if it favors one group over the other, especially if the program is funded equally by both groups. Identifying any differences in these values between rural and urban residents will help to inform policy makers about how to structure environmental programs aimed at improving local water quality or reducing hypoxia in the Gulf of Mexico.

The method I advance in this chapter is the introduction of individualized maps for every scenario on a choice card. This provides the respondent with a map of the area and locates their home for them on the map relative to the areas of the proposed improvements. This advancement requires a series of Python and Stata scripts along with integration with Amazon Web Services and Microsoft Office Suite to execute in way that the respondent now has more—and more accurate—information to chose the scenario that they like

[2]This chapter is co-authored with Amy Ando

best. Including individualized maps on the choice cards reduces error in the model and allows me to more accurately estimate the values people place on changes to their local environment.

In this dissertation, I use empirical methods to address four primary testable hypotheses: 1) *How do people respond to changes in mountain snowpack?*; 2) *What is the marginal willingness to pay for mountain snowpack?*; 3) *How do skiers choose to substitute across resort markets?*; and 4) *Do people value clean rivers and streams?*. I find that marginal changes in mountain snowpack influence visitation to destination resort towns and that snowpack provides nonmarket benefits in the form of outdoor recreation. These skiers respond to changes in mountain snowpack in nearby markets by substituting across markets, in turn influencing the distribution of market shares across the US. I also find that cleaner surface waters provide benefits through local use values such as fishing and swimming, and through nonlocal nonuse values that people have for reducing nutrient transmission to far away bodies of water. The benefits that I quantify in the following chapters provide a benchmark for the magnitude and span of the value of mountain snowpack and clean rivers and streams.

CHAPTER 2

THE RECREATION RESPONSE TO CHANGES IN MOUNTAIN SNOWPACK

2.1 Introduction

Winter recreation generates over $70 billion in economic activity each year across the United States (Outdoor Industry Association, 2017).[1] Worldwide, there are 68 countries with operational ski resorts and established ski culture. Climate change threatens the viability of the snow sports industry by reducing the supply of precipitation, increasing average temperatures, and shortening the length of the snow season (Feng and Hu, 2007; Burakowski, Wake, Braswell, and Brown, 2008; Burakowski and Magnusson, 2012; Dawson and Scott, 2013; Wobus, Small, Hosterman, Mills, Stein, Rissing, Jones, Duckworth, Hall, Kolian, Creason, and Martinich, 2017). Many rural mountain towns rely on snow to provide recreation opportunities that generate a significant portion of their local economic activity (Beaudin and Huang, 2014; White, Bowker, Askew, Langner, Arnold, and English, 2016; Rosenberger, White, Kline, and Cvitanovich, 2017; Burakowski, Hill et al., 2018). These communities may, therefore, be particularly vulnerable to the reductions in precipitation and increases in average temperatures that are predicted by climate models. However, existing research has been limited to spatially and temporally aggregated estimates, which the present study shows may substantially underestimate impacts.

Obtaining estimates of the demand for climate amenities, such as snowpack, is complicated by the fact that markets for snow do not explicitly exist (Champ, Boyle, and Brown, 2017). Instead, economists rely on non-market valuation methods that match variation in the level of the amenity with variation in related market transactions. However, the long-run mean of

[1] Winter recreation can be defined in various ways. Throughout this paper the term will be used to describe all consumers who are responding to the snowpack and snow conditions at a nearby ski resort.

mountain snowpack has exhibited very little variation from historical levels. This limits the applicability of established methods such as hedonic price analysis, which rely upon changes in housing prices to estimate the value of nearby amenities (Taylor, 2017). Short-run changes in snowpack provide a key source of variation for identifying the relationship between recreation demand and snowpack since recreation decisions are often made in response to short-run fluctuations in snow conditions. But market transactions that match the frequency of short-run shocks in snowpack have been largely unavailable. Studies have instead relied upon market data that is aggregated geographically (county or larger), temporally (monthly or larger), or both. This paper addresses this mismatch by compiling daily market transactions (short-term property rentals) together with daily snowpack and weather, which we use to estimate the effect of changes in mountain snowpack on recreational visits for every major resort market across the United States.

Due to the limited availability of high-frequency market transactions, existing work has characterized impacts using changes in snow tourism between high-snow versus low-snow years ("inter-season"). However, inter-season analyses are vulnerable to the confounding effects of other annual trends such as business cycles, fluctuations in macroeconomic growth, or local labor market conditions, all of which are correlated with weather patterns (Burakowski et al., 2018; Kahn, Mohaddes, Ng, Pesaran, Raissi, and Yang, 2019). Existing estimates have also been limited to a single region (Scott, McBoyle, and Minogue, 2007; Dawson and Scott, 2013) or the national level (Mendelsohn and Markowski, 1999; Gilaberte-Brdalo, Lpez-Martn, Pino-Otn, and Lpez-Moreno, 2014; Rosenberger et al., 2017), such that they cannot account for the geographic variation in predicted snowpack as illustrated by climate models. Researchers have emphasized the need for more precise elasticity estimates for quantifying the demand response to changes in snowpack (Loomis and Crespi, 1999).[2] Two decades later, however, no study has provided geographically targeted elasticity estimates that quantify the relationship between recreation and snowpack. The second contribution of our paper responds to this key gap in the climate change literature by providing state-specific elasticities that can be applied to other measures of economic activity related to winter recreation. We show that significant heterogeneity

[2]An *elasticity* is defined as the percentage change in demand divided by the percentage change in the amenity.

in elasticities exists across markets, highlighting the importance of geographically targeted estimates for calculating damages under future climate.

To estimate economic damages under future climate conditions, existing approaches have relied heavily on the assumption that demand is a linear function of season length (Mendelsohn and Markowski, 1999; Rosenberger et al., 2017).[3] Damages are identified in terms of changes on the extensive margin (fewer visits). While it is reasonable to assume that shorter seasons will result in fewer visits, this method fails to capture the demand response to reduced snowpack throughout the season. These existing studies estimate lost revenue (nationally) from a reduction in lift-ticket sales to be between $1 billion and $2 billion under future climate scenarios, equivalent to 20% to 40% of current lift-ticket sales. The climate modeling literature has provided similar estimates of economic losses using similar assumptions about the relationship between season length and visitation (Wobus et al., 2017; Steiger, Scott, Abegg, Pons, and Aall, 2019). The third contribution of our paper relaxes the restrictive assumption that recreational users only respond to season length. Instead, we develop a baseline metric of the value of snowpack that allows us to predict changes in visitation throughout the season. We find that losses could be nearly double the level of damage estimates provided in existing studies.

Prior studies using within-season variation have been limited to a single season and a few resorts (Morey, 1984; Englin and Moeltner, 2004).[4] We find evidence of substantial heterogeneity in snowpack elasticities across states, limiting the external validity of estimates from any particular resort. Other work has used monthly counts of overnight stays and monthly averages of snowpack to estimate the elasticity of overnight stays (Falk, 2010).[5] We test for differences between elasticities that are based on monthly aggregate measures and the daily measure that we use in this paper. Our results indicate that there is a substantial downward bias in the coefficient when elasticities are estimated at the monthly level.

This paper contributes to an emerging literature that uses short-run varia-

[3] A linear relationship assumes that every day a resort is closed due to low snowpack, the predicted losses are equal to the estimated number of daily visits.

[4] Morey (1984) finds an insignificant relationship between snowpack and demand, while Englin and Moeltner (2004) estimate an elasticity of 0.21 in the California-Nevada Tahoe region.

[5] Elasticity estimates from the Austrian Alps are estimated to fall between 0.05-0.07.

tion in climate amenities *and* the demand response to predict damages under future climate scenarios (Chan and Wichman, 2018; Dundas and von Haefen, 2019). We make three primary contributions to the study of climate change: 1) we develop a new method for estimating elasticities for climate amenities by matching the spatial and temporal variation in the level of the amenity (daily snowpack) with the spatial and temporal variation of market responses to the amenity (daily transactions in the short-term property rental market); 2) we derive state-specific elasticity estimates for all major resort markets across the United States and show that significant heterogeneity exists across states; and 3) we estimate the year-to-year variation in the contemporaneous value of snowpack in each state and use these estimates to simulate local economic damages under two future climate scenarios, RCP4.5 and RCP8.5. We find that resort markets could face reductions in local snow-related revenues of -40% to -80% by the end of the century (2080). When this response is applied to expenditures on lift-tickets and overnight stays, the estimated annual damages in each state range from \$1 million (Connecticut) to \$566 million (California). Across the U.S., annual damages total to between \$1.4 billion (RCP4.5) and \$2.36 billion (RCP8.5).

2.2 Empirical Framework

We use a high-dimensional panel fixed effects model to estimate the relationship between weather and recreational visits. This allows us to flexibly control for unobservable time-varying and time-invariant characteristics in each market, while still exploiting detailed variation in the level of the climate amenity (*snowpack*). Daily revenue for property i on day t is either 0 (not reserved), or the asking price on that day. To estimate the elasticity between revenue and snowpack, we transform the dependant variable revenue using the inverse hyperbolic sine (ihs) (Bellemare and Wichman, 2020), allowing revenue to take a value of 0. Our estimating equation is:

$$ihs(revenue)_{it} = \beta log(snowpack)_{rt} + \boldsymbol{S}\boldsymbol{X'}_{rt}\boldsymbol{\delta} + \boldsymbol{X'}_{rt}\boldsymbol{\eta} + \psi_{im} + \varepsilon_{it}. \qquad (2.1)$$

This specification estimates the relationship between daily revenues for property i on each day t and the natural logarithm of *snowpack* in resort market

r on each day t. The elasticity parameter, β, quantifies the effect of a change in mountain snowpack on revenue. The vector $\boldsymbol{SX}$ contains bins (indicator variables) of new *snowfall* (<24 hours). These are classified in bins of 3-inch increments (e.g. 0-3 inches, 3-6 inches, etc.) to accommodate their sparse nature (many zeros) and allow the parameter vector $\boldsymbol{\delta}$ to flexibly control for the relationship between new snowfall and revenue. The vector $\boldsymbol{X}$ includes an indicator for *holiday week*, *weekday*, and a linear and quadratic of daily *mean temperature*; the relationship between these and revenue is summarized by the parameter vector $\boldsymbol{\eta}$. The indicator for *holiday week* assumes a value of 1 for weekdays and weekends following a federal holiday.[6] The parameter ψ is a property-by-month-of-sample fixed effect that captures property-specific revenue trends across the study period. The error term ϵ_{it} is the remaining variation in revenue that is unexplained by the model.

This model assumes that changes in the snowpack at a given resort within a given month of our sample on a given day of the week are random with respect to bookings in the short-run rental market. For example, we assume that variation in the snowpack that occurs across the four Saturdays in a given resort market in February of 2016 is driven by variation in weather that is random in relation to the market for overnight stays. Importantly, variation in snowpack is matched with the consumer decisions in this market. β can be interpreted as the causal effect of *snowpack* on expenditures in the short-term property rental market. In later sections, we discuss the assumptions that are required for linking expenditures on property rentals to other local economic activity directly related to snow recreation.

To estimate a β for each state s, we introduce an interaction term between *snowpack* and a dummy variable indicating the resident state of the resort:

$$ihs(revenue)_{it} = \underbrace{\sum_s \beta_s \; log(snowpack)_{rt}[State = s]}_{\substack{\text{State-specific}\\ \text{Elasticities}}} + \boldsymbol{SX'_{rt}\delta} + \boldsymbol{X'_{rt}\eta} + \psi_{im} + \varepsilon_{it}. \quad (2.2)$$

This allows us to examine heterogeneity in the revenue function by recover-

[6]If a holiday falls on a Thursday, the indicator is equal to 1 for Thursday through Sunday. Similarly, if the holiday is on a Tuesday, the indicator is equal to 1 for Saturday through Tuesday. It is equal to zero otherwise.

ing an estimate of state-specific responses to the climate amenity *snowpack*.[7] β has the following interpretation: a 1 percentage point increase in *snowpack* causes a β percentage point change in expected *revenue*. An important feature of our method is the direct relevance of the resulting coefficient, β, to current climate models. These models provide predictions of percent changes in expected precipitation and snow-water-equivalent measures relative to historical levels. When we combine these locally downscaled estimates from climate models with our localized elasticity estimates, we can use contemporaneous shocks in the weather to simulate responses in local recreation demand given predictions about future climate.

2.3 The Data

We estimate the behavioral response to changes in mountain snowpack using a panel of 13 million daily observations of rental property bookings on the Airbnb platform. Our study area comprises the 219 resort markets that contain active Airbnb listings (AirDNA, 2017).[8] We observe daily transactions from August 2014 through May 2017, comprising three complete ski seasons. 67 resorts fall within 20km of at least one other resort. We study these as unified markets by computing the average level of the snowpack, snowfall, and temperature observed at each resort in the 20km buffer.

Daily snow conditions are recovered from historical records as reported by the resort (OnTheSnow.com, 2017). We recover two measures: 1) *snowpack*, the depth of the snow as reported by the resort each day; and 2) *snowfall*, the new snow that has fallen within the last 24 hours at each resort. *Snowfall* is sparse with many zeros. As such, we classify it in bins of 3 inches and group every observation over 15 inches into the largest bin. The daily mean temperature is acquired from Oregon State's PRISM Climate Group (PRISM, 2018).[9]

To generate expectations of future *snowpack*, we collect locally downscaled

[7] A full description of the estimating equation and alternative specifications can be found in the appendix.

[8] We define a resort market using a 10km buffer around the resort. See appendix for a full discussion.

[9] Summary statistics for the bookings, snowpack, and weather variables used in our analysis can be found in the appendix.

climate projections from the suite of CMIP5 models in 1/8-degree resolution across the U.S. (Reclamation, 2013). These projections offer monthly snow-water-equivalent levels for historical (1950-1999) and projected (2020-2100) for RCP4.5 and RCP8.5 scenarios. We compute resort-specific historical averages and calculate the expected change in snow-water-equivalent for two future periods (2035-2065 and 2065-2095). We average the monthly predictions over each period to generate an expectation of average annual *snowpack* under each RCP scenario. We refer to the first period (2035-2065) as the mid-century "RCP4.5 2050" and "RCP8.5 2050". Similarly, the second period is referred to as the late-century "RCP4.5 2080" and "RCP8.5 2080." We incorporate detailed visitation data for each of our 26 states using industry statistics from the National Ski Area Association (NSAA) (NSAA, 2017, 2018). This provides us with annual ski resort visitation in each of the 26 states and the number of overnight stays.

2.4 A Behavioral Response to Snowpack

We estimate the state-specific response to mountain snowpack in the form of elasticities (β parameters in equation 2.2) that represent the slope of the revenue function in each state. We report these results in Figure 2.1 (left panel). These estimates reveal substantial heterogeneity between states, with the elasticity of snowpack ranging from 0.151 in Colorado to 2.759 in Tennessee. We find that some states like Colorado have large snow-related revenue streams ($2.82 billion annually, Figure A.1), but are less responsive to changes in mountain snowpack ($\beta = 0.151$). State-specific elasticities do not systematically vary with mean snowpack, suggesting each state and market has unique underlying characteristics that drive this variation.

Variation in elasticity estimates across states is important for generating expectations about revenue under future climate scenarios because baseline revenue, snowpack, and future climate conditions all vary significantly across states. These parameters allow for more accurate models of changes in expenditures related to changes in snowpack under future climate scenarios. This is important given the considerable heterogeneity expressed in regional projections of mountain snowpack.

2.5 The Contemporaneous Value of Snowpack

To operationalize the estimation of damages under future climate scenarios, we first develop a baseline metric of the recreation revenue from snowpack. This is done using 13 years of within-sample variation in snowpack and two primary expenditures directly related to snow recreation in each local market.[10] We calculate the amount spent on lift tickets each year using average visitation V and the average price of a daily lift ticket P^{pass} (NSAA, 2018). To recover the average cost of an overnight stay, P^{bed}, we use the panel of properties to estimate an average bedroom price in each resort market and combine this with the average number of overnight stays OS to calculate the amount spent on overnight stays each year (NSAA, 2018). Average annual revenue AR in each state s is then:

$$AR_s = \underbrace{V_s \times P_s^{pass}}_{\substack{\text{Daily} \\ \text{Visits}}} + \underbrace{OS_s \times P_s^{bed}}_{\substack{\text{Overnight} \\ \text{Stays}}} \tag{2.3}$$

To calculate the annual recreation revenue from snowpack, Rev^{snow}, we combine our derived response parameter β_s with AR_s, the historical average depth of snowpack throughout each snow season HS_s, and the contemporaneous snowpack CS_s in each state s and within-sample year t such that:

$$Rev_{st}^{snow} = \underbrace{\beta_s \times \frac{AR_s}{HS_s}}_{\substack{\text{Implicit} \\ \text{Revenue}}} \times CS_{st}. \tag{2.4}$$

The first term in equation 2.4, implicit revenue, is analogous to a conventional implicit price in the nonmarket hedonic price literature. It describes the additional amount of annual revenue generated by an additional inch of snowpack, or the marginal annual recreation revenue from an inch of snowpack. When multiplied by the contemporaneous snow, the second term in equation 2.4, we recover the annual recreation revenue from snowpack for each year of our sample. This provides us with year-to-year variation in the revenue impacts of snowpack that are independent of annual business cycles

[10] The expenditures included to estimate the annual recreation revenue from snowpack are not meant to be comprehensive. We use this spending to provide a baseline of local economic activity directly related to the climate amenity *snowpack*.

and macroeconomic trends.[11]

The average recreation revenue from snowpack in each state varies significantly across states, ranging from \$1.5 million in Connecticut to \$909 million in California (Figure 2.1, right panel). This is the proportion of local economic activity that is directly related to mountain snowpack. It is reasonable to assume there are indirect (spillover) effects of snowpack on local revenues, making these estimates a lower bound (Loomis and Crespi, 1999). A strength of the state-specific elasticity estimates (the β_s's) is that they can be applied to other measures of economic activity that are directly related to snow-related recreation to construct more comprehensive estimates in states where additional data is available.

We then compute the total recreation revenue from snowpack for all 26 states in the sample:

$$\sum_s Rev_{st}^{snow} \tag{2.5}$$

and report these Figure A.6. In the next section, we demonstrate an application to estimate economic damages under future climate scenarios. We present the direct effects of changes in snowpack on two primary expenditures directly related to outdoor recreation.

2.6 Economic Damages

We use the within-sample trends for the period 2005-2017 to construct the baseline seasonal variation in each state and then estimate changes in expected snowpack under future climate scenarios. We estimate the effects of resort-specific predicted changes in snowpack from the suite of CMIP5 climate models (Reclamation, 2013), which yields estimates for 13 years of snowpack trends in each state under RCP4.5 and RCP8.5 scenarios. Using these simulations of year-to-year trends in snowpack, we estimate the annual recreation revenue by modifying equation 2.4 to replace the contemporaneous snowpack CS with the predicted snowpack PS in simulation year t':

$$Rev_{st'}^{snow'} = \beta_s \times \frac{AR_s}{HS_s} \times PS_{st'}. \tag{2.6}$$

[11] See appendix for further discussion of equation 2.3 and 2.4

We report the total recreation revenue in each simulation year t' from equation 2.6:

$$\sum_s Rev_{st'}^{snow'} \tag{2.7}$$

also in Figure A.6. The year-to-year variation and deviation from the historical mean can be seen using the axis on the right side of the figure. 95% confidence intervals are also reported for each simulation.[12] Between 2005 and 2017, we observe the annual recreation revenue from snowpack shifting between -25% and +25% of historical averages. The within-sample deviations in 2007, 2012, and 2015 fall to around \$2.8 billion in annual revenue, which approaches the range predicted by mid-century climate models for RCP8.5. Under RCP8.5 simulations, these estimates indicate that total recreation revenue could fall to between -40% and -60% by mid-century and -60% to -80% by late-century. Revenue in the year with the highest snowpack during the mid-century period is approximately equivalent to the lowest snowpack year in the contemporaneous period. By the late-century period, the highest snowpack year in our simulation will generate half of the economic activity observed during the worst year in our contemporary sample.

The difference between equations 2.4 and 2.6 ($Rev_{st}^{snow} - Rev_{st'}^{snow'}$) captures the annual economic damages in each state. We compute total annual damages across the United States using the sum of the 26 states in our sample:

$$\sum_s (Rev_{st}^{snow} - Rev_{st'}^{snow'}). \tag{2.8}$$

We report the average difference over the 13 years in Figure 2.4. Panel A summarizes the expected annual losses in each state for each RCP scenario and period (mid- and late-century). The 95% confidence intervals represent the variation across the suite of CMIP5 models. The confidence intervals range from the lower-bound of the least damaging scenario (RCP4.5 2050) to the upper-bound of the most damaging scenario (RCP8.5 2080). Panel B presents the aggregate damages across the United States under both RCP scenarios and periods.

Average annual damages under RCP8.5 2080 range from \$1 million in Connecticut (a 67% reduction in revenue from current levels) to \$566 million

[12] See appendix for further discussion and state-level simulations of equations 2.4 and 2.6.

in California (a 62% reduction in revenue). These estimates reflect the lost recreation revenue from snowpack using only the two expenditures stated in equations 2.3 and 2.4 (lift ticket sales and overnight stays). It is reasonable to assume that there are other expenditures directly and indirectly linked to changes in snowpack in each resort market. Our estimates of lost revenues provide a lower bound on consumer surplus. The demand for snow among recreational visitors may greatly exceed the value that is captured in revenue impacts. Other work in progress focuses on estimating these values (Parthum and Christensen, 2020).

Variation in damages is the composite of three underlying factors: 1) each state's unique relationship between snowpack and local economic activity (the state-specific β); 2) the state's baseline level of snow-based revenue (Figure A.1); and 3) the state's predicted change in snowpack under future climate scenarios (also depicted in Figure A.1). California, for example, has large existing levels of snow recreation (over \$1 billion each year) in addition to a large elasticity of snowpack ($\beta = 0.895$) and is also predicted to lose a substantial percentage of the average annual snowpack (-60% to -80%). Other states, such as Colorado, might have much higher annual revenue streams (over \$2.82 billion), but are less responsive to changes in the snowpack ($\beta = 0.151$), and are also predicted to have smaller shocks in average annual snowpack given future climate conditions (-30% to -50%).

2.7 Discussion

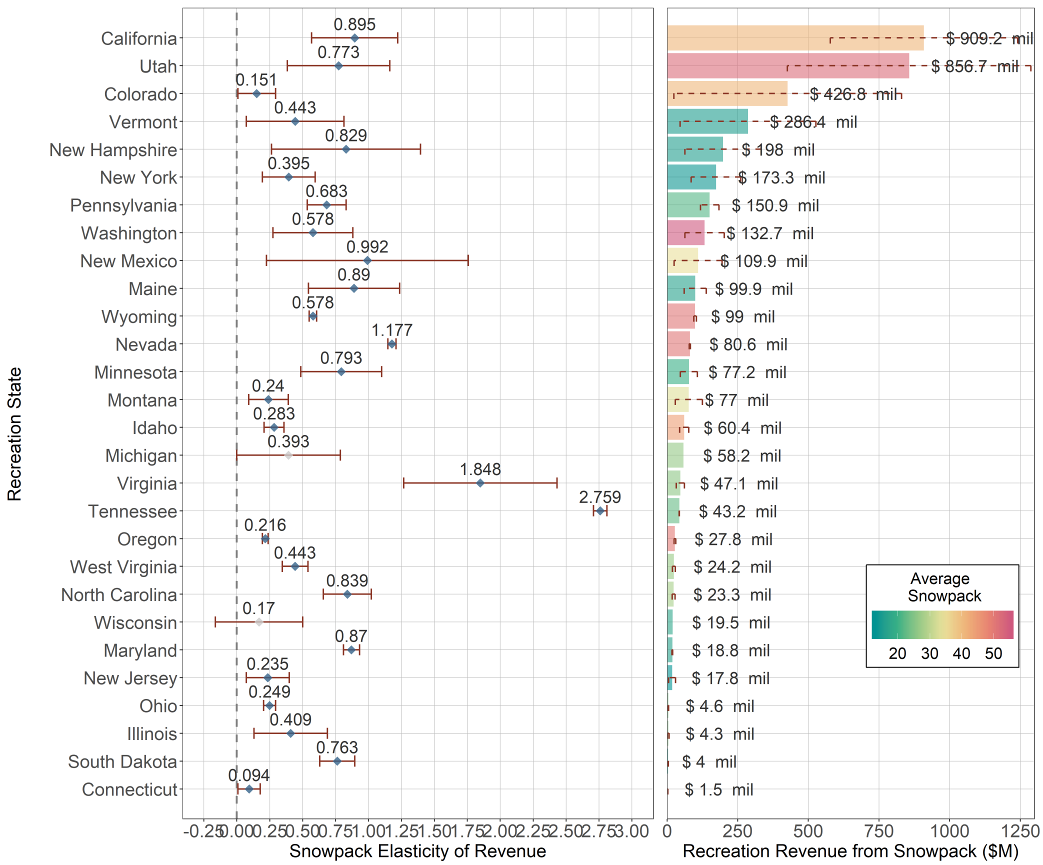
The present study makes three key contributions to current estimates of the damages from climate change: 1) we develop a method for estimating elasticities for climate amenities that vary at high spatial and temporal frequencies using high-resolution, high-frequency transaction data; 2) we derive state-specific snowpack elasticities of revenue in all major resort markets across the United States and show that substantial heterogeneity exists across states; and 3) we simulate the contemporaneous value of snowpack in each state, along with economic damages under two future climate scenarios, RCP4.5 and RCP8.5. We predict damages (lost revenues) in percentage terms, which provide a lower-bound dollar estimate of lost economic activity in each state.

We find that resort markets could face reductions of -40% to -80% of snow-related revenue by the end of the century (2080). This is nearly double the magnitude of existing estimates. When this is applied to existing expenditures on lift-tickets and overnight stays, we estimate damages across the U.S. to be between $1.4 billion (RCP4.5) and $2.36 billion (RCP8.5). The revenue impacts presented in this paper can be interpreted as a lower bound estimate of consumer surplus. The true welfare effects from reductions in snowpack could be substantially larger (Banzhaf, 2018).[13] Further refinement is necessary to better understand how consumers choose to substitute between markets and the implications of climate change on their welfare. Other recent work highlights the uncertainty and potential for much larger variability in climate outcomes than is represented in the available CMIP5 models (Christensen, Gillingham, and Nordhaus, 2018). Industries that depend on snow recreation face the threat of substantial losses if climate continues to warm at faster rates than those reflected by the CMIP5 scenarios.

[13] Estimates of damages that are derived using reduced-form methods, as presented in this paper, have been shown to be a lower-bound (10% of potential losses) on the Willingness to Accept welfare metric (Banzhaf, 2018).

2.8 Figures

Figure 2.1: State-specific Elasticities



Note: The left panel presents the β's described in equation 2.2 and represent the slope of the revenue function in each state market. Coefficients are ranked in order of states with the highest recreation revenue from snowpack (equation 2.4, right panel). These parameters allow for more accurate models of changes in expenditures related to changes in snowpack under future climate scenarios. This is important given the considerable heterogeneity expressed in regional projections of snowpack.

Figure 2.2: Estimates of Relative Revenue by Snowpack Bins

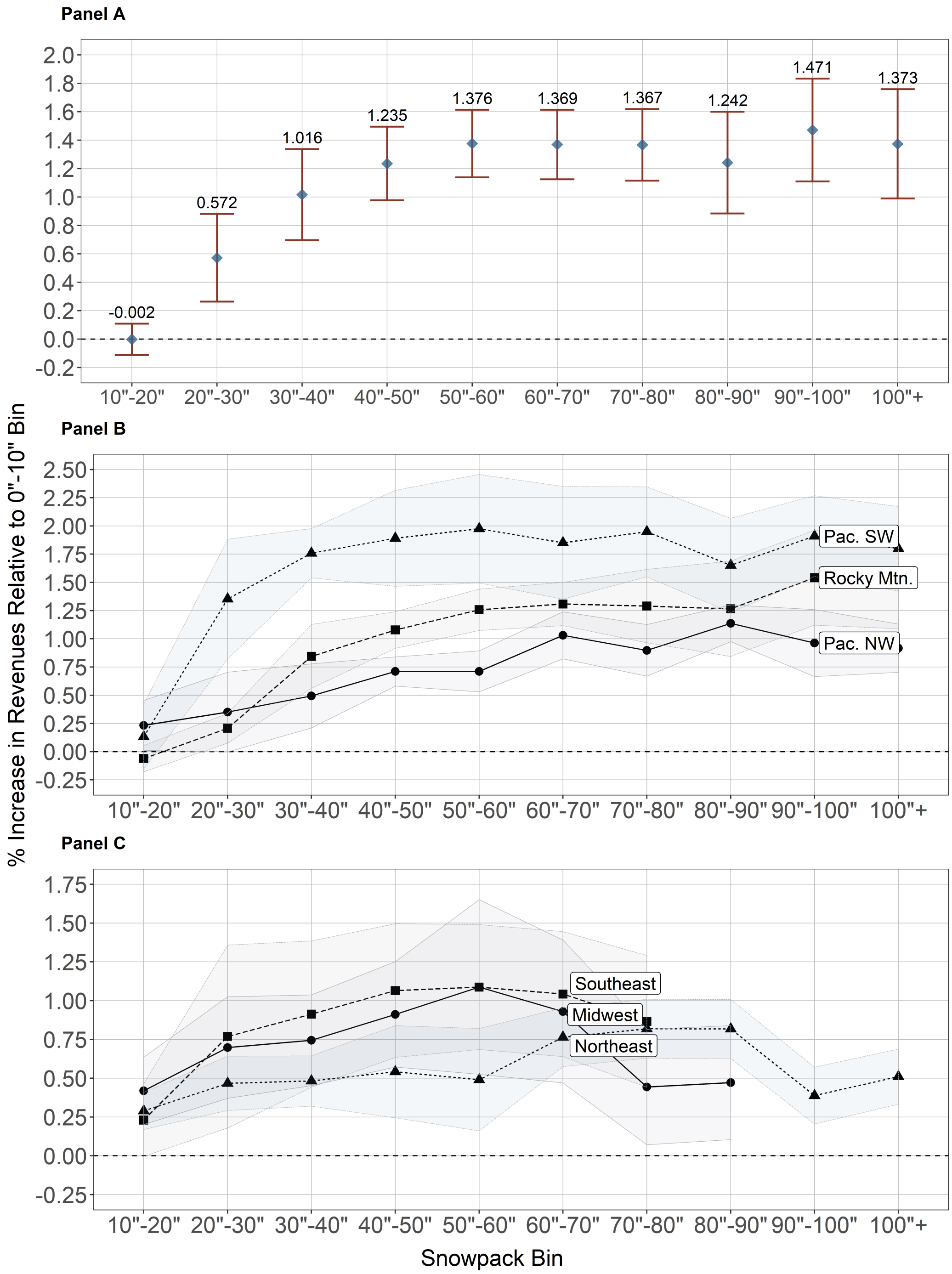
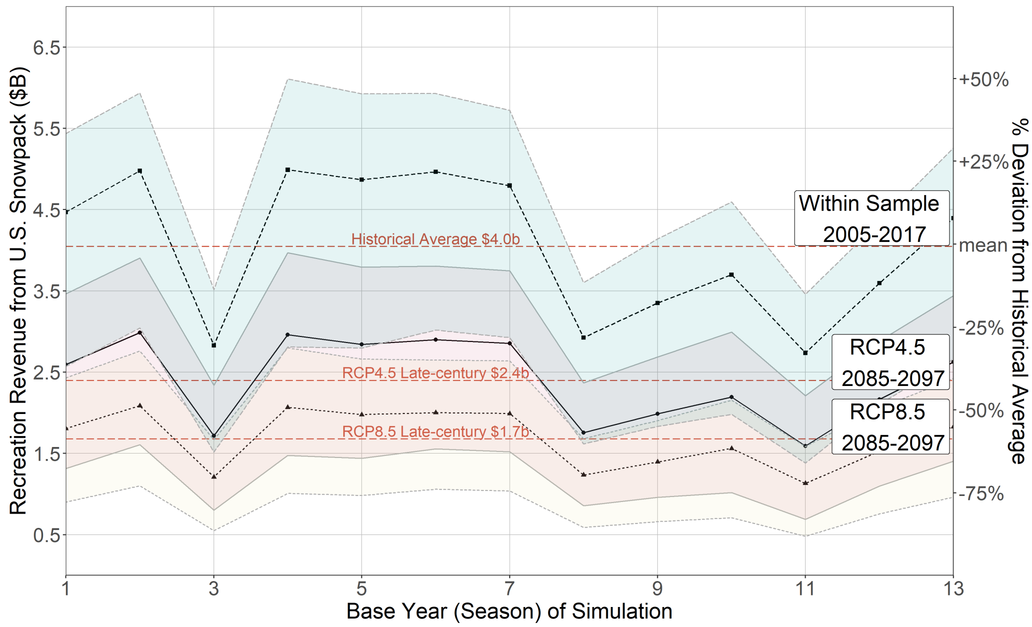
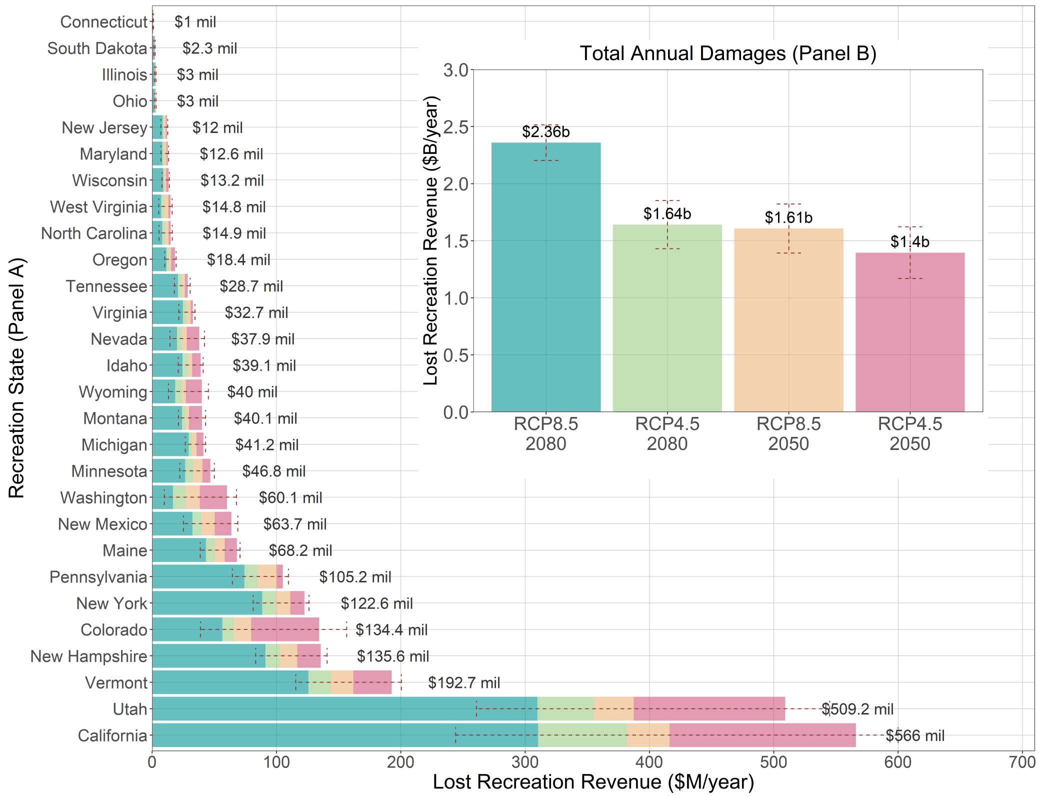


Figure 2.3: Within Sample and Late-Century Simulations



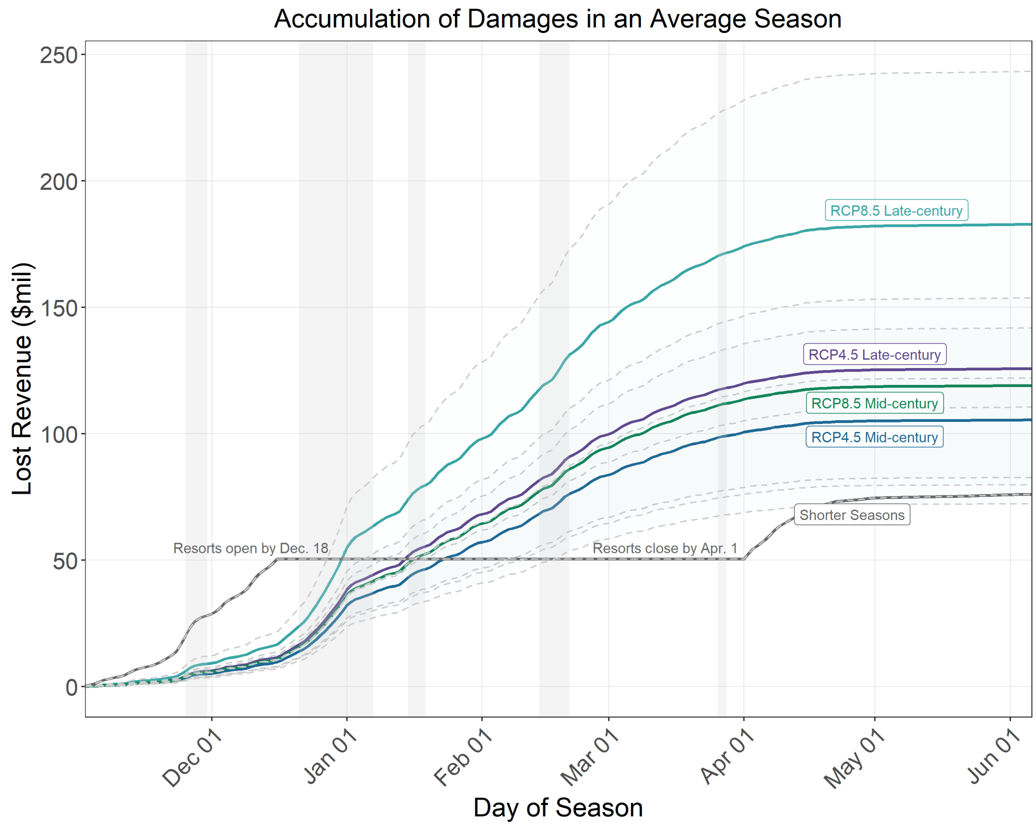
Note: Figure A.6 presents the results of equations 2.5 and 2.7. These use within-sample snowpack and predicted snowpack for RCP4.5 and RCP8.5 to simulate year-to-year variation in the annual recreation revenue from snowpack. The three scenarios represent: 1) an average decade currently (within-sample); 2) an average decade under RCP4.5 by late-century (2075-2100); and 3) an average decade under RCP8.5 by late-century (2075-2100). Values represent the total (aggregated) recreation value of snowpack across the 26 states (left axis) and its deviation from historical averages (right axis). The x-axis represents each year (season) in the simulation. For example, year 1 in the within-sample simulation would be 2005. Similarly, year 1 in the RCP4.5 and RCP8.5 late-century simulation would be 2075.

Figure 2.4: Lost Recreation Revenue



Note: Annual state-level damages are stacked by RCP scenario (Panel A). Total damages (Panel B) are aggregate annual damages across all 26 states by RCP scenario (equation 2.8). The 95% confidence intervals represent the variation across the suite of CMIP5 climate models, and range from the lower-bound of the best-case scenario (RCP4.5 2050) to the upper-bound of the worst-case scenario (RCP8.5 2080).

Figure 2.5: Lost Recreation Revenue versus Shorter Seasons



Note: Using only observed revenues from short term property rentals, we compare conventional estimates that use shorter seasons to estimate damages with the damage function we model that assume no change in season length. For the lost revenues from shorter seasons, we assume that (through the use of snow-making) resorts are still able to open by the holiday rush, December 18, and can remain open through the end of May. These estimates assume no other changes in revenues while the resorts are able to maintain feasible operating level of snowpack (Scott et al., 2007; Steiger, 2011; Dawson and Scott, 2013; Wobus et al., 2017; Steiger and Scott, 2020). The light grey shaded regions of the plot are holidays.

CHAPTER 3

A RECREATION DEMAND MODEL FOR MOUNTAIN SNOWPACK

3.1 Introduction

Mountain snowpack—the amount of packed, dense snow on the ground—is a major driver of participation in outdoor winter recreation (Hamilton, Brown, and Keim, 2007; Shih, Nicholls, and Holecek, 2009; Falk, 2010; Damm, Greuell, Landgren, and Prettenthaler, 2017; Parthum and Christensen, 2020). Its composition and depth can change daily from blowing wind, melting, and from deposits of new snowfall (i.e. snowfall within the most recent 24 hour period). Snowpack is primarily provided by the natural environment as a nonmarket, environmental amenity.[1] In the United States (US), snowpack at mountain resorts accommodates more than 50 million skier visits each year and contributes to a $70 billion snow sports industry (Vanat, 2014; NSAA, 2018). Snowpack is also an environmental amenity that is particularly threatened by climate change (Mendelsohn and Markowski, 1999; Dawson and Scott, 2013; Rosenberger et al., 2017; Wobus et al., 2017). But what is the recreation value of mountain snowpack?

One of the challenges in estimating demand for environmental amenities such as snowpack is that the markets for the amenity of interest rarely exist. Instead, researchers interested in the value of mountain snowpack must rely upon nonmarket valuation methods such as using surveys to construct markets (Rutty, Scott, Johnson, Jover, Pons, and Steiger, 2015a; Steiger, Posch, Tappeiner, and Walde, 2020) or by linking observed (revealed) con-

[1] To supplement naturally occurring seasonal snowpack, many mountain resorts have invested in snow-making equipment. However, snow-making is costly and limited in its capacity to cover large areas (Falk and Vanat, 2016; Scott, Steiger, Rutty, Pons, and Johnson, 2019; Steiger and Scott, 2020). It is also dependent on optimal weather conditions that are suitable for freezing water (Wobus et al., 2017). In this paper, I do not distinguish between naturally occurring snowpack and snow that was made using snow-making equipment.

sumer behavior to fluctuations in the environmental amenity (Morey, 1985; Englin and Moeltner, 2004). Both approaches have their relative strengths and weaknesses (Alberini, 2019). One advantage of stated preference methods is their ability to estimate values when there has been little observed variation in the level of the environmental amenity of interest. But they are often criticized for their hypothetical nature through which bias could be introduced in the estimates when people say they will behave one way and choose to behave another way when actually faced with the decision (Cummings, Harrison, and Rutström, 1995; Champ and Bishop, 2006; Carson and Groves, 2007).

Revealed preference methods, those using observed market behavior, do not face the concerns of hypothetical bias because consumer behavior is actually observed. However, revealed methods are not without their own unique challenges. Data on observed market behavior is typically hard to come by, and when such data do exist, they are notoriously plagued by endogeneity and unobserved characteristics or traits that influence demand. I address both of these challenges in this paper. I use a unique set of daily short-term property rentals that serve as a repeated cross-section of recreation decisions. I also address endogeneity concerns using a high-dimensional fixed effect model to control for unobservable characteristics that affect recreation decisions, coupled with a two-stage least squares (2SLS) approach to instrument for unobserved characteristics that are likely correlated with price.

Previous attempts to quantify welfare in the alpine skiing market have been few. But those that do, typically provide estimates of average consumer surplus per trip.[2] Estimates of the average surplus per trip have been derived using specific resorts (Morey, 1985), a small group of resorts (Adrangi, 1983; Englin and Moeltner, 2004), and nationally (Bergstrom and Cordell, 1991; Loomis and Crespi, 1999; Mendelsohn and Markowski, 1999; Bowker, Starbuck, English, Bergstrom, Rosenburger, and McCollum, 2009). These values range anywhere from \$14 for a day of skiing (Morey, 1985), to \$277 (Bowker et al., 2009), with an average value of a trip at \$77 for alpine skiers (Rosenberger et al., 2017). Each has noted that refinements should be made to understand how consumers benefit on the margin to environmental amenities. For example, Bowker et al. (2009) state that there are significant

[2]See Rosenberger et al. (2017) for a survey of this literature.

limitations of their approach including the ability to model "anything that would include using site characteristics to explain variation in visits" and the "exclusion of substitution behavior."

Per trip consumer surplus is helpful for quantifying value on the extensive margin (the number of trips taken) but does not separate welfare into its component parts based on the characteristics of each trip. For example, a skier might value a trip more if there is a deeper snowpack (fewer visible rocks, more ski-able terrain, etc.), but still decide to make the same number of trips. Parsing per trip consumer surplus to identify estimates of the marginal willingness to pay (MWTP) for trip characteristics allows for estimates of value on the intensive margin. In this paper, I exploit a repeated cross-section of daily visitation to resort markets in the US. I use a discrete choice framework (McFadden, 1973; Hanemann, 1984) to provide estimates of the MWTP for mountain snowpack for all major markets in the continental US. These values can be used to provide guidance to policy makers who are interested in the recreation value of snowpack, but also by firms who are making investment decisions in snow-making equipment—particularly in the face of a changing climate (Scott et al., 2007; Dawson and Scott, 2013; Wobus et al., 2017; Wilson, Green, and Mack, 2018; Steiger et al., 2019).

Site substitution is a well-known and important phenomenon to consider when modeling recreation behavior (Peterson, Stynes, Rosenthal, and Dwyer, 1985; Phaneuf, 2002; DeValck and Rolfe, 2018; Dundas and von Haefen, 2019). However, it has received little attention in the context of alpine skiing decisions. Substitution effects have been examined between a few resorts as a form of adaptation to climate change in Austria (Steiger and Scott, 2020), Ontario (Rutty et al., 2015a; Rutty, Scott, Johnson, Jover, Pons, and Steiger, 2015b), and the Northeastern US (Dawson and Scott, 2013), but remains an area of necessary research (Unbehaun, Pröbstl, and Haider, 2008; Rosenberger et al., 2017). In this paper, I explore how skiers choose to substitute across resort markets in the continental US. For example, if Colorado receives a shock in snowpack levels, how do people in Vermont respond? I use a structural demand model at the market-level (Berry et al., 1995; Nevo, 2001) to recover a matrix of snowpack substitution parameters (elasticities) that estimate how people choose to move across resort markets in response to changes in mountain snowpack.

I make two primary contributions in this paper: 1) I provide estimates of the MWTP for mountain snowpack at the national and regional levels; and 2) I construct a matrix of substitution elasticities between US resort markets. Both contributions invoke random utility maximization (RUM) (McFadden, 1974) to estimate structural parameters in the utility functions of alpine skiers. For the first contribution (1), I maintain trip-level micro data to estimate marginal utilities subsequent MWTP. I develop a new instrument to address price endogeneity concerns for use in a 2SLS instrumental variables approach. I discuss this model and its results first. For the second contribution (2), I aggregate the trip-level data to market-level and calculate daily market shares (Berry, 1994; Berry et al., 1995; Nevo, 2001). This allows me to recover substitution patterns in the form of elasticities, providing insight into how skiers move across markets based on changes in mountain snowpack. Both contributions are important for understanding consumer welfare in the alpine skiing market and the implications of a changing climate.

3.2 Demand for Mountain Snowpack

In the spirit of the recreation demand literature (Hanemann, 1984; Bockstael, Hanemann, and Strand, 1989), I estimate a discrete choice, travel cost model using daily micro data on visitation to ski resort markets over three complete ski seasons.[3] The data—described in detail in section 3.3—are from the short-term property rental market. The geographical coverage includes 13 US states and 137 individual resorts. Each observation is assumed to be a discrete decision made by a skier. The term 'skier' can be used to describe a variety of winter recreationists, but in this paper I use the term to describe the decision maker.

I model the discrete choice to either make the trip or to opt-out. The decision to opt-out can include staying home (which I do not observe), but can also include any outside option that the skier faces such as making a trip to another resort (which I observe), or staying in accommodations outside the short-term property rental market (which I do not observe). Using this framework, I estimate: 1) average marginal utilities for all skiers, and 2) heterogeneity in the means of the marginal utilities by geographical regions (Mountain-West vs. Central-East, and by NSAA resort regions, Figure B.1).

[3] I discuss trip-level estimation first. Market-level is discussed in section 3.5.

The discrete choice is made as follows: a skier i makes the decision to make a trip to resort j each day t, or decides to opt-out. This means that the dependent variable in the model takes a value of 1 if a trip was made (i.e. a short term property was rented) and 0 otherwise. The choice is characterized in the RUM framework of McFadden (1974): $U^i_{jt} = V^i_{jt} + \varepsilon^i_{jt}$, where V is the representative component of utility and ε is the unobserved individual-specific utility in the model, distributed extreme value. The utility received from choosing the outside option is normalized to be equal to 0. The probability that skier i chooses alternative j is:

$$P^i_{jt} = Prob(V^i_{jt} + \varepsilon^i_{jt} > 0), \tag{3.1}$$

resulting in the standard logit choice probabilities:

$$P^i_{jt} = \frac{1}{1 + exp(-V^i_{jt})}. \tag{3.2}$$

The parameters recovered from a logit regression are the marginal utilities for each attribute in the model—the ratio of which can provide meaningful information about the marginal rate of substitution between two attributes. When one of the attributes is the price of the trip, the econometrician can estimate the MWTP for the non-monetary attributes by taking the ratio of their parameters (the numerator) and the parameter on price (the denominator).

3.3 The Data

Daily bookings in short term properties are acquired from a private firm who collect the universe of Airbnb, VRBO, and HomeAway listings across the US (AirDNA, 2017). Rental transaction data for each property include the reservation date, availability (available or not available to rent), the price paid, and property characteristics such as the number of bedrooms, bathrooms, and the approximate coordinates of the home. The dataset includes more than 1.4 million properties and 410 million bookings spanning the contiguous US.

I identify all properties located within 10km of a ski resort to construct an empirical sample of 33,636 unique properties and 6.6 million observed property-days. Owners of these properties have the option of "blocking" the property for their own use, or have it listed as "available." When a property is rented, it is recorded as "reserved" and the date that the reservation was made is recorded.

The environmental amenities, snowpack and snowfall, are acquired from a website (OnTheSnow.com, 2017) that provides daily reports for all 137 resorts in the sample. These amenities are as reported by the ski resort on each day and matches the information that a tourist see when making the decision to make a trip. I developed a web scraper to recover historical daily data from their website, as well as any resort characteristics and lift ticket prices available. 34 resorts fall within 20km of one or more other resorts (i.e. resorts that have overlapping 10km buffers). I classify these as unified markets and take the average levels of the environmental amenities observed at each resort (snowpack, snowfall, and temperature).

Daily mean temperature is acquired from Oregon State's PRISM Climate Group (PRISM, 2018), which provides a dedicated API that allows researchers to efficiently recover interpolated weather values in a raster format. From the raster files, I extract the daily mean temperature in each resort market. Summary statistics of all the variables are in the Appendix (Tables B.3, B.4, and B.5).

3.4 The Model

The utility U of person i from choosing alternative j on day t at resort r is:

$$U_{jt}^{i} = -\lambda price_j + \boldsymbol{\beta'} snowpack_{rt} + \boldsymbol{X'_{rt}} \boldsymbol{\phi} + \boldsymbol{Z'_{j}} \boldsymbol{\gamma} + \Omega_t + \theta_r + \varepsilon_{jt}. \tag{3.3}$$

It is worth noting that each alternative j is nested within its respective resort r such that *snowpack*, the environmental amenity of interest, varies at the level of the resort. The cost attribute, *price*, includes the cost to travel to the resort and any expenses related to accessing the ski slope: 1) the per-bedroom price of the property; 2) the driving distance to the nearest metropolitan area (in miles) multiplied by \$0.33; and 3) the price of a lift ticket at the nearby resort. The variable *snowpack* includes a linear and quadratic polynomial to allow for diminishing marginal utility of snowpack; $\boldsymbol{\beta}$ is a vector consisting of two parameters (β_1, β_2) summarizing the nonlinear relationship between snowpack and utility.[4]

The vector $\boldsymbol{X}$ includes characteristics of the resort that also vary at the daily level: 1) six bins of new snowfall received at the resort within the most recent 24 hours; a linear and quadratic of 2) the total new snowfall within the past week; 3) mean temperature; 4) the total number of available properties on each day; and 5) average snowpack, weekly snowfall, and mean temperature at nearby substitute resorts (other resorts that are in the same state). Including the average characteristics of nearby resorts (excluding resort r) helps to control for the relative utility of the outside option (normalized to be equal to 0). The parameter vector $\boldsymbol{\phi}$ summarizes the marginal utilities of the characteristics in $\boldsymbol{X}$.

The vector $\boldsymbol{Z}$ includes information about the alternative j such as number of bedrooms, bathrooms, and other characteristics of the property that I observe but remain fixed throughout the panel—discussed in more detail below. The parameter vector $\boldsymbol{\gamma}$ summarizes the marginal utilities of the characteristics in $\boldsymbol{Z}$. Lastly, the fixed effect Ω_t includes an indicator for the day-of-sample to capture the mean utility for every day in the sample. This controls for differential utility due to holidays, weekends, or anything else that is unobservable and might increase or decrease utility on any given day. θ_r is a resort fixed effect to capture preferences for time-invariant and unobservable characteristics of resort r.

I am interested in estimating the MWTP for mountain snowpack. When estimating equation 3.3, MWTP can be recovered by taking a simple ratio of the parameters (marginal utilities) on snowpack and price such that $MWTP^{snow} = (\beta_1 + \beta_2)\lambda$. One issue with this specification is that price is likely correlated with other unobservable features of j that influence the decision to make a trip (i.e. correlated with the error term ε). If this is true, the estimate of λ will be biased towards 0, inflating subsequent estimates of MWTP (Lewbel, Dong, and Yang, 2012).

In the same way that I control for time-varying unobservables with Ω_t, I want to control for unobservable factors that are specific to alternative j—particularly those that affect the observed price of a trip—to mitigate

[4] I also estimate a non-parametric binned regression model, discussed in section 3.4.3.

the bias associated with correlations between the variables in the model and the error term. I address this concern by introducing an alternative specific constant δ_j such that any unobservable and time-invariant characteristics of j are captured in this parameter. However, doing so subsumes λ, the marginal utility of price, and any other parameters associated with characteristics that only vary across alternatives.

The addition of δ_j to the model sets the stage for a two-step estimation to recover unbiased estimates of the marginal utilities of j that dictate the decision to make a trip or to opt-out (Murdock, 2006; Timmins and Murdock, 2007; Klaiber and von Haefen, 2019). More specifically, I define the alternative specific constant $\delta_j(p_j, \boldsymbol{Z}_j, \xi_j)$ as the collection of attributes that are specific to alternative j. The price of the trip p_j is the three-part price discussed above. The vector $\boldsymbol{Z}$ includes other observable characteristics of j.[5]

The third parameter in $\delta_j(p_j, \boldsymbol{Z}_j, \xi_j)$, captures the characteristics of j that are only observable to the decision maker (i.e. unobservable to the econometrician) and influence the decision to choose alternative j. This can be thought of as features or amenities contained within the pictures of the property, the presence of a fireplace, a desirable view-shed, or even its exact location—such as ski-in-ski-out accommodations or access to public transportation. Plugging $\delta_j(p_j, \boldsymbol{Z}_j, \xi_j)$ into equation 3.3, person i's utility function becomes:

$$U^i_{jt} = \delta_j + \boldsymbol{\beta'} snowpack_{rt} + \boldsymbol{X'_{rt}}\boldsymbol{\phi} + \Omega_t + \theta_r + \varepsilon_{jt} \tag{3.4}$$

where

$$\delta_j = -\lambda price_j + \boldsymbol{Z'_j}\boldsymbol{\gamma} + \xi_j. \tag{3.5}$$

I estimate equation 3.4 using a standard logit specification, recovering the β's and the vector of parameters associated with the alternative specific con-

[5]The full set of characteristics includes: the number of bedrooms* and bathrooms*, maximum number of guests*, the number of photographs in the listing*, the distance to the resort (in meters)*, the total number of days the property was available in the sample*, the median home price in the census block*, whether or not an owner is considered a "superhost", an indicator for if the listing is an entire home or private room, and resort (location) fixed effects. Asterisks (*) indicate that a linear and quadratic polynomial was included to flexibly model the utility from these characteristics.

stants δ_j.[6] The large size of δ_j (33,636×1, or one estimate for each property j in the sample) is important for identifying the parameters in equation 3.5. To allow for correlation across observations, I cluster standard errors at the level of the market (Wooldridge, 2006; Abadie, Athey, Imbens, and Wooldridge, 2017).[7] I estimate equation 3.5 using 2SLS to recover λ and γ, also clustering standard errors at the level of the market. As mentioned, price is endogenous in the model described so far. I propose my instrument, along with a comparison to alternative instruments, in the following section.

3.4.1 The Endogenous Price of a Trip

The price characteristic in equation 3.5 is likely correlated with other unobservable features of j that influence the decision to make a trip. I address this problem by first including a property fixed effect (equation 3.4) that subsumes the endogenous price. In the second regression (equation 3.5), I use a 2SLS approach that is common in the industrial organization literature (Berry et al., 1995; Nevo, 2001; Bayer, Ferreira, and McMillan, 2007). Typical instruments either include average prices of the outside option (Price-IV) or the average of any observable product characteristic of the outside options (BLP-IV). The assumption with these instruments is that the price and characteristics of alternative k, where $k \neq j$, only affect utility of alternative j through prices, conditional on other observable characteristics of the market.

A unique feature of my data is that I observe the property owner's decision to block their property for their own private use. This is made according to their own personal schedule, uncorrelated with demand shocks associated with the skier's decision to make a trip. The assumption here is that the owner has their own schedule and does not choose to block or unblock their listing according to daily shocks in demand. Any deviation from this assumption and the instrument will have a weak first-stage. I estimate this variable, Υ_j, for each property j as the ratio of blocked days to the total

[6] One might be concerned about the incidental parameters problem (IPP) when estimating a nonlinear model with large unit and time fixed effects (Neyman and Scott, 1948; Fernández-Val and Weidner, 2016). Potential bias, arising from IPP, is mitigated when estimating the model using Stammann (2017) and integration of post-estimation outlined in Cruz-Gonzalez, Fernández-Val, and Weidner (2017).

[7] I examine correlation structures at the property, market, and state levels. Those results and discussion can be found in the appendix (Table B.1). Significance is robust to alternative clustering—I choose market-level for the primary analysis.

observed days (blocked + available) in the sample and introduce this as an additional instrument for the endogenous price (Schedule-IV). My first-stage equation is:

$$price_j = \boldsymbol{Z_k'}\Pi_1 + \Pi_2\Upsilon_j + \boldsymbol{Z_j'}\Gamma + \theta_r + \upsilon_j. \tag{3.6}$$

The vector Z_k includes the typical BLP-IV instruments—average price and property characteristics of the outside options. Υ_j is the property owner's share of blocked days (Schedule-IV). X includes all observable characteristics of property j and θ_r is a resort fixed effect. I examine robustness of results using 1) only the average price of the outside option (Price-IV), 2) the traditional BLP-IV instruments, and 3) the BLP-IV plus the Schedule-IV, as outlined in equation 3.6. Results of a Wald test estimate the strongest set of instruments is (3), the joint use of the BL-IV and Schedule-IV. Table 3.3 provides a complete comparison of the three approaches.

3.4.2 Heterogeneity in Marginal Utilities

I have, so far, described a model that estimates the average marginal utilities for skiers across the US. Underlying a national market, regional differences emerge in both the preferences (ski culture) and the geographical characteristics (elevation, terrain, etc.) of recreation decisions and opportunities. That is to say, the marginal utility of snowpack in the western US (e.g. California, Nevada, Utah, Colorado, etc.) might differ from the preferences for snowpack in the eastern US (e.g. Pennsylvania, Vermont, New Hampshire, etc.).

To allow for heterogeneity in the marginal utility of snowpack, I introduce two alternative specifications. The first splits the US into two distinct regions: Mountain-West and Central-East. The Mountain-West region includes the states of Montana, Idaho, Wyoming, Colorado, Utah, and California. The Central-East region includes Michigan, New York, Massachusetts, Connecticut, New Hampshire, Vermont, and Maine. The second type of region classification is determined by the NSAA regions: Westcoast, Rocky Mountain, Midwest, and Northeast (Figure B.1). The marginal utilities of the other attributes in the model (new snowfall, mean temperature, etc.) are preserved as national averages and assumed constant across the sample. I also assume the diminishing marginal utility of snowpack ($snowpack^2$ in the model) does not vary across regions. Utility is represented in region m by:

$$\begin{aligned} U_{jt}^{i} =& \delta_j + \sum_m \beta_m snowpack_{rt}[region = m] \\ &+ \beta_2 snowpack_{rt}^2 + \boldsymbol{X'}_{rt}\boldsymbol{\phi} + \Omega_t + \theta_r + \varepsilon_{jt}, \end{aligned} \tag{3.7}$$

where $\delta_j = -\lambda price_j + \boldsymbol{Z'}_j\boldsymbol{\gamma} + \xi_j$. The only difference between equations 3.4 and 3.7 is the addition of the interaction between snowpack and region.

3.4.3 A Binned Regression Model

Up until now, the relationship between snowpack and utility has been assumed to be diminishing quadratically in depth. To accommodate a more flexible functional form between snowpack and utility, I estimate a model that groups snowpack into increments of 10 inch bins, with anything above 100 inches grouped in the largest bin. This allows me to trace out the nonlinear relationship between snowpack and marginal utilities in each snowpack bin b:

$$\begin{aligned} U_{jt}^{i} =& \delta_j + \sum_b \beta_b snowpack_{rt}[bin = b] \\ &+ \beta_2 snowpack_{rt}^2 + \boldsymbol{X'}_{rt}\boldsymbol{\phi} + \Omega_t + \theta_r + \varepsilon_{jt}, \end{aligned} \tag{3.8}$$

where $\delta_j = -\lambda price_j + \boldsymbol{Z'}_j\boldsymbol{\gamma} + \xi_j$. Similar to the regional specification in equation 3.7, the only difference here is replacing continuous specification of *snowpack* with the binned snowpack. As a final step, I introduce regional variation in the binned model by including an interaction between the region and the snowpack bin:

$$\begin{aligned} U_{jt}^{i} =& \delta_j + \sum_m \sum_b \beta_{bm} snowpack_{rt}[region = m][bin = b] \\ &+ \beta_2 snowpack_{rt}^2 + \boldsymbol{X'}_{rt}\boldsymbol{\phi} + \Omega_t + \theta_r + \varepsilon_{jt}, \end{aligned} \tag{3.9}$$

where $\delta_j = -\lambda price_j + \boldsymbol{Z'}_j\boldsymbol{\gamma} + \xi_j$. No changes are made in the 2SLS specification that is used to estimate the parameters of $\delta_j(p_j, \boldsymbol{Z}_j, \xi_j)$ (equation 3.5) when exploring heterogeneity in the marginal utility of snowpack.

3.4.4 Results of Trip-level Estimation

I find that skiers have large and statistically significant preferences for deeper snowpack (Table 3.1).[8] I also find that utility is, in fact, nonlinear and diminishing in the level of snowpack. When I introduce regional variation in the utility function, the marginal utility of snowpack is greater in the Central-East than the Mountain-West region. Parsing utility into NSAA regions, I find that the marginal utility of snowpack is largest in the Northeast, followed by the Rocky Mountain, Westcoast, and Midwest regions (respectively).

The 2SLS estimates of the marginal utility of price are negative (as expected) and consistent across national and regional specifications (Table 3.1). I compare the strengths of the Price-IV, BLP-IV, and Schedule-IV instruments and find that the full set of instruments (BLP-IV + Schedule-IV) are the strongest predictors of price based on the results of the Wald F-statistic (Table 3.3). The naïve OLS estimate of λ is half the magnitude when compared to the 2SLS estimate using the full set of instruments—supporting the hypothesized attenuation bias in the coefficient on price.

But what is the MWTP for mountain snowpack? I estimate empirical distributions of MWTP using 5,000 bootstrapped replications of the ratio: β/λ (Krinsky and Robb, 1986). The mean MWTP for one inch of snowpack in the US is \$2.40 and diminishing at approximately \$0.01 for each additional inch (Table 3.2). I do find substantial regional variation, ranging from \$1.38 in the Midwest to \$4.24 in the Northeast. As mentioned earlier, the regional variation in the recreation value of snowpack is likely driven by differences in ski culture, snowpack composition, and geographical characteristics or the resorts (Vanat, 2014).

I also estimate utility using the binned specification in equation 3.8. This allows me to estimate the WTP in each snowpack bin, in contrast to the previous results that derive the MWTP for each inch of snowpack in a parametric functional form. This is particularly useful for estimating welfare on a given day. For example, for each day a resort has 40"-50" of snowpack, I estimate the WTP for that snowpack at \$110.23. Similarly, a day with 30"-40" of snowpack (one bin down), the WTP is \$80.97, or approximately \$30 less than the next higher bin (Figure 3.1). I also examine regional variation in the binned estimates and find that while the Central-East has higher mean

[8] Results for all attributes in the model can be found in the Appendix (B.2).

WTP in most bins, the point estimates are not statistically different than the Mountain-West estimates for the same bin.

3.5 Market Shares and Substitution

To estimate geographical substitution across resort markets, I introduce variation in the outside option by asking the question: conditional on going, where do people choose to go and why? I do this in the framework of Berry (1994) and Berry et al. (1995) using a market share inversion. Each state-day pair is observed to have a share of the total visits in each season. A "market" in this context is a single day in the sample, and the "product" is a state. Market shares sum to 1 each ski season. This allows skiers to choose both when and where they go to ski, while also providing substantial variation in the product characteristics across markets.

Market shares s are the number of reserved beds q in state j on day t in season y divided by the total number of reserved beds Q in season y: $s_{jty} = q_{jty}/Q_y$. The other variables in the model are the averages of the observed characteristics in each state-day pair in the sample: price, snowpack, weekly snowfall, and mean temperature.

Average snowpack varies substantially across resort markets. I account for this difference in levels by using the natural logarithm of snowpack. This normalizes the level of snowpack and allows for a more intuitive interpretation of the derived substitution parameters. I estimate a random parameter model with unobserved heterogeneity in λ and β such that they are both indexed by i. The utility of skier i from choosing state j on day t is: $U^i_{jt} = \omega_{jt} + \varepsilon^i_{jt}$. The term ε is, again, unobserved individual-specific utility of alternative j on day t, and the mean utility ω_{jt} is:

$$\omega_{jt} = -\lambda_i price_{jt} + \beta_i log(snowpack)_{jt} + \boldsymbol{X'}_{jt}\boldsymbol{\phi} + \Psi_j + \Omega_y + \theta_h + \xi^i_{jt}. \quad (3.10)$$

The parameter $\boldsymbol{\phi}$ includes both the linear and quadratic of weekly snowfall and mean temperatures. Ψ_j, Ω_y, and θ_h are fixed effects that capture baseline utility in each state, each season, and from making a trip during a holiday week. ξ, as before, captures the utility from the characteristics of j that are only observed by the skier (unobserved by the econometrician).

3.5.1 Results of Market Share Inversion

Estimation is carried out numerically using the contraction mapping algorithm of Berry et al. (1995) to predict the market shares s in state j on day t such that:

$$s_{jt} = \frac{exp(\omega_{jt})}{1 + \sum_j exp(\omega_{jt})}. \tag{3.11}$$

I use the average characteristics of the outside options k on day t to instrument for price (BLP-IV). The marginal utilities from estimating the regression are summarized in Table 3.4. As expected, I find that skiers have a positive and significant marginal utility of snowpack and a negative and significant marginal utility of price. Price has a statistically significant standard deviation; however, I find no unobserved heterogeneity in the marginal utility of snowpack (i.e. the standard deviation of $log(snowpack)$ is not statistically different than 0). One could also estimate MWTP from these parameters; however, the trip-level approach described in section 3.2 is better suited to do so. The market-level approach, described here, is particularly useful for estimating substitution across resort markets, something that the trip-level approach is unable to estimate.

To recover the elasticity of substitution η between alternatives j and k, I take the partial derivative of s_{jt} with respect to snowpack (denoted by x) such that:

$$\eta_{jkt} = \frac{\partial s_{jt}}{\partial x_k}\frac{x_k}{s_j}. \tag{3.12}$$

I average the resulting η's over markets, dropping the subscript t, to recover a matrix of own and cross-snowpack elasticities. It is reasonable to assume that skiers are more likely to substitute within a particular NSAA region (e.g. skiers in Vermont are more likely to respond to changes in snowpack in New Hampshire than changes to snowpack in California). I accommodate this assumption by specifying a group structure on ε that nests the correlation (denoted by σ) within each state's NSAA region m. In doing so, the elasticities are:

$$\eta_{jk} = \begin{cases} \frac{\beta_x x_k}{1-\sigma_m}(1-(1-\sigma_m)s_k - \sigma_m s_{k|m}) & \text{if } j = k; j,k \in m \\ \frac{\beta_x x_k}{1-\sigma_m}((1-\sigma_m)s_k + \sigma_m s_{k|m} & \text{if } j \neq k; j,k \in m \\ \beta_x x_k s_k & \text{if } j \neq k; j \in m; k \notin m \end{cases} \tag{3.13}$$

With this specification, as the correlation $\sigma_m \to 0$, the cross-snowpack elasticity between j and k when they are the same nest, approaches the elasticity between j and k when they are not in the same nest. That is to say, that the cross-snowpack elasticity is larger in magnitude when state j is in the same NSAA region m as the substitute state k.

I summarize the derived own and cross-snowpack elasticities in Figure 3.2. The columns of the matrix define the state where the change in snowpack occurs (i.e. the "dose" state) and the rows are the states that experience a change in predicted market shares (i.e. the "response" state). The diagonals of the matrix are the own-snowpack elasticities, and the off-diagonals are the cross-snowpack elasticities.

Substitution is larger in the Mountain-West states: California, Utah, Idaho, Montana, Wyoming, and Colorado, suggesting that skiers in these states are quite responsive to changes in snowpack within their own region. The Central-East states do experience substitution, but relatively smaller in magnitude than their western counterparts. One interesting finding is that Vermont is particularly affected when it experiences an increase in snowpack. Western states such as Utah, Wyoming, and Colorado, observe a 0.4 percentage point drop in market shares when Vermont receives a 1 percent increase in snowpack. This is likely due to Vermont skiers staying in their own state when conditions are good, but traveling to western states when conditions are bad.

3.6 Discussion

I estimate a flexible discrete choice model to derive marginal utilities of winter recreationists in the United States. I use a trip-level model of random utility to estimate the marginal willingness to pay for mountain snowpack. I find that skiers place a significant value on this particular environmental amenity, and that their values are not uniform across regions. This finding is important for welfare estimation in the sense that it allows measures of consumer surplus to vary on the intensive margin. More specifically, if the level of snowpack is expected to change under future climate, one could estimate the lost welfare from this change even if the number of trips remains the same. Alternatively, I provide estimates of willingness to pay for snowpack that are binned into increments of 10 inches. This provides a unique opportunity to estimate the consumer welfare for a day of skiing in each bin in the model. This is particularly useful for estimating differences in welfare when the number of trips a skier takes remains the same, but they experience more days in one bin than in another.

The market-level model I use allows me to derive substitution parameters that map market shares to snowpack. I present these in the form of snowpack-elasticities (own and cross). I find that market shares are, in fact, sensitive to the level of snowpack in local and nonlocal markets. While skiers are more likely to substitute across markets within their own region, I find that even markets that are geographically distant rely on the environmental amenities in the far away markets. Recognizing the degree to which markets are interconnected is important when considering the heterogeneous changes in snowpack accumulation predicted by climate change. Markets that are relatively better off (i.e. have smaller losses from base levels relative to other markets) should plan for substantial increases in market shares and visitation under future climate.

The models I use in this paper build on a long-history of recreation demand literature, extending well-established practices and methods into a relatively less-researched market of outdoor winter recreation. The models are simple but sound, and could be improved upon as computational advances emerge and estimation algorithms become more efficient. The trip-level model could be expanded to accommodate random parameters that might allow for more refined estimates of marginal utilities. Additionally, the market-level model could be improved by incorporating other supply-side considerations that might affect the resulting market shares. Both models could be improved if one were to have a panel of consumers (compared to the repeated cross-section, or panel of properties, used in this paper), this would allow the incorporation of demographic characteristics that determine demand.

The takeaway from this paper is that skiers do value and respond to marginal changes in mountain snowpack. This means that considering welfare on the intensive margin will be important for estimating damages under a changing climate. Estimates that use only measures of surplus on the extensive margin may over-predict changes in welfare by assuming that people will not substitute across markets, and under-predict changes in welfare by failing to account for changes in value on the intensive margin.

3.7 Tables

Table 3.1: Marginal Utilities from Trip Decisions

	(1) National Average	(2) West-East Regions	(3) NSAA Regions
Snowpack	0.01242***		
	(0.00392)		
Snowpack × Mtn.-West		0.01159***	
		(0.00070)	
Snowpack × Central-East		0.02044***	
		(0.00159)	
Snowpack × West-coast			0.00914***
			(0.00076)
Snowpack × Rocky Mtn.			0.01146***
			(0.00070)
Snowpack × Midwest			0.00727*
			(0.00405)
Snowpack × Northeast			0.02235***
			(0.00164)
Snowpack^2	-0.00004*	-0.00004*	-0.000009*
	(0.00002)	(0.00002)	(0.000004)
Price (2SLS)	−0.00526***	−0.00528***	−0.00526***
	(0.00077)	(0.00077)	(0.00075)
Property j FE	Yes	Yes	Yes
Day-of-sample FE	Yes	Yes	Yes
Clustered. SE	Market	Market	Market
Observations	6,610,513	6,610,513	6,610,513
McFadden ρ^2	0.29	0.29	0.29
BIC	6,770,282.87	6,770,005.61	6,760,126.80
F-stat (Wald: IV)	204.02***	204.09***	203.4***

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Note: Column 1 summarizes the results from equation 3.4 and the 2SLS estimate of *price* from 3.5. The parameters represent the average marginal utilities associated with the attributes in the model. Standard errors are clustered at the market level. Results for the full set of covariates in equation 3.4 are in the appendix (Table B.2). Full results for the 2SLS estimates for equation 3.5 are in table 3.3. Column 2 and 3 introduce heterogeneity in the marginal utility of snowpack and are recovered for each region using an interaction term between snowpack and the corresponding region of the resort (equation 3.7).

Table 3.2: Marginal Willingness to Pay for Snowpack

	(1) National Average	(2) West-East Regions	(3) NSAA Regions
Snowpack	\$2.40 [2.38, 2.43]		
Snowpack × Mtn.-West		\$2.22 [2.20, 2.24]	
Snowpack × Central-East		\$3.93 [3.89, 3.98]	
Snowpack × West-coast			\$1.79 [1.74, 1.82]
Snowpack × Rky. Mtn.			\$2.18 [2.17, 2.19]
Snowpack × Midwest			\$1.38 [1.33, 1.42]
Snowpack × Northeast			\$4.24 [4.22, 4.26]
Snowpack^2	-\$0.01 [-0.01, -0.01]	-\$0.01 [-0.01, -0.01]	-\$0.002 [-0.002, -0.002]

Krinsky-Robb 95% confidence intervals in brackets

Note: MWTP are calculated using the ratio of the marginal utilities in table 3.1 such that $MWTP = \beta/\lambda$. Empirical distributions of MWTP are calculated using the Krinsky-Robb approach (Krinsky and Robb, 1986).

Table 3.3: 2SLS Results with Different Price Instruments

	2SLS			OLS
	(1)	(2)	(3)	(4)
	BLP-IV and Schedule-IV	BLP-IV Only	Price-IV Only	Reduced Form
Price	-0.00526^{***}	-0.00307^{***}	-0.00319^{***}	-0.00243^{***}
	(0.00077)	(0.00047)	(0.00051)	(0.00031)
Bedrooms	-84.01^{***}	-52.72^{***}	-54.53^{***}	-43.71^{***}
	(13.35)	(7.37)	(8.35)	(5.94)
Bedrooms^2	24.56^{***}	15.21^{***}	15.76^{***}	12.52^{***}
	(5.56)	(3.69)	(4.05)	(3.11)
Bathrooms	21.50^{***}	2.37	3.48	−3.14
	(8.05)	(4.86)	(5.44)	(3.46)
Bathrooms^2	8.88^{**}	6.38^{**}	6.52^{**}	5.66^{*}
	(4.06)	(3.10)	(3.11)	(2.97)
Maximum Guests	32.42^{***}	19.97^{***}	20.69^{***}	16.39^{***}
	(5.65)	(4.33)	(4.40)	(4.02)
Maximum Guests^2	−0.83	3.31	3.07	4.50^{*}
	(3.38)	(2.66)	(2.64)	(2.64)
Superhost	0.38^{***}	0.43^{***}	0.43^{***}	0.44^{***}
	(0.04)	(0.05)	(0.05)	(0.05)
Number of Photos	18.78^{***}	15.87^{***}	16.04^{***}	15.04^{***}
	(5.16)	(5.10)	(5.08)	(5.09)
Number of Photos^2	-6.36^{*}	−4.64	−4.74	−4.14
	(3.70)	(3.22)	(3.25)	(3.20)
Distance (meters)	-20.97^{***}	-14.85^{***}	-15.21^{***}	-13.09^{***}
	(5.29)	(3.83)	(4.00)	(3.58)
Distance^2 (meters)	7.79	4.72	4.90	3.84
	(4.98)	(3.72)	(3.80)	(3.29)
Entire Home	0.99^{***}	0.67^{***}	0.69^{***}	0.58^{***}
	(0.17)	(0.17)	(0.16)	(0.15)
Private Room	0.35^{**}	0.22	0.23	0.18
	(0.17)	(0.16)	(0.16)	(0.16)
Total Days Available	-65.27^{***}	-63.62^{***}	-63.71^{***}	-63.14^{***}
	(6.23)	(6.50)	(6.48)	(6.40)
Total Days Available^2	42.42^{***}	44.36^{***}	44.24^{***}	44.91^{***}
	(4.01)	(3.76)	(3.78)	(3.85)
Median Home	-28.81^{***}	-15.27^{***}	-16.06^{***}	-11.38^{***}
	(6.16)	(4.13)	(4.39)	(3.51)
Median Home^2	91.84^{***}	91.75^{***}	91.75^{***}	91.72^{***}
	(32.30)	(30.27)	(30.38)	(29.77)
Market FE	Yes	Yes	Yes	Yes
Clustered. SE	Market	Market	Market	Market
Observations	33,636	33,636	33,636	33,636
Adjusted R^2	0.188	0.226	0.225	0.228
Deg. of Fred.	33,524	33,524	33,524	33,524
F-stat (Wald: IV)	204.02^{***}	76.55^{***}	68.74^{***}	—

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Table 3.4: Market-level Marginal Utilities

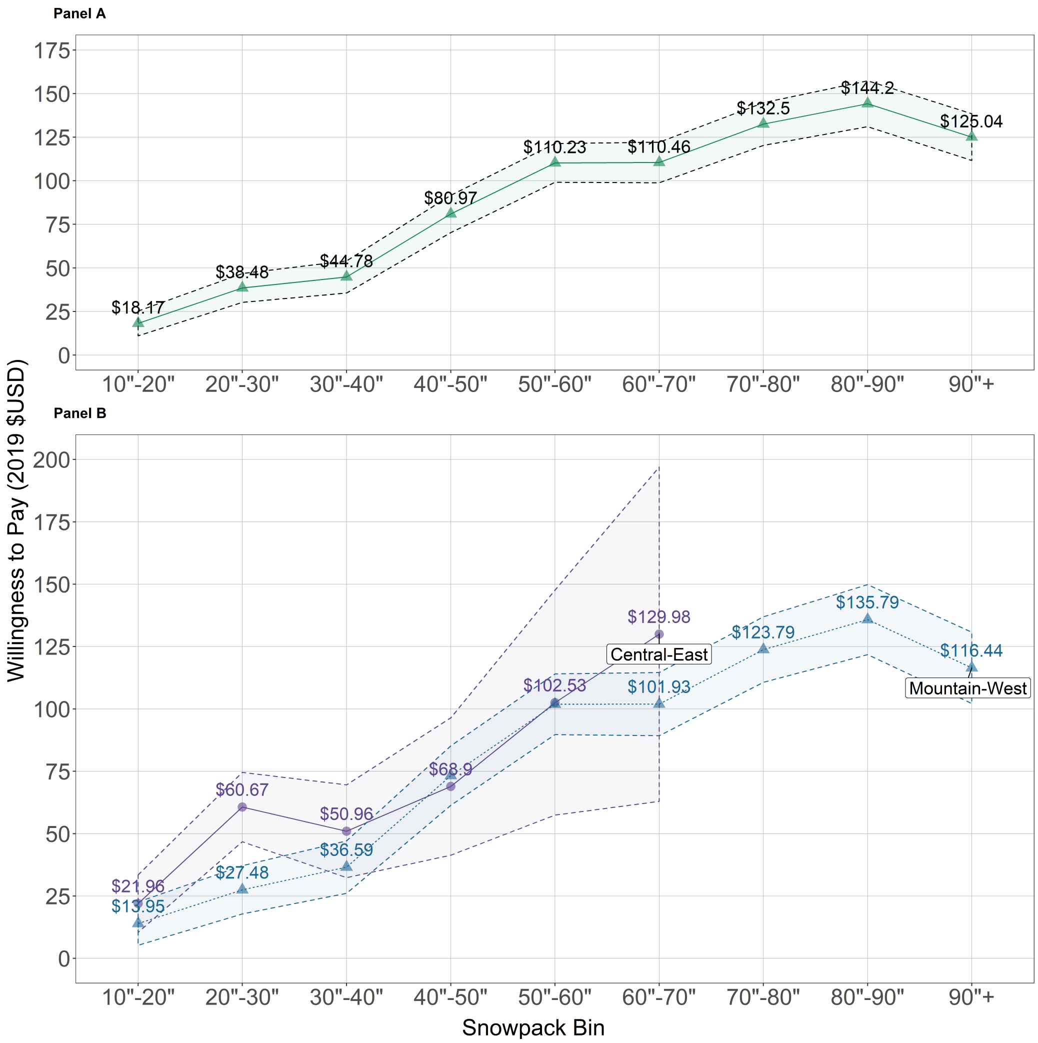
	(1) Mean (λ, β)	(2) Std. Dev
Price	-0.040***	0.023***
	(0.012)	(0.005)
log(snowpack)	0.827***	0.016
	(0.122)	(0.622)
State FE	Yes	
Season FE	Yes	
Holiday FE	Yes	
Clustered. SE	NSAA Region	
Observations	5,937	
F-stat (Wald: IV)	81.02***	

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Note: Skiers have a positive and significant marginal utility of snowpack and a negative and significant marginal utility of price. Price has a statistically significant standard deviation; however, I find no unobserved heterogeneity in the marginal utility of snowpack (i.e. the standard deviation of $log(snowpack)$ is not statistically different than 0).

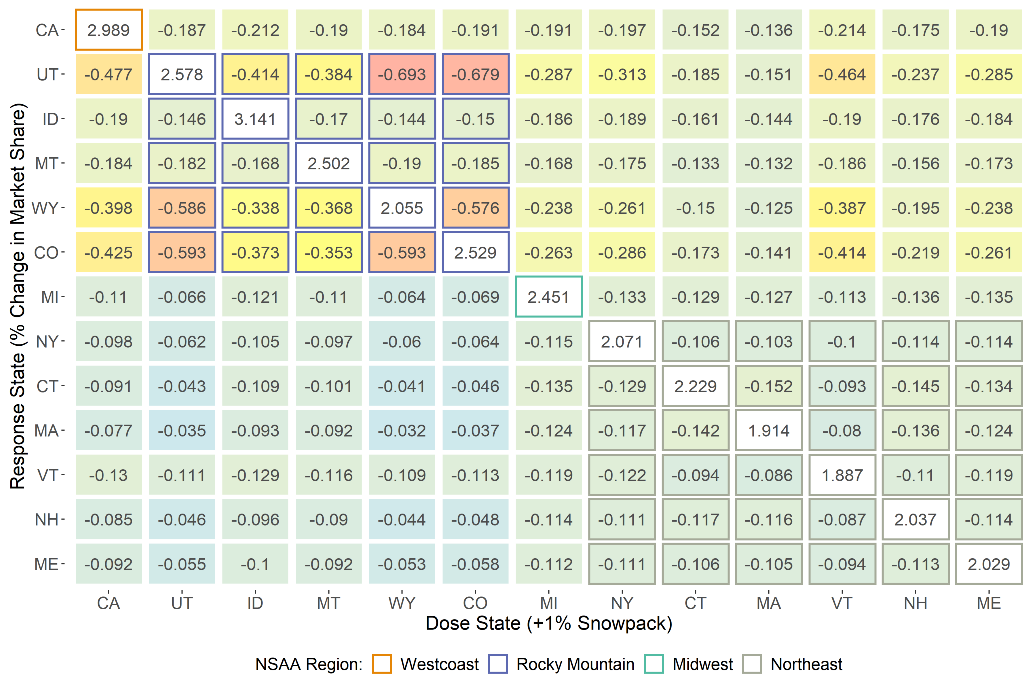
3.8 Figures

Figure 3.1: Willingness to Pay for Discrete Snowpack Bins



Note: Willingness to Pay is nonlinear in snowpack. Here, I present discrete bins of WTP for snowpack nationally (Panel A) and for Mountain-West and Central-East Regions (Panel B). This is WTP for snowpack only, not accounting for other characteristics of a trip that the skier might value separately. Regions are largely similar in WTP. However, the Mountain-West region is steadily increasing and statistically distinct in each incremental bin with deeper snowpack up to 70-80 inches and then flattens out—not statistically different between each bin above the 70-80 inch bin.

Figure 3.2: Own and Cross Snowpack Elasticities



Note: Substitution is larger in the Mountain-West states: California, Utah, Idaho, Montana, Wyoming, and Colorado, suggesting that skiers in these states are quite responsive to changes in snowpack within their own region. The Central-East states do experience substitution, but relatively smaller in magnitude than their western counterparts. One interesting finding is that Vermont is particularly affected when it experiences an increase in snowpack. Western states such as Utah, Wyoming, and Colorado, observe a 0.4 percentage point drop in market shares when Vermont receives a 1 percent increase in snowpack. This is likely due to Vermont skiers staying in their own state when conditions are good, but traveling to western states when conditions are bad.

CHAPTER 4

OVERLOOKED BENEFITS OF NUTRIENT REDUCTIONS IN THE MISSISSIPPI RIVER BASIN

4.1 Introduction

Nutrient pollution and hydrological disruption cause water quality impairments throughout the Mississippi River Basin (MRB) and serious problems with widespread oxygen depletion called hypoxia in the Gulf of Mexico (U.S.EPA, 2008).[1] The U.S. Environmental Protection Agencys 2008 Gulf Hypoxia Action Plan (GHP) tasked the 12 upstream states with the responsibility of reducing their transmission of nutrients such as nitrate-nitrogen and phosphorus by 45% by the year 2040. In an approach similar to the other states in the MRB, agencies in Illinois created the Illinois Nutrient Loss Reduction Strategy (INLRS) to coordinate efforts in that state to meet the nutrient reduction targets. The INLRS promotes voluntary efforts by farmers to reduce nutrient runoff into local waters, but a major policy change such as state subsidies will be needed to accomplish the 2040 goals (Coppess, 2016). State agencies and lawmakers are, therefore, interested in how much their own residents would support efforts to meet the INLRS targets. How much value do residents of the MRB gain from changes to water quality in their local watersheds, and to what extent do people in a state like Illinois value their local watersheds contribution to non-local improvements such as reducing the scale of the hypoxic dead zone in the Gulf of Mexico?

Integrated assessment of surface water quality policies and management actions can benefit from information about the total values of changes in water quality and the distribution of those values among different groups of people. A host of previous studies has shed light on the values people place on some dimensions of pollution reduction in particular parts of the U.S. That work is surveyed in Bergstrom and Loomis (2017); meta-analyses

[1]This chapter is based in part on work funded by USDA-NIFA Grant #1008843.

of those studies have informed benefit transfer efforts to estimate aggregate benefits of water quality changes at the national level (Johnston, Besedin, and Stapler, 2017; Moeltner, 2019). Use values for water quality have been directly estimated at the national scale by quantifying the impact of the Clean Water Act on average housing prices (Keiser and Shapiro, 2018). There is also a long line of research exploring the differences between use and nonuse values from local and nonlocal improvements in surface water quality in the U.S. (Greenley, Walsh, and Young, 1981; Lant and Roberts, 1990; Carson and Mitchell, 1993; Johnston, Besedin, and Wardwell, 2003; Houtven, Powers, and Pattanayak, 2007) and recent work has emphasized the need to examine these relationships when considering the benefits from policies that reduce hypoxia in the Gulf of Mexico (Babcock and Kling, 2015; Keiser, Kling, and Shapiro, 2019). This paper advances research on water quality valuation and integrated assessment with a choice experiment survey that estimates three conventional benefits of water quality improvements (improvements in local fish populations, fish diversity, and reductions in local algal blooms) and previously overlooked benefits (local contributions to reaching a regional nutrient reduction target) that arise from policies targeting hypoxia in the Gulf of Mexico.[2] We then illustrate how to use those values in a spatially disaggregate integrated assessment of a land-use policy or management plan and explore two dimensions of value heterogeneity.

Benefit-cost analyses often aggregate the benefits of environmental improvements to all people affected by the policy. However, many policy makers and interest groups are particularly concerned about the net impact of agricultural-environmental policies on rural residents (Gibbs, 2016; Farber, 2018). Evidence regarding preference heterogeneity between rural and urban areas is mixed. Some academic research shows that urban residents give more support for environmental policies than people in rural areas of the U.S. (Salka, 2001). However, other research in environmental sociology finds little difference between rural and urban residents in their interests for environmental quality (Arcury and Christianson, 1993; Mobley, 2016). Racevskis and Lupi (2006) find rural residents in Michigan are less likely to support

[2]Phaneuf (2002) estimates use values within a watershed for achieving total maximum daily load targets (nutrient reductions). We extend this analysis to estimate the local (within the watershed) benefits of contributing to regional, downstream (outside the watershed) nutrient reduction targets.

forest management efforts involving conservation, but conclude this is likely because those rural communities rely on forests products for production or exports. (Melstrom, Lupi, Esselman, and Stevenson, 2015) find that urban rivers and streams are less valued than rural rivers for recreational fishing, but do not estimate the differences in preferences between rural and urban recreationists themselves. Thus, we fill a knowledge gap by testing whether the values that people place on water quality improvements vary between people in urban and rural areas in the heart of the Mississippi River Basin (MRB).

Previous research in stated preference valuation shows that spatial dimensions matter in other important ways. First, willingness to pay (WTP) for an environmental improvement can vary widely across space (Johnston and Duke, 2007; Brouwer, Martin-Ortega, and Berbel, 2010). In particular, people often have higher WTP close to the improvement (Sutherland and Walsh, 1985; Hanley, Schlpfer, and Spurgeon, 2003; Czajkowski, Budziski, Campbell, Giergiczny, and Hanley, 2017a; Glenk, Johnston, Meyerhoff, and Sagebiel, 2019). Second, researchers have found that when estimating WTP for a change that has a specific location in the landscape, the quality of responses from stated preference surveys depends on how clearly the survey describes the location of the change relative to the respondent (Schaafsma and Brouwer, 2013; Johnston, Holland, and Yao, 2016). Our survey shows respondents exactly where they live relative to the proposed improvements. We also vary distance from the improvement experimentally across alternatives to identify how WTP varies with exogenous distance from the good.

We find that people place economically significant positive and significant values on local water quality improvements and on helping to achieve basin-wide success in reducing hypoxia in the Gulf of Mexico. We do not find evidence of joint differences in preferences between rural and urban residents in the same watershed. We do, however, find that rural residents and people who are familiar with nutrient pollution problems place more value on moving away from the status quo conditions in the watershed regardless of the improvements a program produces. Finally, we demonstrate how these estimates can be used in spatially disaggregated integrated assessments, where benefit totals and distributions depend on spatial details of the improvements and the population that stands to gain.

4.2 Application

Freshwater systems throughout the U.S. Midwest have been severely altered due to decades of intensive agriculture production (Manifold and Swamp, 1998; Alexander, Smith, Schwarz, Boyer, Nolan, and Brakebill, 2008). Tributaries located within the upper MRB carry excess nutrients, byproducts of intensive agriculture production, to the Mississippi River where they are eventually released into the northern Gulf of Mexico. An overabundance of these nutrients contributes to the large seasonal hypoxic dead zone off the cost of Louisiana and Texas (Diaz and Rosenberg, 2008; Rabalais, Daz, Levin, Turner, Gilbert, and Zhang, 2010; Rabotyagov, Kling, Gassman, Rabalais, and Turner, 2014).

This paper surveys people in the Upper Sangamon River Watershed (USRW) in central Illinois 4.1. This watershed is listed as a priority watershed due to its high levels of nitrate-nitrogen and phosphorus transmission within the MRB (U.S.EPA, 2008, 2013). The population in the study area is diverse and includes large swaths of rural landscape with several urban clusters. The characteristics of the USRW are representative of many watersheds in the MRB. This, this area provides an excellent setting for examining value differentials and policy-induced distributional effects across rural and urban populations in the MRB.

State agencies, Extension personnel, researchers at the University of Illinois, and people from groups like the Illinois Farm Bureau have been active communicating about the INLRS in the state, explaining the goals of the INLRS and how agricultural practices such as cover crops, reduced tillage, and riparian buffers can reduce nutrient loadings. It has been shown that stated preferences for environmental goods, and the underlying latent consequentiality of a survey, are more reliable when the policies that are being proposed include established practicesas is the case in our survey (Whitehead, Blomquist, Hoban, and Clifford, 1995; LaRiviere, Czajkowski, Hanley, Aanesen, Falk-Petersen, and Tinch, 2014; Czajkowski, Giergiczny, and Zawojska, 2015; Czajkowski, Vossler, Budziński, Wiśniewska, and Zawojska, 2017b).

4.2.1 Choice experiment methodology

Choice experiments are widely used to elicit preference for nonmarket environmental amenities such as water quality in rivers and streams. Using this platform allows us to model preferences in the random utility (RUM) framework (McFadden, 1974). Preferences are characterized by estimating the probability a respondent chooses a scenario from a set of alternatives with varying levels of environmental quality (Hanley, Wright, and Adamowicz, 1998).

Each respondent began the survey by reading a consent form describing the purpose and nature of the survey and gave consent to continue with the survey. They were then presented with a background section that provided basic information about nutrient pollution problems in the MRB and the general nature of the improvements to be evaluated in the survey. After the respondent read the background section, they answered six choice questions and supplemental questions about personal characteristics.

We held a series of focus groups throughout the watershed with attendees from the general population. They were asked to take the survey and participate in a 30-minute follow-up discussion. In response to focus group feedback, we revised the survey to incorporate their suggestions regarding ambiguities in management mechanisms and wording of the attribute changes. We deployed the survey in a pre-test with 79 completed surveys (474 observations) and adjusted the levels of the cost attribute so that all levels were chosen with some frequency. Finally, we distributed the survey to a randomly selected group of respondents living within the watershed.

4.2.2 Consent and background

Several features of the survey were designed to increase respondent belief in consequentiality and prevent concern about agricultural regulation that might trigger protest responses. The consent form explained that "information from this survey will help policy makers, economists, and watershed managers choose how and how much to improve water quality in your area." The University of Illinois is regionally known to be connected to state policy makers and agricultural decision makers, supporting the claim that the survey will be consequential.

The background section of the survey tells respondents about the national goal for nutrient loss reduction to reduce the size of the hypoxic zone and the nutrient pollution reduction target for Upper Sangamon River watersheds contribution to that goal. This section explains that the proposed environmental changes would come from changes in local agriculture such as expanded cover crops, reduced tillage, and riparian buffers; these voluntary and subsidized practices can reduce sediment and nutrient runoff from the surrounding area and are currently well-accepted and widely used by farmers throughout the region. The survey scenarios with water quality improvements from such changes in agricultural practices are within the range of future actions actually being discussed in the state, and thus not entirely hypothetical. In the survey background we explicitly state "change will NOT result in a change in agricultural acreage or profits" to further prevent concern about the profitability of local agriculture from being confounded with the value people would gain from environmental improvements.[3]

4.2.3 Choice questions

A choice question is posed in a "card" that shows a set of scenarios and asks the respondent to choose the scenario they like most. In our survey, each scenario in a choice card has seven experimentally varied attributes. Four of those attributes relate to biophysical characteristics of water quality, two capture spatial heterogeneity, and one is the payment necessary to implement the proposed improvements. Table 1 summarizes each attribute, specifying the status quo and improved levels of each attribute. Our CE survey is tightly coupled to biophysical models of watershed improvements; the levels of the biophysical attributes were informed by the work of hydrological and ecological modelers in the USRW. Botero-Acosta, Chu, and Huang (2019) modeled predicted changes in nutrient levels throughout the USRW resulting from hypothetical changes in local agricultural practices. Andres, Chien, and Knouft (2019) use these predicted changes in nutrient levels, climate, and data from 110 monitoring sites across the USRW, to model changes in aquatic biodiversity.

Three of the four biophysical attributes related to water quality are local

[3] The full survey text can be found in C.1.

and one is non-local. Number of fish species and population of fish (two independent attributes) are local quantitative measures summarizing the current average number of distinct species of fish (diversity) and populations of individual fish per 100 linear yards of river (density). Dissanayake and Ando (2014) find that Illinois residents have positive value for both species diversity and faunal density in grassland birds; we test whether people value two such attributes of fish in inland streams. Local water quality improvement is captured as percent reductions in the frequency of occurrence of algal blooms in the local watershed including streams and ponds; that ranged from 0% to 75% reduction. The fourth nutrient-pollution attribute describes the likelihood that this watershed succeeds in meeting its targets for reductions in the level of nutrient transmission to the Gulf are met and ranges from 0% (definitely will not succeed) to 100% (certain to succeed).

Local water quality-related changes from a nutrient-loss reduction strategy are not uniform throughout a watershed, but rather depend on local details such as depth, flow rate, and shade. We partition the watershed into four equally sized sections. Each choice scenario alternative specified the section of the watershed in which water quality attributes improved. The location attribute varies as part of the experiment design; as a result, distance (measured as the distance from each respondent to the improved section of the watershed) also varies experimentally.

The final attribute in the choice scenarios is the household payment necessary to achieve the proposed improvements, cost. We use an increase in annual county fees as the payment vehicle, verifying with focus groups that this is a salient and credibly binding mechanism for payment. The survey states that the fee will be passed on to renters through an annual increase in rent charged by the landlord. An example of a survey is in C.1. 4.2 shows that all attribute levels were chosen with some frequency by respondents

We designed the survey to increase estimation efficiency while maintaining reliability in WTP estimates. In theory, choice experiments are only demand revealing if they are incentive compatible (Carson and Groves, 2007) and while a dichotomous choice design (one status quo and one alternative) is often argued to be incentive compatible, trichotomous choice (one status quo and two alternatives) is not. However, trichotomous choice increases the amount of information recovered from each survey response and some research shows that values are similar between the two mechanisms (Collins and Vossler, 2009; Czajkowski et al., 2017a). Thus, we include two alternatives along with the status quo on every choice card.

In stated preference research, hypothetical bias can influence estimates of WTP (Cummings et al., 1995; Cummings and Taylor, 1999), we include a modified cheap talk script in the information section of the survey and an opt-out reminder on each choice card to mitigate such bias (Ladenburg and Olsen, 2014).[4] After each choice card, we also include certainty questions asking how sure the respondent was of the selection they just made (Ready, Champ, and Lawton, 2010; Penn and Hu, 2020).[5]

4.2.4 Experimental design

We develop an optimal orthogonal choice matrix resulting in a D-efficient experiment design (Adamowicz, Louviere, and Swait, 1998b; Hensher, Rose, and Greene, 2005; Street and Burgess, 2007; Ferrini and Scarpa, 2007). As recommended in Ferrini and Scarpa (2007), the design is optimized for main effects with zero priors ($\beta = 0$) to produce a reliable design when the true underlying data generating process is unknown and prior information on parameter values is not available. We produce 18 unique choice cards from the full factorial design, divided into three blocks of six choice cards. Respondents are randomly assigned one of the three blocks of six choice cards. The number of cards and alternatives are chosen to limit cognitive burden for the respondents while maintaining statistical power to estimate WTP (Swait and Adamowicz, 2001; Caussade, de Dios Ortzar, Rizzi, and Hensher, 2005).

After an initial design was created, we impose two additional conditions for the final design and re-run the design if the conditions are not met. The first condition is a no-free-lunch restriction (improvement in any attribute will

[4]The cheap talk script included in the information section read: "Experience from previous similar surveys is that people often say they would be willing to pay more money for something than they actually would. For example, in one study, 80% of people said they would buy a product, but when a store actually stocked the product, only 43% of people actually bought the new product. It is important that you make each of your upcoming selections like you would if you were actually facing these exact choices in reality. Note that paying for environmental improvement means you would have less money available for other purchases."

[5]The question asked: "How confident are you in your answer?" With the range: "0 - not at all confident"; "1 - somewhat confident"; and "2 - very confident." We use these responses to re-code any uncertain responses to the status quo alternative. Results and discussion are available in the appendix (Table C.6).

come at a non-zero cost) and a welfare improving restriction (no improvement across all attributes cannot come at a cost). The second condition checks if any of the 18 resulting choice cards had an alternative that was strictly dominated by another alternative on the same card (e.g. a higher level of improvements at a lower cost). After seven iterations of the two-step procedureeach iteration consisting of many design iterations in the first stepall conditions are met.[6]

With the exception of location and distance, we allow the status quo level of each attribute to be randomly included in the improved (non-status quo) scenarios. We include an alternative specific constant (ASC) in the experimental design (and regressions) to represent the status quo alternative on the choice card. The ASC captures preferences that the respondent may have for maintaining the status quo that are unobservable and not otherwise contained in our experimental design.

4.2.5 Individualized maps and choice card generation

Following recommendations highlighted in Johnston et al. (2016), each alternative on a choice card includes an individually geocoded map highlighting the section of river that would experience the improvements and a marker locating the respondent within the watershed relative to the proposed improvements. Each map is created for the individual respondent and geocoded using ArcPy integration in ArcGIS. Eight towns and city centers distributed throughout the watershed are geolocated to provide a you are here marker in each map. The total number of combinations of choice cards, alternatives, and geolocations results in 432 different individualized maps and 432 different levels for the distance attribute listed as an attribute on the choice card.

In order to accommodate the individualization of alternatives and choice cards, we create images of the choice cards by integrating the mail-merge capabilities of Microsoft Publisher, referencing an underlying matrix of all individualized combinations of the experiment design. The resulting pages of the document are then extracted by the survey protocol using Python to cre-

[6] We generated the design using the *dcreate* package implemented in Stata (Hole, 2015). We created a wrapper for the *dcreate* package that allows us to impose the additional conditions on the design.

ate an image for each page representing a choice card in the experiment. The 432 choice cards images are then stored online using Amazon Web Services and referenced in real-time while the respondent was taking the survey.

4.2.6 Other survey questions

We designed the survey instrument to test for potential preference heterogeneity between residents who identify as rural, and those who identify as urban. That characteristic was examined in two dimensions: 1) geographical affiliation; and 2) cultural affiliation. The first, geographical affiliation, is simply determined using the U.S. Census Bureaus classification of rurala census block group area with less than 1,000 residents per square mile (Ratcliffe, Burd, Holder, and Fields, 2016). Respondents who fit this designation are classified as living in a geographically rural area, all others are classified as living in an urban area. The second, cultural affiliation, is determined by the respondents stated affiliation in the post-survey questionnaire. The question is phrased as: "Do you consider where you live to be rural?" Respondents in our sample overwhelmingly responded with a cultural affiliation that aligned with their geographical affiliation. Our design allows us to test the hypothesis that preferences for water quality are the same between those who live in a geographically and culturally rural area and those who live in a geographically and culturally urban area.

To understand other characteristics of the respondents in our survey sample, we ask two sets of personal questions. Three questions come before the choice questions and ask about the frequency with which people had seen algal blooms, how often respondents visit the river to go fishing, and how often they recreate nearby the river. A section after the choice questions contains common demographic and socioeconomic questions.

4.2.7 Survey administration

The survey was administered online using a Qualtrics panel of respondents through their survey interface, paired with additional JavaScript and HTML to incorporate the individualized choice cards.[7] Respondents were recruited

[7] The first wave of survey responses was collected from January, 2019, through February, 2019. A second collection period was administered January, 2020, through February, 2020.

from the 42 zip codes contained within the watershed. Once a respondent received an invitation to take the survey, they would arrive at the online interface where they were asked to enter their zip code. If the zip code was not one of the 42 qualifying, they would be screened and exited from the survey. The next step individualizing the CE was to ask respondents which of the eight locations (towns or city centers) they lived closest to. Their response would then cue the system to load a randomly ordered set of choice cards. Our final sample has complete responses from 343 individuals.

4.3 Econometric Framework

Following choice experiment methodology (Hanley et al., 1998), we assume that a respondent derives utility based on the observable characteristics contained within the choice card, and some characteristics unobservable to the researcher Specifically, U is the utility respondent i derives by choosing alternative j on choice card t:

$$U_{ijt} = -\alpha_i p_{jt} + \boldsymbol{\beta}_i' \boldsymbol{x}_{jt} + e_{ijt} \tag{4.1}$$

where $\boldsymbol{x}$ is a vector of attributes is, p is the price (cost) of the scenario, and e is the stochastic component (taste-shock) capturing unobservable characteristics influencing the respondents choice and is IID distributed extreme value. Included in x is an alternative specific constant (ASC) that is equal to 1 for the status quo alternative in each choice set, and 0 otherwise. β is the vector of preference coefficients, and α is the coefficient on cost. Both β and α are indexed to be respondent-specific when estimated using a random parameter logit model (Train, 1998).

The variance of error term also varies with each respondent such that: $Var(e_{ijt}) = k_i^2(\pi^2/6)$ where k is the scale parameter for respondent i. Variation in the error term can be attributable to scale heterogeneity or other forms of correlation between the model attributes, particularly so in panel (repeated choice occasion) settings such as ours (Swait and Louviere, 1993; Train and Weeks, 2005; Hess and Train, 2017). Dividing the preference parameters by the scale parameter where $\lambda_i = (\alpha_i/k_i)$ and $c_i = (\beta_i/k_i)$ results in a specification that has the same variance for all respondents:

$$U_{ijt} = -\lambda_i p_{jt} + \boldsymbol{c}_i'\boldsymbol{x}_{jt} + \varepsilon_{ijt} \tag{4.2}$$

where ε is IID type-one extreme value, now with a constant variance: $\pi^2/6$. With k in the denominator of each coefficient, allowing the coefficients to be independent (not correlated) would constrain the scale parameter to be constant for the sample while allowing the preference parameters to vary, or vice versa (Louviere, Street, Carson, Ainslie, Deshazo, Cameron, Hensher, Kohn, and Marley, 2002). Equation 4.2 is the model in preference space (Train and Weeks, 2005). To avoid the postestimation difficulties in deriving empirical distributions of WTP (Train, 1998; Daly, Hess, and Train, 2012; Carson and Czajkowski, 2019), we choose to estimate our model in willingness to pay space directly (WTP-space) (Train and Weeks, 2005; Scarpa, Thiene, and Train, 2008).[8] This is a standard reparameterization of equation 4.2 such that $wtp_i = (c_i/\lambda_i)$; utility is then represented by:

$$U_{ijt} = -\lambda_i p_{jt} + \lambda_i \boldsymbol{wtp}_i'\boldsymbol{x}_{jt} + \varepsilon_{ijt}. \tag{4.3}$$

Equation 4.3 is the specification in WTP-space (Train and Weeks, 2005). We specify the vector of WTP parameters $\boldsymbol{wtp}$ to be distributed normal and the coefficient on cost, λ, is distributed log-normal as recommended by Train and Weeks (2005). We specify the distributions of the random parameters to be fully correlated, estimating a full covariance matrix and corresponding correlation coefficients for the random parameters in the model. We follow Thiene and Scarpa (2009) and estimate the model using maximum simulated likelihood. Halton draws were used in the maximum-likelihood simulation. The first N prime numbers were used to generate the draws, where N is equal to the number of random parameters in the model.[9]

To develop estimates of total WTP and its distribution throughout the watershed for hypothetical improvements in water quality, we allow for location-specific and individual-specific heterogeneity in estimates of MWTP by recov-

[8] We also estimate our models using conventional preference-space specifications. These specifications, along with their discussion, can be found in the appendix (Tables C.7 and C.8.

[9] All specifications and analyses are modeled using the *gmnl* package in R (Sarrias and Daziano, 2017). All data and replication files can be found at the following DOI: doi.org/10.5281/zenodo.3692738.

ering the conditional individual specific means of the parameters in equation 4.3 (Greene, Hensher, and Rose, 2005; Meyerhoff, Boeri, and Hartje, 2014). This is discussed in more detail in section 4.5 when we discuss the integrated assessment exercise.

4.4 Results

Our sample is evenly divided between people in rural (53%) and urban (47%) areas, and 56% of the sample own homes instead of renting (Table C.1). Respondents are predominantly white (78%) and female (68%); the former is consistent with the actual demographics of the area. Our sample has broad representation of age, income, and education categories, and the distributions in our sample are similar to the U.S. Census demographics for this area (Table C.2).[10] This is an area with little in-migration; half the people in our sample have lived in the area for more than 30 years, and only 10% have lived there for 10 years or fewer. Table C.3 summarizes the results of testing for observable differences between rural and urban respondents. The two subsamples are mostly similar, except that urban respondents are more likely to hold a graduate degree and less likely to participate in recreational fishing and hiking.[11]

Figures 4.3 shows the distributions of answers to qualitative questions about familiarity with local algal blooms and water quality concerns described in the survey. Nearly 80% of the sample reported having at least some familiarity with the water quality issues discussed in the survey and about the same number of respondents reported experience with algal blooms in the rivers or connected bodies of water. Fewer than 20% of respondents report having fished in the USRW at all. However, nearly 50% reported having visited the river or walked trails near the river (Figure C.1).

Table 4.2 presents the main regression results, estimating equation 3 (WTP-space) for the full sample. The regression in Column 1 includes just the core model parameters. The regression in Column 2 introduces an interaction term between the status quo dummy (ASC) and respondent characteristics.

[10] Figure C.2 maps data from the 2013-2018 American Community Survey (ACS) for the watershed (U.S.Census, 2019).

[11] The results of testing for observable differences between rural and urban respondents can be found in the appendix (Tables C.7 and C.8).

All mean WTP coefficients in Column 1 are statistically significant at the 1% level or better. The coefficient on the status quo (no program) option is large and negative and suggests respondents strongly prefer having a water-quality improvement program than not. The coefficient on distance is also negative—people prefer a program focused on the river close to where they live. The coefficients on fish species and fish population are positive; people would be willing to pay nearly $5 per year to have an additional species of game fish in the river, and they separately place a positive value on the total number of individual fish in the river. The coefficients on algal blooms and nutrient target are positive. People would gain utility from reducing the frequency of these local problems in their watershed, with an average annual MWTP of $0.77 for a one percent reduction in the frequency of algal blooms. Respondents also place a large value on nutrient target, with an average annual MWTP of $0.95 for a one percentage point increase in the likelihood of achieving the watersheds nutrient loss target.

The large MWTP to move away from the status quo suggests that respondents have strong preferences for having a new program instead of the status quo regardless of the variable attributes in our choice scenarios. Column 2 explores two factors contributing to these preferences. Respondents who live in more rural areas of the watershed and respondents who were familiar with surface water issues in the area are willing to pay significantly more for moving away from the status quo. Rural residents are estimated to value this move from status quo $49 more than urban residents. Those who reported being familiar, very familiar, or very familiar and involved with watershed quality issues value this move from the status quo $66 more than those who were less aware.

Full regressions for the separate urban and rural sub-samples are in Table C.4 of the appendix. A LR test of joint preference stability tests the fit of separate regressions for the two sub-samples against the constrained pooled sample in column 1 (see Table C.4). We fail to reject the null that MWTP are jointly similar across the two sub-samples. While preferences for the status quo may vary, the holistic set of preferences is consistent between urban and rural respondents in this watershed.

4.5 Integrated Assessment Application

To illustrate how benefits from water quality improvements are distributed throughout the watershed, we recover the conditional individual-specific means of MWTP for every respondent in our sample (Greene et al., 2005). We use the primary specification in our analysis 4.2 to recover conditional individual-specific means. For each zip code in our sample, we average the MWTP over the respondents who lived in that zip code. This gives us zip code level variation in the MWTP for each attribute.

Zip codes are considered rural if there are fewer than 1,000 residents per square mile, and urban otherwise (Ratcliffe et al., 2016; U.S.Census, 2019). This allows us to tally welfare changes separately for the rural and urban areas in the USRW. The distributions of MWTP in the rural and urban zip codes are as expected and have significant overlap.[12]

Policy simulations, or state-of-the-world experiments, simulate a change in the levels of the environmental attributes to recover an individuals total WTP for the suite of improvements over the status quo level (Holmes, Adamowicz, and Carlsson, 2017). For example, an individuals WTP for a change in attribute x_1 is their MWTP for x_1 multiplied by the change in x_1's level: $WTP_{x_1} = MWTP_{x_1} \times \Delta x_1$. If more than one attribute is changing, then the individuals WTP for changes in both attributes is the sum of their WTP for each attribute j that is changing:

$$WTP = \sum_{j} MWTP_{x_j} \times \Delta x_j. \tag{4.4}$$

Because we have zip code specific MWTP for each attribute, we estimate changes in welfare for each zip code under different states of the world. Moreover, in zip code z over households N, the total WTP for improvements in a set of attributes indexed by j is:

$$WTP_z = \sum_{n} \sum_{j} (MWTP_{x_j|z} \times \Delta x_j)_{n|z}. \tag{4.5}$$

From equation 4.5, the total WTP in the watershed is simply the sum of WTP_z over all zip codes in the USRW.

[12] A full summary of the recovered conditional individual-specific means of the MWTP for each attribute can be found in the appendix (Figure C.3).

Table 4.3 summarizes the results of our policy simulations. Panel A identifies the scenarios, Panel B considers benefits from only the environmental attributes in the model, and Panel C adds to Panel B by also including the benefits from moving away from the status quothe MWTP associated with the ASC in our model. The first scenario models a 50% reduction in only the frequency of algal blooms in river section A. Scenario 2 models this same improvement except for river section C. This allows us to hold all other attributes constant to see how benefits might accrue differently depending on where the improvement takes place. Scenario 3 models a 75% likelihood that the watershed reaches it nutrient loss target of 45% by the year 2040. Scenario 4 introduces a more complete improvement scenario where river section A sees a 75% reduction in the frequency of algal blooms, sections A and B receive an additional 50 fish (population) per 100 yards of river, section A receives an additional 2 species of game fish per 100 yards of river, and a 100% likelihood of reaching the watersheds nutrient target.

Reducing the frequency of local algal blooms in just one of the four reaches of the watershed yields around $1 million to $1.6 million per year depending on the location of the improvement (Table 4.3, Panel B, columns 1 and 2). A 75% likelihood of reaching the nutrient target is worth $4.4 million per year (Table 4.3, Panel B, column 3). Finally, the most comprehensive scenario (Table 4.3, Panel B, column 4) yields benefits of around $7 million per year.

Table 4.3 also provides a summary of the average values per household for each of the scenarios. Household WTPs are calculated at the zip code level. We provide the average WTP for each scenario throughout the watershed as well as the average WTP in the rural and urban areas separately. Reducing algal blooms by 50% has an average value of $9 or $15 per year depending on where in the watershed it occurs, and the average value of a 75% change of the watershed doing its part for hypoxia reduction is $39 per year per household. The comprehensive scenario in column 4 produces average benefits of $63 per year per household.

To see where the benefits from the policy simulations accrue throughout the watershed, Figure 4.4 provides maps of both the total WTP (Panel A) and the per household WTP (Panel B) in each zip code. Benefits are most dense where population is most dense (Panel A). However, when we map benefits based on per household estimates, we see the distribution is often higher in the rural areas throughout the watershed (Panel B).[13] Rural areas tend to receive larger benefits because the river sections—and the corresponding improvements—are mostly in rural areas of the watershed.

4.6 Discussion

We have carried out a CE survey to estimate how much people in a sub-watershed of the Mississippi River Basin are willing to pay to improve local fish diversity and populations in their rivers, reduce the prevalence of local algal blooms, and ensure that their watershed does its part to hypoxia in the Gulf of Mexico. While current efforts in the MRB to reduce nutrients and sediment are driven by concern about water quality far away in the Gulf, we find that people in our study area would gain significant benefit from the local environmental improvements that could result from reduced nutrient pollution and from helping to reduce environmental problems in the Gulf.

Much traditional research on water quality values has focused on generic measures of whether waters are boatable, fishable, and swimmable, and the resulting values can be quite small (Keiser et al., 2019). In contrast, we find that people would gain large value from reducing the frequency of local algal blooms, with respondents willing to pay nearly $40 per year to reduce the frequency of nearby algal blooms by 50%. Algal blooms are becoming more prevalent as climate change expands hot summer conditions; our result implies that economists and water quality modelers should pay increased attention to the impact of management and policies on those particularly harmful manifestations of nutrient pollution.

Residents of the central Midwest gain no use value from reducing hypoxia in the Gulf of Mexico. However, we find that people in our study area would gain utility from increasing the likelihood that their watershed reaches the target set for it under the Illinois Nutrient Loss Reduction Strategy; the average respondent would be willing to pay $48 to have even a 50% chance of the watersheds goal being met. This finding provides further compelling

[13] Refinements could be made when modeling WTP throughout the watershed, or for use in transfer to similar watersheds, using spatial regression methods such as those discussed in Johnston, Besedin, and Holland (2019) or DeValck and Rolfe (2018). However, the focus of this paper is to provide a proof of concept for estimating the distributional effects of policies related to water quality that span geographically and culturally diverse landscapes.

rationale for the work on nutrient loss in which government agencies, NGOs, and industry groups are all currently engaged.

Our estimates suggest that people in this landlocked part of the Midwest would gain large value from improving local game fish diversity and fish populations. This result seems to be capturing significant non-use values for having thriving river ecosystems in the region since only a small fraction of respondents reported engaging in local fishing. Most previous research on the value of fish species and populations comes from travel cost and recreational site-choice models that can only capture use values (Phaneuf, von Haefen, Mansfield, and Van Houtven, 2013; Melstrom et al., 2015). The large nonuse values we estimate in this study support the well-known claim that revealed preference estimates may not capture the full range of benefits from environmental improvements (Adamowicz, Boxall, Williams, and Louviere, 1998a; Hanley and Czajkowski, 2019).

Economists, other social scientists, and policy makers have wondered if there is a rural-urban divide in the values people place on environmental improvements. In this case, we find that rural and urban preferences are similar. If anything, rural residents may place more value on a move away from the status quo towards environmental improvement. This finding implies that people in the rural areas that implement many of the changes needed to improve water quality may also have high willingness to pay for those improvements themselves.

Finally, the results from our simple simulations suggest that the total values water quality improvement could bring to a watershed like our study area are not trivial. For the USRW alone, total WTP for reaching a 75% likelihood of reaching nutrient reduction targets (scenario 3) is estimated at approximately $4.4 million dollars annually. And when modeled with improvements that will likely come as compliments for any policy targeting reductions in nutrient loss and transmission to the Gulf (scenario 4), total annual benefits within this small watershed are estimated to exceed $7 million dollars per year.

Debate over nutrient loss reduction strategies continues. To inform that debate, analysts should quantify the full range of costs and benefits and how costs and benefits are distributed among groups of people in the landscape. Our findings can play an important role in that effort. However, more work needs to be done in order to further uncover and understand the overlooked benefits of reductions in nutrient loss and transmission. Future research would do well to explore how values vary throughout the MRB for improving local fish habitat, avoiding local algal blooms, and solving regional environmental problems like hypoxia in the Gulf. Additional work is also needed to understand the factors driving people in our study to express such strong antipathy for a status quo that does nothing to address pervasive surface water pollution in the U.S.

4.7 Tables

Table 4.1: Survey Attributes and Levels

Attribute	Levels (SQ)	Description
Fish Species	(1), 2, 3, 5	Number of different recreational game fish species per 100 yards of river
Fish Population	(15), 30, 45, 150	Number of all fish (any species) per 100 yards of river
Algal Blooms (%)	(0), 25, 50, 75	Percent reduction in the frequency of local algal blooms
Nutrient Target (%)	(0), 50, 75, 100	Likelihood that nutrient runoff from this watershed is reduced by the target of 45 percent by 2040
Location	A, B, C, D	The section of river where the improvements will be received
Distance	(varies)	The distance in miles from the respondent to the nearest point on the location attribute. This depends on where the respondent lives and which location is represented in the scenario.
Annual cost	(0), 5, 15, 30, 60	Payment vehicle: annual county fee (e.g. property tax)

Note: Status quo levels for each attribute are presented in parentheses. All attributes listed except for distance were included in the experiment design.

Table 4.2: MWTP to Reduce Nutrient Transmission to the Gulf of Mexico

	(1) Full Sample		(2) ASC Heterogeneity	
	Mean MWTP	Std. Dev.	Mean MWTP	Std. Dev.
Distance (miles)	-0.67***	92.57***	-0.68***	1.22***
	(0.15)	(18.69)	(0.15)	(0.26)
Fish Species	4.73**	1.06***	4.72**	12.32***
	(1.48)	(0.26)	(1.55)	(2.14)
Fish Population	0.17**	6.58***	0.16**	0.38***
	(0.06)	(2.12)	(0.06)	(0.08)
Algal Blooms (%)	0.77***	0.35**	0.88***	0.96***
	(0.11)	(0.09)	(0.1)	(0.13)
Nutrient Target (%)	0.95***	0.85***	1.14***	0.89***
	(0.13)	(0.16)	(0.13)	(0.12)
Status Quo (No Program)	-69.49***	1.42***	-20.25	77.02***
	(14.78)	(0.23)	(13.48)	(21.19)
Status Quo × Rural			-48.79***	171.45***
			(14.33)	(26.29)
Status Quo × Aware of Water Issues			-65.82***	106.84***
			(16.34)	(21.01)
λ (cost coefficient)	-3.17***	0.85***	-2.71***	0.77***
	(0.32)	(0.13)	(0.42)	(0.12)
Observations (Respondents)	2058 (343)		2058 (343)	
Log-likelihood	-1717.19		-1717.77	
AIC	3506.38		3527.54	
McFadden ρ^2	0.15		0.15	

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Note: Column 1 provides the results of the WTP-space model for the pooled (full) sample. Column 2 introduces an interaction between the Status Quo dummy and respondent characteristics. Correlation matrices of the random parameters can be found in the appendix (Table C.5).

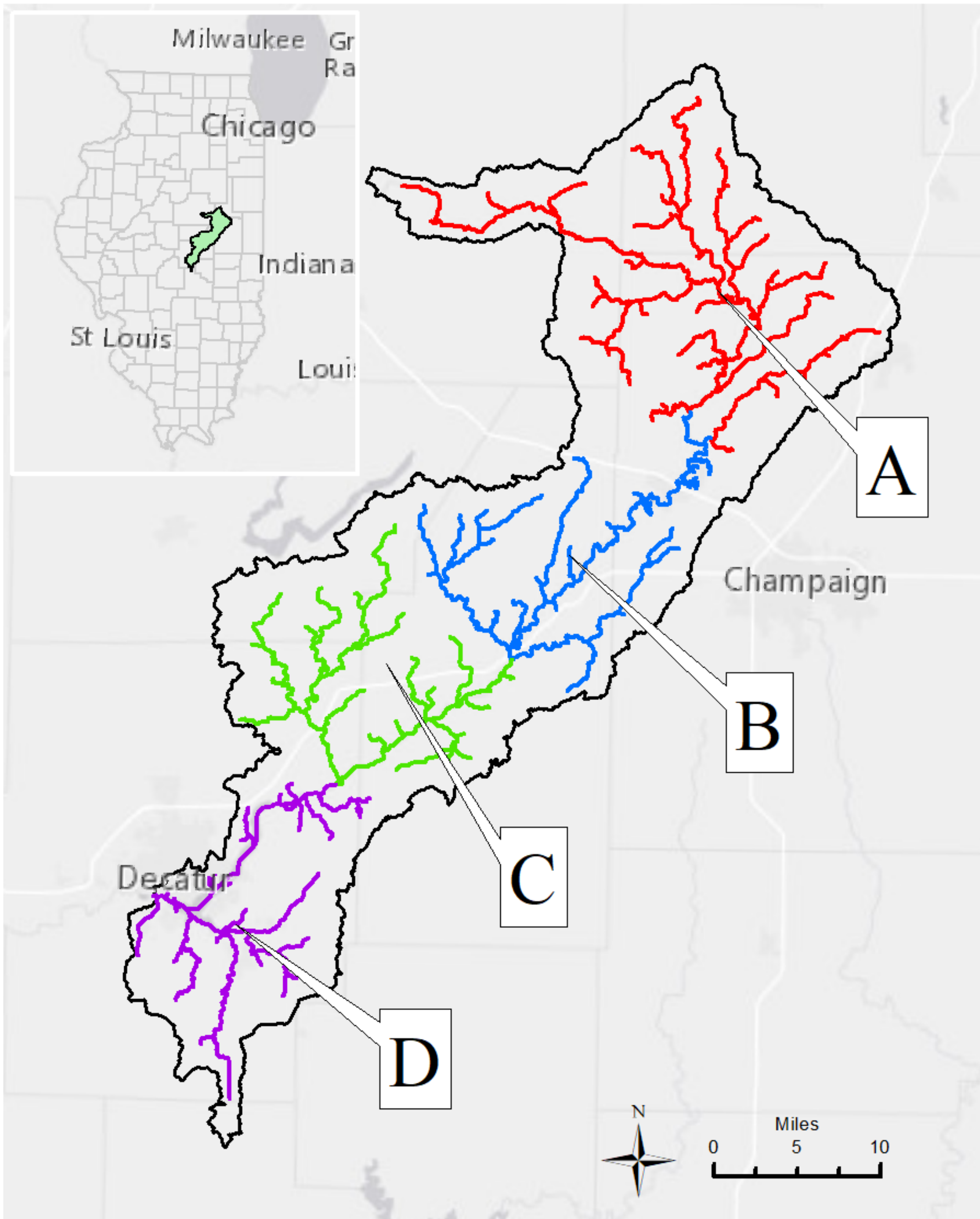
Table 4.3: Sample Integrated Assessment Value Estimates (total WTP)

Panel A: Scenarios	(1)	(2)	(3)	(4)
Algal Blooms	50% reduced Area A only	50% reduced Area C only	-	75% reduced Area A only
Nutrient Target	-	-	75% likelihood	100% likelihood
Fish Species	-	-	-	+2 species Area A only
Fish Population	-	-	-	+50 population Area A and B
Panel B: No ASC				
Annual Benefits	$1,057,497	$1,697,818	$4,406,411	$7,126,757
Rural Areas	$768,279	$985,443	$2,612,890	$4,512,142
Urban Areas	$289,218	$712,376	$1,793,521	$2,614,615
Per Household	$9.30	$14.93	$38.75	$62.67
Rural Areas	$13.51	$17.33	$45.95	$79.35
Urban Areas	$5.09	$12.53	$31.54	$45.98
Panel C: With ASC				
Annual Benefits	$3,648,648	$4,288,969	$6,997,562	$9,717,908
Rural Areas	$2,413,881	$2,631,044	$4,258,491	$6,157,744
Urban Areas	$1,234,768	$1,657,925	$2,739,071	$3,560,165
Per Household	$32.08	$37.71	$61.53	$85.45
Rural Areas	$42.45	$46.27	$74.89	$108.30
Urban Areas	$21.72	$29.16	$48.17	$62.61

Note: Benefits are estimated using equation 5. These are estimates of compensating variation for the improvements modeled in the IAM exercise. In aggregate, rural areas of the watershed stand to benefit nearly twice as much as the urban clusters. Rural areas of the watershed also tend to have a higher per household WTP for each scenario. This is largely because a majority of the improvements will be realized in more rural areas of the watershed.

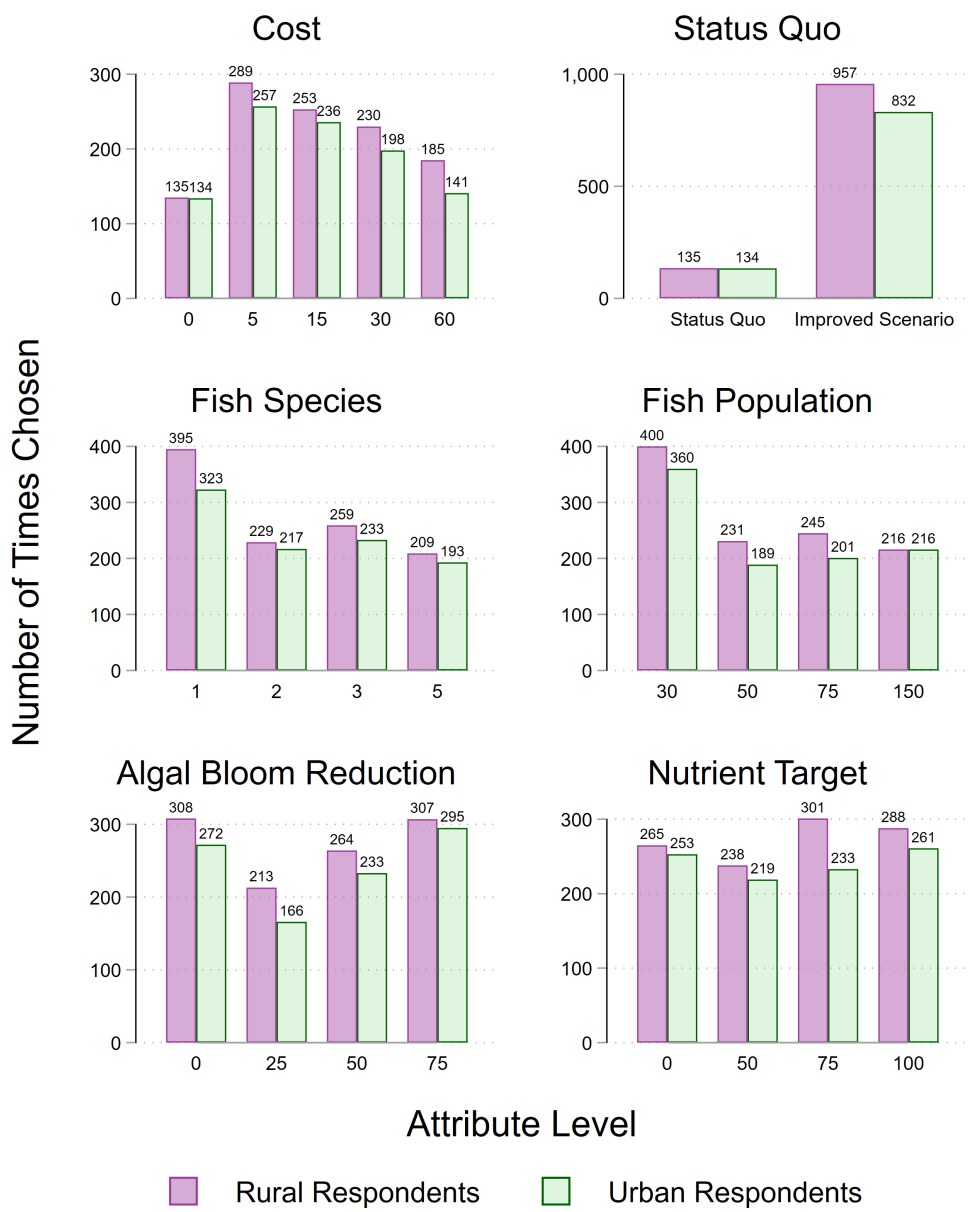
4.8 Figures

Figure 4.1: Study Area in Upper Sangamon River Basin, Central Illinois



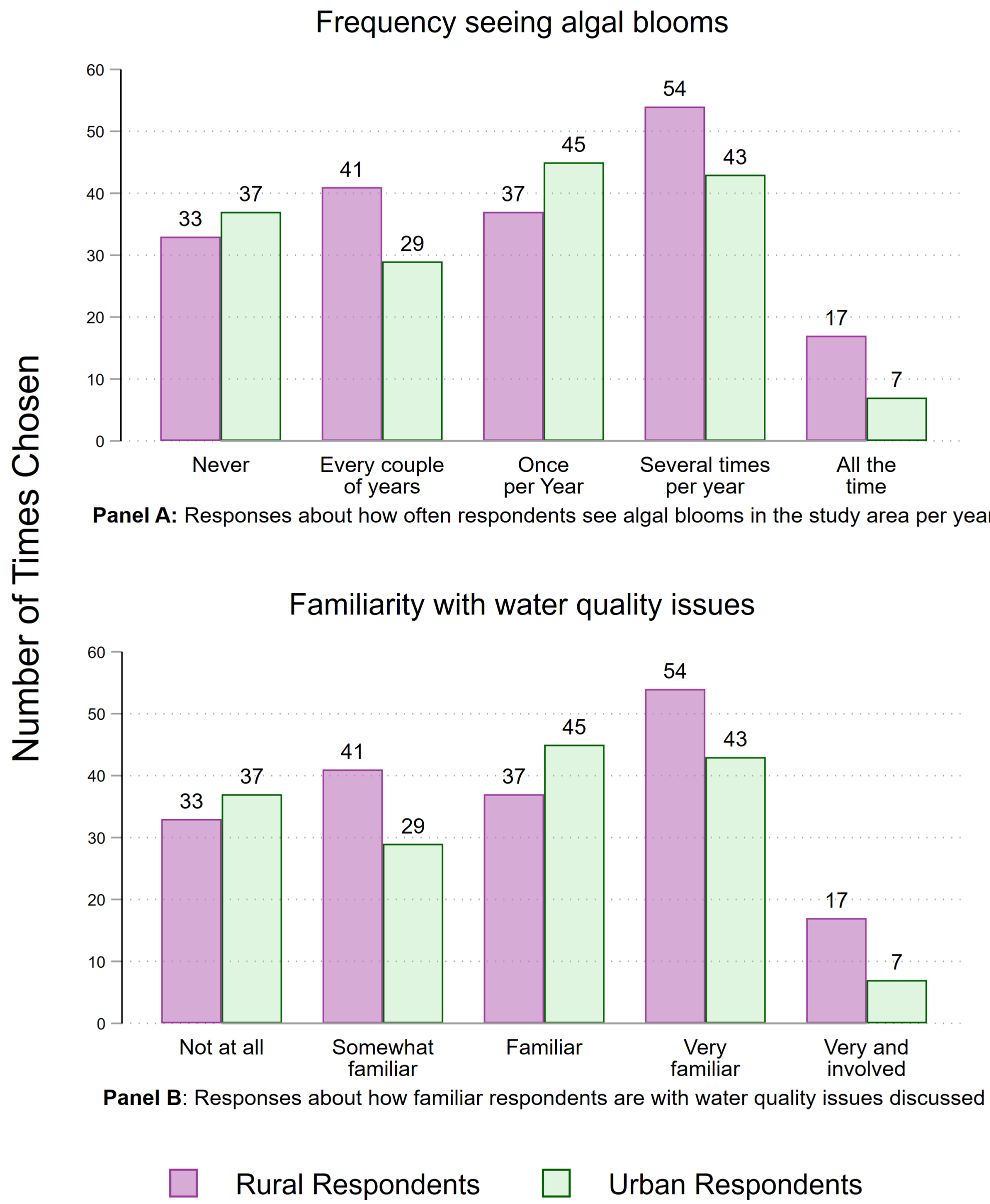
Note: The Upper Sangamon River Watershed, located in central Illinois. It is listed as one of the EPAs prioritized watershed for high transmission of nutrients to the Gulf of Mexico. The four sections of river (A, B, C, D) are highlighted, and included as attributes on the choice card.

Figure 4.2: Frequency of Chosen Attribute Levels



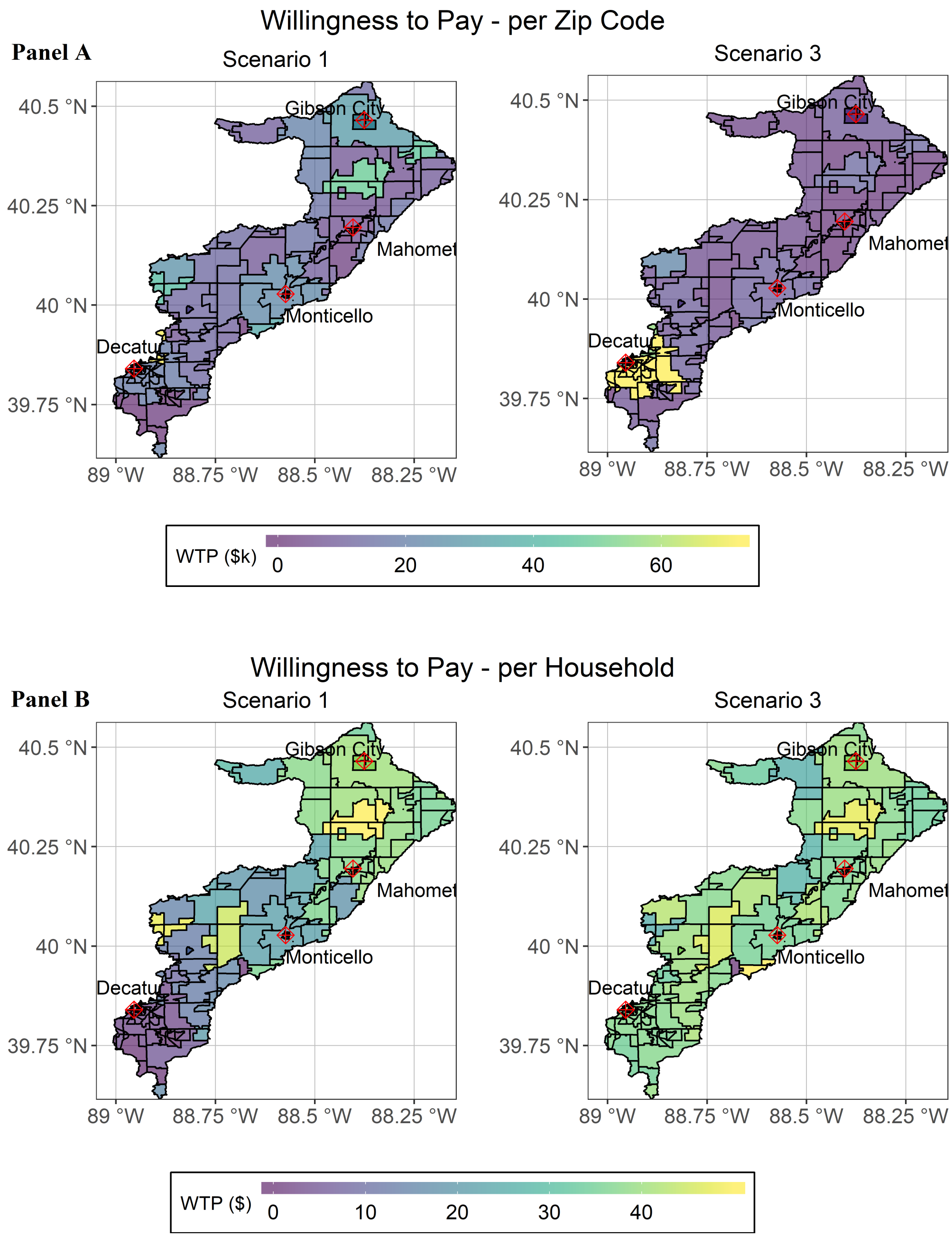
Note: Plots show substantial variation in the levels of each attribute as indicated in the chosen alternative from each choice card. Status quo levels of each attribute are represented in the far-left column of each plot. Fish species and fish population are more represented by the status quo level than the other four attributes.

Figure 4.3: Responses to Questions about Surface Water Quality Awareness



Note: Responses to the post-survey questionnaire about how familiar respondents are to water quality issues in the watershed, and how frequently they experience algal blooms in or in nearby surface water the Upper Sangamon River. Algal blooms are quite frequently observed by respondents and is likely closely related to their awareness of water quality issues. Rural respondents reported more frequently seeing algal blooms and being more familiar with the water quality issues discussed in the survey.

Figure 4.4: Sample Integrated Assessment Value Estimates



Note: Spatial distribution of total WTP in each zip code throughout the watershed (Panel A) and per household MWTP (Panel B). Total benefits accrue in urban clusters where the population is dense. However, on a per household basis we see higher WTP in rural areas than in the urban clusters within the watershed.

CHAPTER 5

CONCLUSION

Throughout this dissertation, I have used both positive and normative approaches to describe environmental goods and services. I have applied empirical methods, supported by economic theory, to quantify several benefits that humans receive from the natural environment. Each chapter is motivated by the idea that one person's actions can often have unsolicited and uncompensated effects on another person. These effects, or externalities, can be distributed to others through channels such as wintertime precipitation and surface waters. In quantifying the benefits that people derive from these environmental amenities, we can say something about how well off people are in different states of the world.

How do people respond to changes in mountain snowpack? In chapter 2, I quantify the behavioral response in outdoor recreation to marginal changes in mountain snowpack. I provide an exposition of what recreation demand might look like under future climate; suggesting that mountain economies stand to lose billions of dollars in revenues each year due to predicted reductions in annual snowpack accumulation. I find a positive relationship between spending on short term property rentals and the amount of snow at a nearby resort. I estimate, on average, that a 1 percent increase in snow at the resort predicts a 0.291 percent increase in revenues from overnight stays. I estimate that by the end of the century, total reductions in revenues for the 26 US states could be between \$1.4 billion and \$2.4 billion dollars per year.

What is the marginal willingness to pay for mountain snowpack? Chapter 3 builds on the previous chapter to provide estimates of the marginal willingness to pay for mountain snowpack. I find that on average skiers in the United States are willing to pay \$2.40 for each inch of snowpack on the ground the day of their trip. This is diminishing at approximately \$0.01 for each additional inch. I do find substantial regional variation, ranging from \$1.38 in the Midwest to \$4.24 in the Northeast. The regional variation in the recreation value of snowpack is likely driven by differences in ski culture, snowpack composition, and geographical characteristics or the resorts. I also estimate a more flexible functional form in the utility function of skiers using a binned specification. This allows me to estimate the WTP in each snowpack bin, which is particularly useful for estimating welfare on a given day. For example, for each day a resort has 40"-50" of snowpack, I estimate the WTP for that snowpack at $110.23. Similarly, a day with 30"-40" of snowpack (one bin down), the WTP is $80.97, or approximately $30 less than the next higher bin. I also examine regional variation in the binned estimates and find that while the Central-East has higher mean WTP in most bins, the point estimates are not statistically different than the Mountain-West estimates for the same bin.

How do skiers choose to substitute across resort markets? In chapter 3, I also derive substitution parameters that map changes in snowpack to recreation decisions. I find that substitution is larger in the Mountain-West states: California, Utah, Idaho, Montana, Wyoming, and Colorado, suggesting that skiers in these states are quite responsive to changes in snowpack within their own region. The Central-East states do experience substitution, but relatively smaller in magnitude than their western counterparts. One interesting finding is that Vermont is particularly affected when it experiences an increase in snowpack. Western states such as Utah, Wyoming, and Colorado, observe a 0.4 percentage point drop in market shares when Vermont receives a 1 percent increase in snowpack. This is likely due to Vermont skiers staying in their own state when conditions are good, but going to western states when conditions are bad relative to Utah, Wyoming, and Colorado.

Do people value clean rivers and streams? In chapter 4, I quantify the benefits of clean surface waters in local rivers and streams. I also estimate local benefits from nonlocal improvments such as reducing nutrient loading far downstream in the Gulf of Mexico. I find that residents of this watershed place a large and positive value on reducing the frequency of algal blooms in their area and the likelihood that their watershed will meet its nutrient transmission reduction targets. They also value on the number of different types of game fish (species) and the total number of all types of fish in the river (population). I also find that values are largely similar across rural and urban residents. The amount that an average person in the watershed is willing to pay for a one percent reduction in the frequency of algal blooms is \$0.77 per year. For a one percent increase in the likelihood of reaching nutrient targets, they are willing to pay \$0.95 per year. The average value of an additional game fish species is \$4.73, and \$0.17 per additional fish of any species. When I aggregate these values across the population in the watershed and simulate feasible changes in the environment such as a 75% reduction in algal blooms, 100% likelihood of reaching nutrient reduction targets, 2 additional fish species and 50 additional fish per 100 yards of river, the total values in the watershed exceed \$7 million per year.

My findings are summarized using assigned values (Segerson, 2017). These are particularly useful for supporting discussions about climate and environmental policy. Externalities from actions and behaviors that drive climate change endanger benefits that stem from mountain snowpack. Externalities from agricultural and urban storm water runoff reduce the benefits people gain from clean surface waters. In both cases, Pigovian taxes could be used to internalize these externalities into the firms and individuals contributing to climate change or polluting rivers and streams. Coasian solutions could involve voluntary contributions from those who benefit from the environmental goods and services. In the case of mountain snowpack, those who value winter outdoor recreation should, in theory, be willing to pay to preserve snowpack and the benefits they receive from the amenity. For example, a \$20 surcharge on a lift ticket would be well below the benefits I estimate from a day of skiing. In the case of surface waters, people who would benefit from cleaner rivers should be willing to pay to maintain or provide these benefits. Revenues from voluntary contributions could be used to directly incentivize the individuals responsible for generating the externalities. Alternatively, the polluters could reimburse the recreationists for the damages they are causing to the environmental amenities. While it is the responsibility of careful policy design to determine the direction of compensation and the existence of property rights, the benefits that I have quantified in the previous chapters provide a benchmark for the magnitude and span of the benefits from mountain snowpack and clean surface waters. They are not, however, comprehensive benefits and should be considered pieces to a much larger puzzle in environmental economics.

APPENDIX A

SUPPLEMENTAL MATERIALS FOR CH. 2

A.1 Primary Specification and Empirical Framework

We use a panel fixed effects model to estimate the relationship between overnight stays (short-term property rentals) and snowpack. We use a $ihs - log$ specification to estimate the elasticity of revenue with respect to changes in snowpack. Elasticities provide a clear interpretation and link directly to the percentage change in snow-water-equivalent (snowpack), which is the relevant parameter given by climate models. The dependent variable (daily revenue) takes a zero when the property is vacant. We assume that it may not be optimal for profit maximizing owners to rent properties on all days as a result of variable costs (maintenance, wear and tear, cleaning, management, etc.). We allow for an equilibrium with vacancies. Any exogenous changes in the owner's profit function (such as a decrease in snowpack) will directly affect expected revenue.

The primary model specification in our paper is the state-specific (s) revenue function:

$$\begin{aligned} ihs(revenue)_{it} = & \underbrace{\sum_s \beta_s \; log(snowpack)_{rt}[State = s]}_{\substack{\text{State-specific} \\ \text{Elasticities}}} \\ & + \boldsymbol{S X'_{rt} \delta} + \boldsymbol{X'_{rt} \eta} + \psi_{im} + \varepsilon_{it}. \end{aligned} \tag{2.2}$$

The β_s in our model can be explicitly defined as:

$$\beta_s = \frac{\partial ihs(revenue)_s}{\partial log(snowpack)_s}. \tag{A.1}$$

We can recover the implicit revenue in state s, analogous to an implicit price in a traditional hedonic specification, using the following equation:

$$Implicit\ Revenue_s = \beta_s \times \frac{\overline{Revenue_s}}{\overline{Snowpack_s}}. \tag{A.2}$$

Implicit revenue can be interpreted in terms of the additional dollar of revenue generated per inch of snowpack in the nearby resort in state s. These are typically evaluated at the mean, using the average revenue and the average snowpack when calculating the implicit value of the nonmarket amenity (Taylor, 2017). Equation A.2 is also the first part of equation 2.4:

$$Rev_s^{snow} = \underbrace{\beta_s \times \frac{AR_s}{HS_s}}_{\substack{\text{Implicit}\\ \text{Revenue}}} \times CS_s. \tag{2.4}$$

The average annual revenue (the numerator in equation 2.4) is the average annual estimate of demand for lift tickets and overnight stays from equation 2.3:

$$\begin{aligned} Annual\ Revenue_s = & \underbrace{Visits_s \times Price_s^{lift\ ticket}}_{\substack{\text{Daily}\\ \text{Visits}}} \\ & + \underbrace{Overnight\ Stays_s \times Price_s^{bed}}_{\substack{\text{Overnight}\\ \text{Stays}}} \end{aligned} \tag{2.3}$$

The average annual revenue term in equation 2.3 consists of two components: (1) daily visits, defined as the average annual number of visits in each state multiplied by the average price of a lift ticket in state s; and (2) overnight stays, defined as the average annual number of overnight stays multiplied by the average price of an overnight stay in state s (the average price per bed from the short term property rentals in our sample). We use this approach to estimate year-to-year variation in the recreation revenue from snowpack that is driven entirely by the level of snowpack each year, and is relative to historical (within sample) averages (independent of annual business cycles and macroeconomic trends).

We compute the historical average recreation revenue from snowpack using the following:

$$Rev_s^{snow} = \beta_s \times \frac{AR_s}{HS_s} \times HS_s = \beta_s \times AR_s. \tag{A.3}$$

The historical recreation revenue from snowpack is defined as the expected annual revenue at the an average snowpack for any year in state s. This quantity reflects the proportion of annual revenue that can be directly attributed to snowpack at the resort. These are reported for each state alongside our main elasticity estimates in Figure 2.1 and in Panel B of Figure A.4.

A.2 Additional Data Descriptions

Daily bookings in short term properties are acquired from a private firm, Airdna.co, which collects the universe of Airbnb, VRBO, and HomeAway listings across the United States (AirDNA, 2017). Rental transaction data for each property include the reservation date, availability (as opposed to blacked out and not available for rent), the price paid, and property characteristics including the number of bedrooms, number of bathrooms, and the approximate coordinates of the home. Coordinates are randomized at the sixth decimal place to maintain the anonymity of an owner's exact location, but are accurate to within 2km. The supply of these properties in each market is updated monthly, which fixes supply within any given month of the sample. The dataset includes more than 1.4 million properties and 410 million bookings spanning the contiguous United States.

We identify all properties located within 10km of the sample of 219 ski resorts in the United States. We construct an empirical sample of 60 thousand unique properties within this radius and 13 million observed property-day bookings. We examine the sensitivity of our revenue function to the choice of a 10km threshold. Estimates generated with a sample that includes all properties within 20km from a resort are nearly identical to the main results, except for larger standard errors that reflect increasing noise associated with booking behavior further away from resorts. Owners of these properties have the option of "blocking" the property for their own use, or have it listed as "available." When a property is rented, it is recorded as "reserved" and the date of the reservation (booking) is recorded.

The climate amenities, *snowpack* and *snowfall*, are acquired from a website (OnTheSnow.com, 2017) that provides daily reports for all 219 resorts in our sample. These amenities are as reported by the ski resort on each day and directly matches the information that a tourist see when making the decision to make a trip. We developed a web scraper that recovers all historical daily climate amenity data from their website, as well as any resort characteristics and lift ticket prices available.

We observe 219 ski resorts in 26 states across the contiguous United States. While approximately 481 resorts exist in the United States, the sample accounts for all major ski areas that contain a rental property within 10km. The resorts not in the sample are in the lower quantiles of ski-able acreage, capacity, and do not represent a significant portion of the economic activity in the population of ski resorts for any single region. 67 resorts fall within 20km of one or more other resorts (resorts that have overlapping buffers). We classify these as unified markets and take the average climate amenity levels observed at each resort (*snowpack*, *snowfall*, and *mean temperature*).

Daily mean temperature is acquired from Oregon State's PRISM Climate Group (PRISM, 2018), which provides a dedicated API that allows researchers to efficiently extract interpolated weather values in raster format. From the raster files, we record the daily mean temperature in each resort market.

Table A.4 provides summary statistics for the data used in our analysis. Column 1 summarizes our full sample and column 2 summarizes the sample when restricted to include only properties that are full-time rentals (no blackout days). Daily rents (*revenue*) range from \$0 to \$5k. All dollar values provided in this paper are measured in real terms using year 2017 \$USD. In our primary sample, the climate amenity *snowpack* ranges from 0 to 225 inches, which reflects the range of daily measurements of snow levels on the ground in each resort. These two variables, *revenue* and *snowpack*, are the primary variables of interest.

A.3 Alternative Specifications and Discussion

A more general form of our primary estimating equation (equation 2.1) consists of a national average revenue function using all markets in the sample.

This specification omits the interaction between *snowpack* and an indicator for each state. Table A.1 summarizes these results. Column 1 estimates the average revenue function for all resort markets and provides a baseline estimate for the parameter of interest β. We estimate the average snowpack elasticity of revenue to be 0.262. This implies that for every 1% reduction in mountain snowpack, revenues will decline by 0.262% on average across the Unites States. To estimate regional heterogeneity in the revenue function, we introduce regional interaction terms with *snowpack* to recover the snowpack elasticity specific for each region k:

$$\begin{aligned} ihs(revenue)_{it} = & \sum_k \beta_s \; log(snowpack)_{rt}[Region = k] \\ & + \boldsymbol{SX'_{rt}\delta} + \boldsymbol{X'_{rt}\eta} + \psi_{im} + \varepsilon_{it}. \end{aligned} \tag{A.4}$$

We explore two forms of regional classification. The first splits the U.S. into two distinct regions, Central-East and Mountain-West. The Central-East region captures everything east of the eastern-most boarders of Montana, Wyoming, Colorado, and New Mexico. The Mountain-West captures Montana, Wyoming, Colorado, and New Mexico, as well as every state west of these four (of the lower 48 contiguous states). The second region classification is determined by the NSAA regional codes shown in Figure A.7.

Columns 2 and 3 in Table A.1 summarize the underlying heterogeneity in the revenue function identified using equation A.4. Column 2 introduces an interaction between *snowpack* and two general regions, Central-East and Mountain-West. Column 3 introduces an interaction between *snowpack* the six regions as determined by the NSAA. Coefficients reported in this table have the same interpretation as our state-specific elasticities. On average, we observed greater responsiveness to marginal changes in snowpack in the eastern regions of the U.S., while the western regions who receive much higher average annual snowfall and more favorable snowpack are less responsive (as measured in percentage point reductions in revenue). All models control for binned *snowfall*, property-by-month-of-sample fixed effects, a cubic of *mean temperature*, and an indicator for *holiday week*.

The underlying characteristics of each rental property might vary with the level of the snowpack at the resort on a given day. For example, when the snowpack is greater, perhaps renters are willing to pay more to be closer to the resort. In order to explore this heterogeneity, we introduce and interaction between *snowpack* and various characteristics, C, of the property:

$$\begin{aligned} ihs(revenue)_{it} = &\sum_{c} \beta_s \ log(snowpack)_{rt}[C = c] \\ &+ \boldsymbol{S X'_{rt} \delta} + \boldsymbol{X'_{rt} \eta} + \psi_{im} + \varepsilon_{it}. \end{aligned} \tag{A.5}$$

Here, C represents variables defining property characteristics. Table A.2 summarizes the results of equation A.5. In column 1 we include the results of the main specification, equation 2.1. Column 2 of table A.2 introduces an interaction between *snowpack* and full-time rentals (properties that are always available for the public to rent — no "blackout days" scheduled by the owner). This sample addresses potential simultaneity resulting from property owners that list their property for rent only when demand is high (Farronato and Fradkin, 2018). This larger coefficient on the rental properties suggests that renters can sort into full-time rentals more quickly, or that owners maintain a personal schedule (blackout days) that is unaffected by demand shocks. Columns 3 and 4 introduce an interaction between *snowpack* and other property characteristics to examine substitution behavior when snowpack is low versus when snowpack is high. We find that revenues increase for nearby properties when snowpack is higher.

We estimate an alternative functional form to model the relationship between *snowpack* and *revenue* by binning *snowpack* into ten 10-inch bins. Explicitly:

$$\begin{aligned} ihs(revenue)_{it} = &\sum_{d} \beta_s \ log(snowpack)_{rt}[Snowpack = d] \\ &+ \boldsymbol{S X'_{rt} \delta} + \boldsymbol{X'_{rt} \eta} + \psi_{im} + \varepsilon_{it}. \end{aligned} \tag{A.6}$$

We also estimate the binned *snowpack* regression within the regional specification:

$$\begin{aligned} ihs(revenue)_{it} = &\sum_{d} \sum_{k} \beta_{dk} \ log(snowpack)_{rt}[Snowpack = d][Region = k] \\ &+ \boldsymbol{S X'_{rt} \delta} + \boldsymbol{X'_{rt} \eta} + \psi_{im} + \varepsilon_{it}. \end{aligned} \tag{A.7}$$

The (now) categorical variable *snowpack* represents the vector of dummy variables for binned snowpack and *Region* specifies if the resort falls in the Central-East or Mountain-West regions. For example, if on day t we observe resort r reporting 35 inches of snow depth, D would be equal to 1 for the 30-40 inch bin. This is represented in Figure 2.2 where the β's are relative daily revenues for each snowpack bin (the reference level of revenue is 0). For example, a coefficient estimate of 1.239 (the 50-60 inch bin) indicates that an additional day with snowpack between 50-60 inches results 123.9% higher revenues relative to no snowpack on the same day. Panel A summarizes the national revenue function using binned *snowpack* (equation A.6, and panel B summarizes the regional binned *snowpack* (equation A.7). In both cases, the revenue functions exhibit diminishing returns to scale. The regional model, however, suggests that losses in the Mountain-West states could be much larger than we estimate if snowpack falls to below 30-40 inches of average snowpack. This poses a particularly large threat to these states and local economies if changes in snowpack falls above the mean predicted by climate models.

As discussed in the introduction of the main text, we demonstrate the implications of using a more coarse level of analysis (monthly) to derive elasticity estimates. This model uses total revenue and the average levels of weather and snowpack in each calendar month. This is comparable to the estimation strategy used in Falk (2010). We do this for both the national average revenue function (the monthly version of equation 2.1) and the state-specific revenue functions (the monthly version of equation 2.2). For month m of season y in resort market r this is:

$$ihs(revenue)_{rm} = \beta \log(snowpack)_{rm} + \boldsymbol{X'_{rm}}\boldsymbol{\delta} + \boldsymbol{\eta}_{rm} + \psi_y + \varepsilon_{rm}. \tag{A.8}$$

The state-specific revenue functions at the monthly level for state s is then:

$$\begin{aligned} ihs(revenue)_{rm} = &\sum_s \beta_s \ log(snowpack)_{rm}[State = s] \\ &+ \boldsymbol{X'_{rm}}\boldsymbol{\delta} + \boldsymbol{\eta}_{rm} + \psi_y + \varepsilon_{rm}. \end{aligned} \tag{A.9}$$

In this monthly specification, the vector $\boldsymbol{X}$ includes the average new snowfall and temperature (containing both a linear and quadratic polynomial) on each day throughout the month; the parameter δ summarizes their relationship with revenue. The parameter η is a resort market by calendar-month fixed effects (i.e. January through December indicator variables). The parameter ψ is a operating season (year) fixed effect. Results from our monthly estimation can be found in Figure A.3. We present state-specific elasticities estimated using monthly data (left), daily data (middle), and the bootstrapped difference between the two (right). We find that the average magnitude of the error ($\beta^{monthly} - \beta^{daily}$) is large. Most states suggest attenuation in the coefficient when we aggregate from daily estimates up to monthly. This can be seen when the difference between the two is less than zero (right panel). The monthly aggregates even yield negative elasticities in some cases, suggesting additional bias in specifications that do not match the temporal variation in amenity levels with the temporal variation in market transactions. The differences were obtained by bootstrapping the estimation of both daily and monthly models 200 times and taking the difference between the coefficients in each iteration. Statistically insignificant coefficients are indicated by a lighter (greyed) shade of marker.

A.4 Additional Tables

Table A.1: Regional Heterogeneity

	(1) National Average	(2) Two Regions West-East	(3) NSAA Regions
log(Snowpack)	0.291**		
	(0.137)		
log(Snowpack) × Mtn.-West		0.278**	
		(0.136)	
log(Snowpack) × Cent.-East		0.537***	
		(0.077)	
log(Snowpack) × Pac. NW			0.260***
			(0.042)
log(Snowpack) × Pac. SW			0.900***
			(0.159)
log(Snowpack) × Rocky Mtn.			0.207**
			(0.105)
log(Snowpack) × Midwest			0.384***
			(0.129)
log(Snowpack) × Northeast			0.507***
			(0.092)
log(Snowpack) × Southeast			0.855***
			(0.217)
Prop. × Month of Sample FE	Y	Y	Y
Weekday FE	Y	Y	Y
Clu. SE: Market	Y	Y	Y
Observations	12,903,718	12,903,718	12,903,718
Adjusted R^2	0.396	0.396	0.396

Standard errors in parentheses — *p<0.1; **p<0.05; ***p<0.01

Note: Column 1 presents the most general specification used in this study, estimating the average revenue function across all 219 resort markets in our data (equation 2.1). Columns 2 and 3 begin to dissect the underlying spatial heterogeneity in the average revenue function (equation A.4). Column 2 introduces an interaction between *snowpack* and two general regions, Central-East and Mountain-West. Column 3 introduces an interaction between *snowpack* the six regions as determined by the NSAA. The coefficients presented in this table are interpreted in the same way as our state-specific elasticities of demand.

Table A.2: Property Characteristics

	(1) Full Sample	(2) Full Time Rentals	(3) Distance From Resort	(4) Other Characteristics
log(Snowpack)	0.291**	0.166**	0.276**	0.156*
	(0.137)	(0.080)	(0.136)	(0.081)
log(Snowpack) × Rental		0.454**		
		(0.210)		
log(Snowpack) × < 2km			0.100*	
			(0.044)	
log(Snowpack) × km				−0.006***
				(0.001)
log(Snowpack) × Beds				−0.033*
				(0.019)
log(Snowpack) × Baths				0.013
				(0.013)
log(Snowpack) × Max Guests				0.011*
				(0.006)
Prop. × Month of Sample FE	Y	Y	Y	Y
Weekday FE	Y	Y	Y	Y
Clu. SE: Market	Y	Y	Y	Y
Observations	12,903,718	12,903,718	12,903,718	12,903,718
Adjusted R^2	0.396	0.396	0.396	0.396

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Note: Column 1 again presents the most general specification used in this study, estimating the average revenue functions for all reservations and all resorts (equation 2.1). Columns 2 through 4 examine sensitivity of this general specification to certain characteristics of the property (equation A.5). Column 2 introduces an interaction between full-time rental properties (i.e. no "blackout" days) and *snowpack*. The average elasticity is larger for rental properties. We hypothesize that this difference is largely due to the fact that owners who occasionally occupy their property likely do so when the snow conditions are most desirable. Column 3 introduces an interaction between *snowpack* and a variable indicating whether or not a property is within 2km of the resort. This result suggests that when snowpack is larger, people prefer to be closer to the resort. The final specification, column 4, further desegregates the characteristics of the property and their relationship with *snowpack*. When snowpack is larger, people prefer to be closer to the resort and exhibit some trade-offs between the number of bedrooms, bathrooms, and maximum number of guests. This suggests that people are substituting for smaller properties that are closer to the resort but allow for more guests (e.g. bunk beds).

Table A.3: Monthly vs. Daily Specifications

	(1) Monthly	(2) Daily
log(Snowpack)	0.125**	0.291**
	(0.054)	(0.137)
Market × Month FE	Y	N
Season FE	Y	N
Clu. SE	Market	Market
Property × Month of Sample FE	N	Y
Weekday FE	N	Y
Observations	2,201	12,903,718
Adjusted R^2	0.756	0.395

Standard errors in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

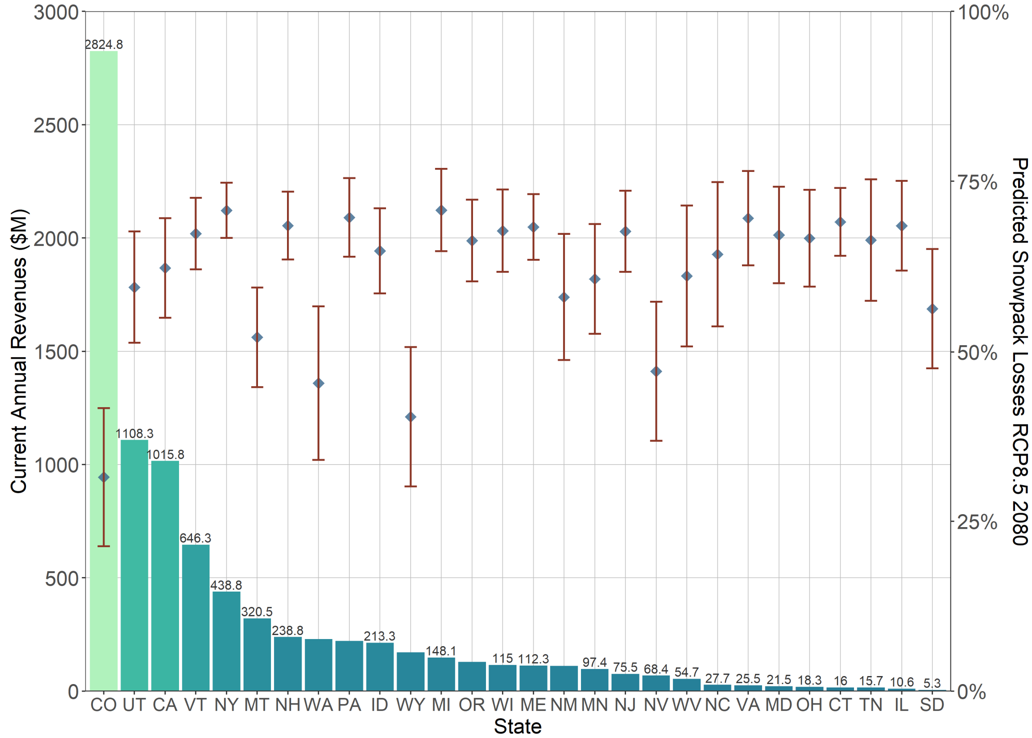
Note: Here we compare average revenue functions when estimated at different temporal scales (equations A.8 and 2.1). Column 1 represent the results of the monthly-level of observations (equation A.8). Monthly-level analyses are the finest (most granular) temporal scale offered in the existing literature. Column 2 estimates using the full set of daily observations (equation 2.1), which is the method we develop in this paper. The average snowpack elasticity of revenue is 45% smaller than the estimate derived from the daily specification. The attenuation could be due to various forms of bias that are introduced when aggregating to the monthly level. First, measurement error (classical) can be exacerbated during aggregation. Second, monthly observations must relax the vector of fixed effects from a *property* × *month-of-sample* controls to a more vulnerable set of two additive controls: (1) *market* × *month*; and (2) *season* fixed effects. Relaxing these can introduce unobservable variation across months (time varying) as well as unobservable variation in the market structure of the rented properties (time invariant). Figure A.3 summarizes the difference between monthly and daily estimates at the state level, along with bootstrapped differences between the point estimates.

Table A.4: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Revenue	12,903,718	86.62	257.46	0	0	0	4,990
Snowpack	12,903,718	41.36	31.82	0.00	16.00	59.55	225.00
Snowfall ($<$ 24hrs)	12,903,718	0.81	2.35	0	0	0.2	48
Reserved	12,903,718	0.17	0.38	0	0	0	1
Reservation Lead-time	12,903,718	67.40	69.07	1.00	20.00	87.00	364.00
Holiday Week	12,903,718	0.11	0.31	0	0	0	1
Mean Temp (F)	12,903,718	30.22	11.18	-17.09	23.05	38.43	71.49
Distance to Resort (m)	12,903,718	4,769.14	2,994.52	6.77	2,135.41	7,589.33	9,998.69
Bedrooms	12,903,718	2.47	1.24	1	2	3	7
Bathrooms	12,903,718	2.14	1.08	0	1	3	8

A.5 Additional Figures

Figure A.1: Current Annual Revenue and Predicted Snowpack Loss

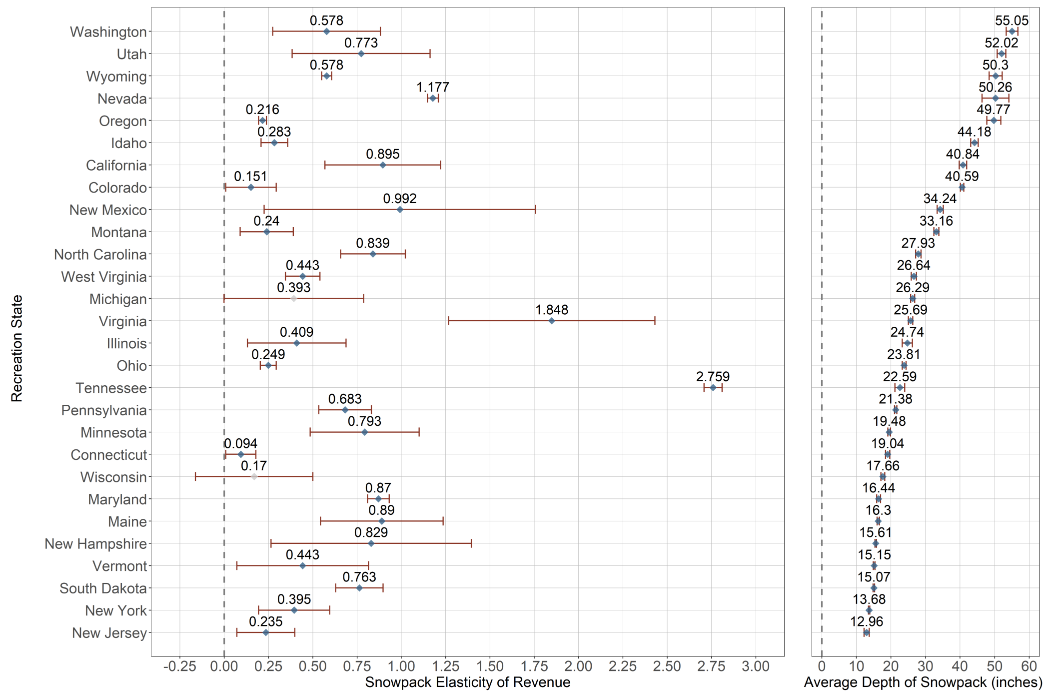


Note: Figure A.1 provides a summary of current (average) annual revenues and the predicted loss in average snowpack under RCP8.5 according to the suite of CMIP5 climate models. Current (average) annual revenues (in millions) in each state s consist of 2 cost components and are calculated as:

$$\begin{aligned} Annual\ Revenue_s = \quad & Annual\ Visits_s \times Lift\ Ticket\ Price_s \\ & + Annual\ Overnight\ Stays_s \times Mean\ Overnight\ Price_s. \end{aligned}$$

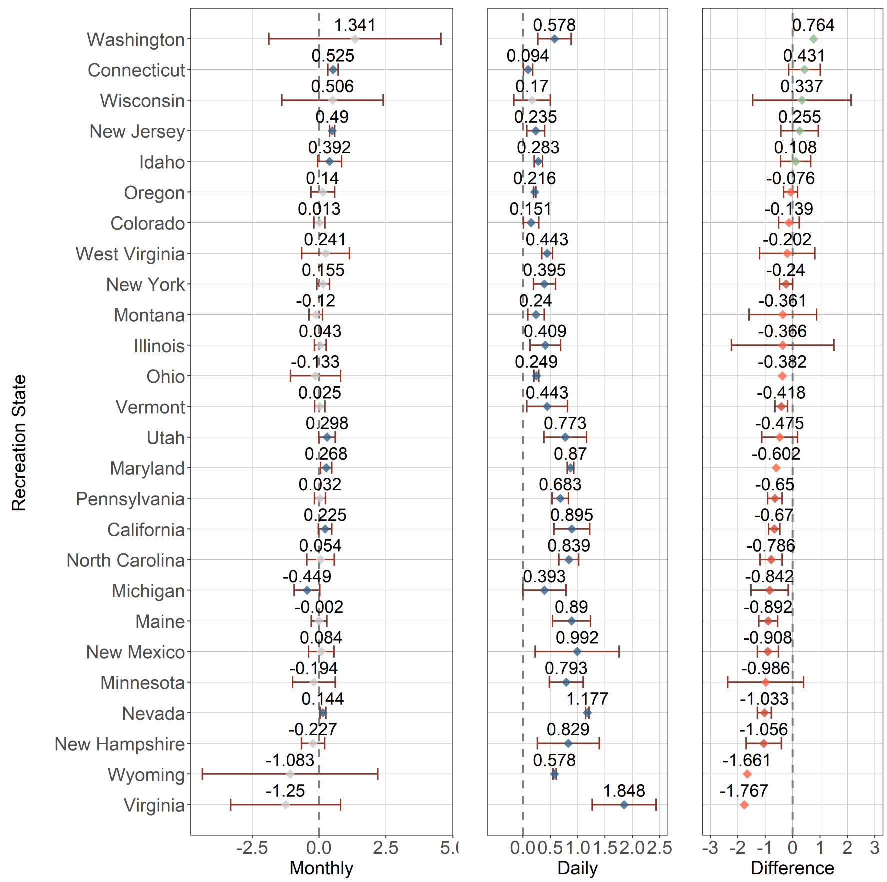
This is also equation 2.3 from the main text. Visitation statistics are drawn from NSAA (2018). Total average annual revenue across all 26 states is estimated at $8.82 billion per year.

Figure A.2: State-specific Elasticity Estimates



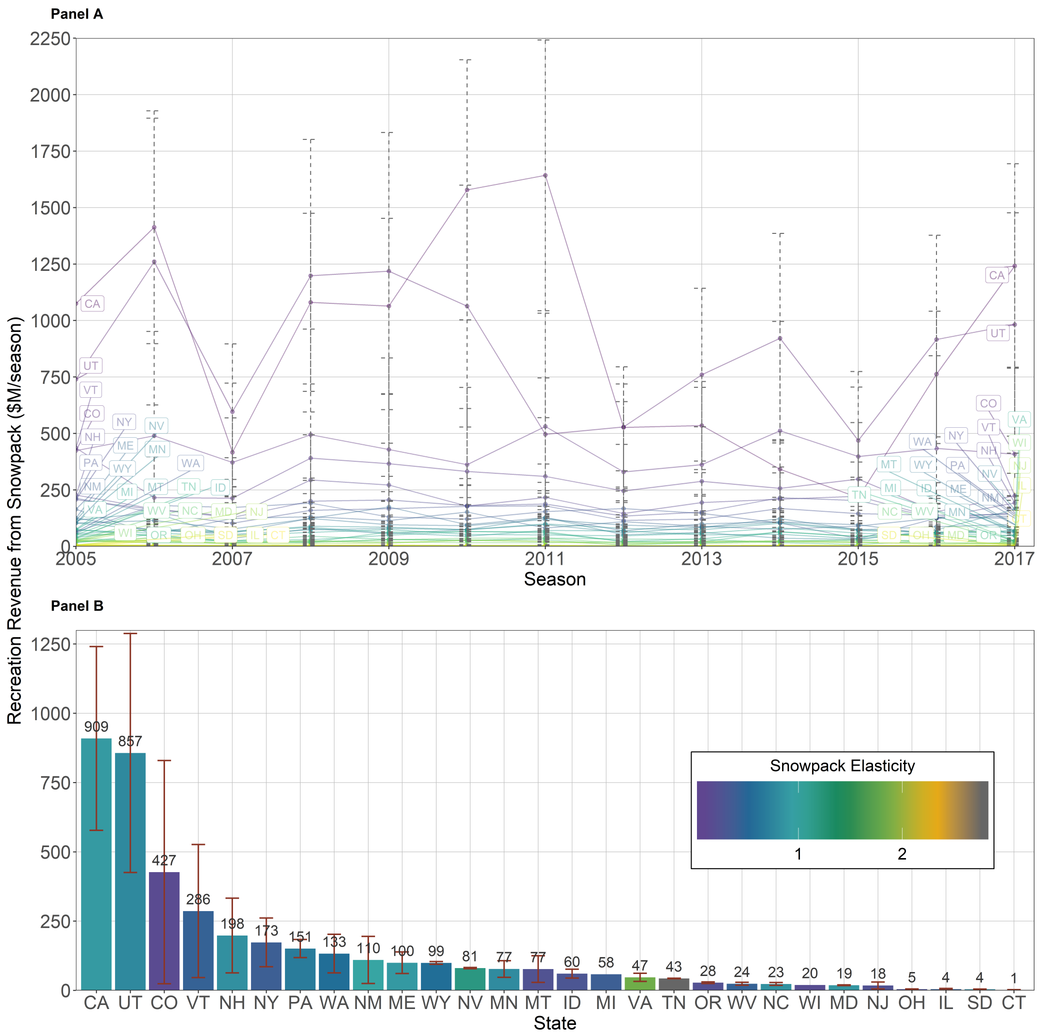
Note: Figure A.2 presents heterogeneity in elasticity estimates by state. Each represents the slope of the revenue function in each market, the state-specific β's specified in equation 2.2. Coefficients are ranked in order of states with the highest average snowpack (top) to states with the lowest average snowpack (bottom). This is an alternative presentation of figure 2.1 that ranks coefficients by average recreation revenue from snowpack. The elasticity estimates in Figure 2.1 and Figure A.2 are the same, and are used to estimate the annual recreation revenue from snowpack in each state (equation 2.4). Variation in elasticity estimates across states is important for generating expectations about revenue under future climate as baseline revenue, contemporaneous snowpack, and future climate, all vary significantly across states. Providing state-specific estimates of snowpack elasticities allows each state to update their own expectations of annual revenues with the responsiveness of snow-tourists to their state's changing snowpack.

Figure A.3: Monthly vs. Daily Estimates



Note: Figure A.3 presents state-specific elasticities estimated using monthly data (left), daily data (middle), and the bootstrapped difference between the two (right). The daily estimates are the primary estimates used throughout our analysis. The average magnitude of the error ($\beta^{monthly} - \beta^{daily}$) is large. Most states suggest attenuation in the coefficient when we aggregate daily observations up to the monthly level. This can be seen when the difference between the two is less than zero (right panel). In many cases, the monthly aggregates even yield negative (although statistically insignificant) elasticities, suggesting additional bias is introduced in the estimation of a model that does not match the temporal variation in the level of the amenity with the frequency at which the market transactions are taking place. The differences were obtained by bootstrapping the estimation of both daily and monthly models using 200 iterations and taking the difference between the coefficients in each iteration. In the right panel, if the confidence interval bounds zero (almost all do) then monthly and daily are not statistically different from each other. If there is no confidence interval, it was too large to show and also bounds zero. South Dakota and Tennessee are omitted from the monthly analysis as we do not have enough monthly observations to estimate these states. Statistically insignificant coefficients from the monthly and daily models are indicated by a lighter (greyed) shade of marker.

Figure A.4: Annual Recreation Revenue from Snowpack in each State



Note: Figure A.4 presents estimates of the recreation revenue from snowpack in each state s and within-sample year t:

$$Revenue\ from\ Snowpack_{st} = \beta_s \times \frac{Annual\ Revenue_s}{Historical\ Snowpack_s} \times Contemporaneous\ Snowpack_{st} \quad \text{(A.10)}$$

This is also equation 2.4 from the main text. Panel A present the year-to-year recreation revenue from snowpack in each of the 26 states from 2005 to 2017 operating seasons. Panel B presents the average annual recreation revenue from snowpack over this period. These state-level simulations are an intermediate step for aggregate estimates presented in figures A.6, A.5, and 2.3.

Figure A.5: Within Sample and RCP4.5 Simulations

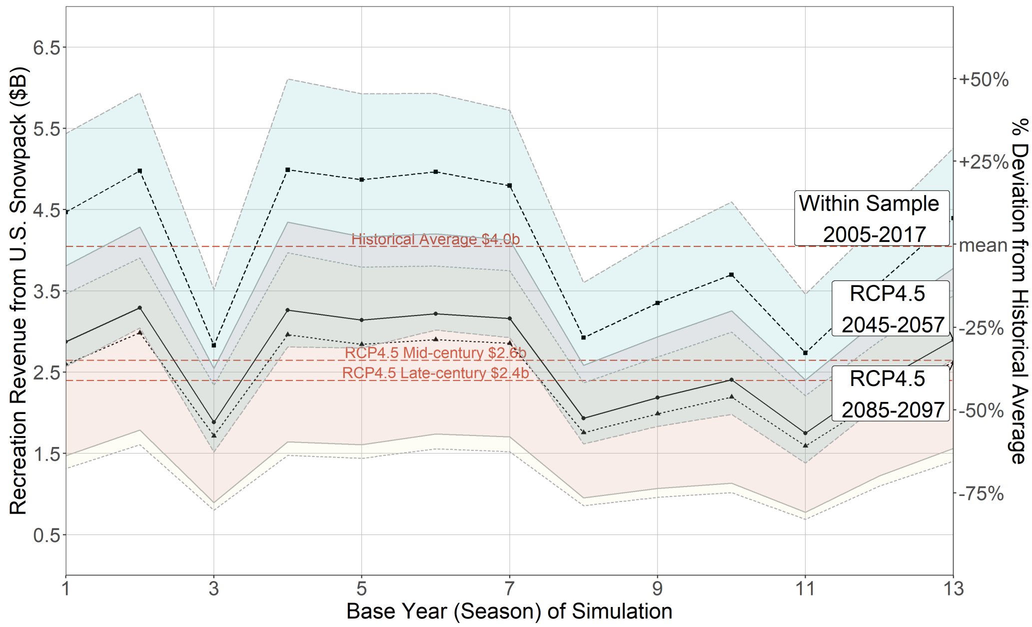


Figure A.6: Within Sample and RCP8.5 Simulations

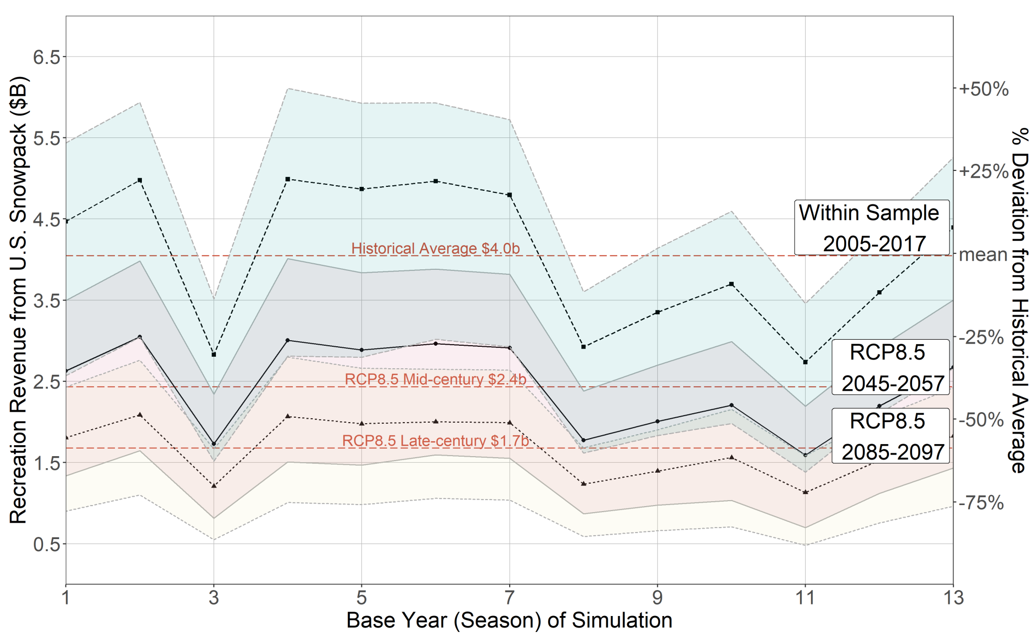
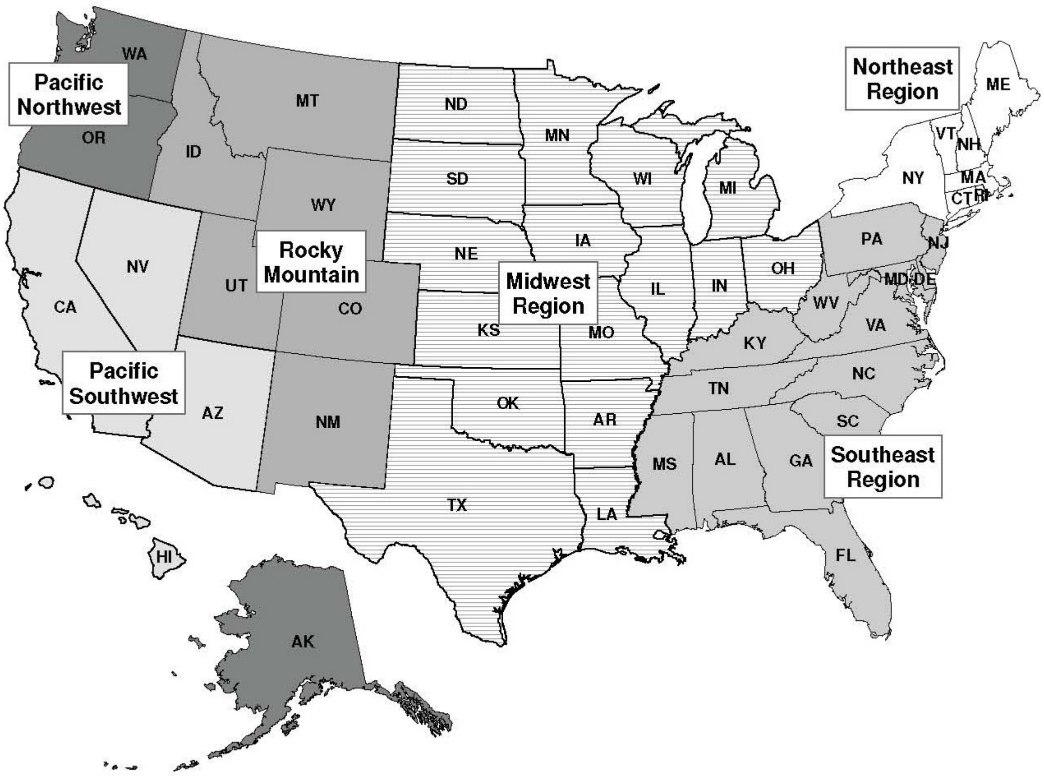
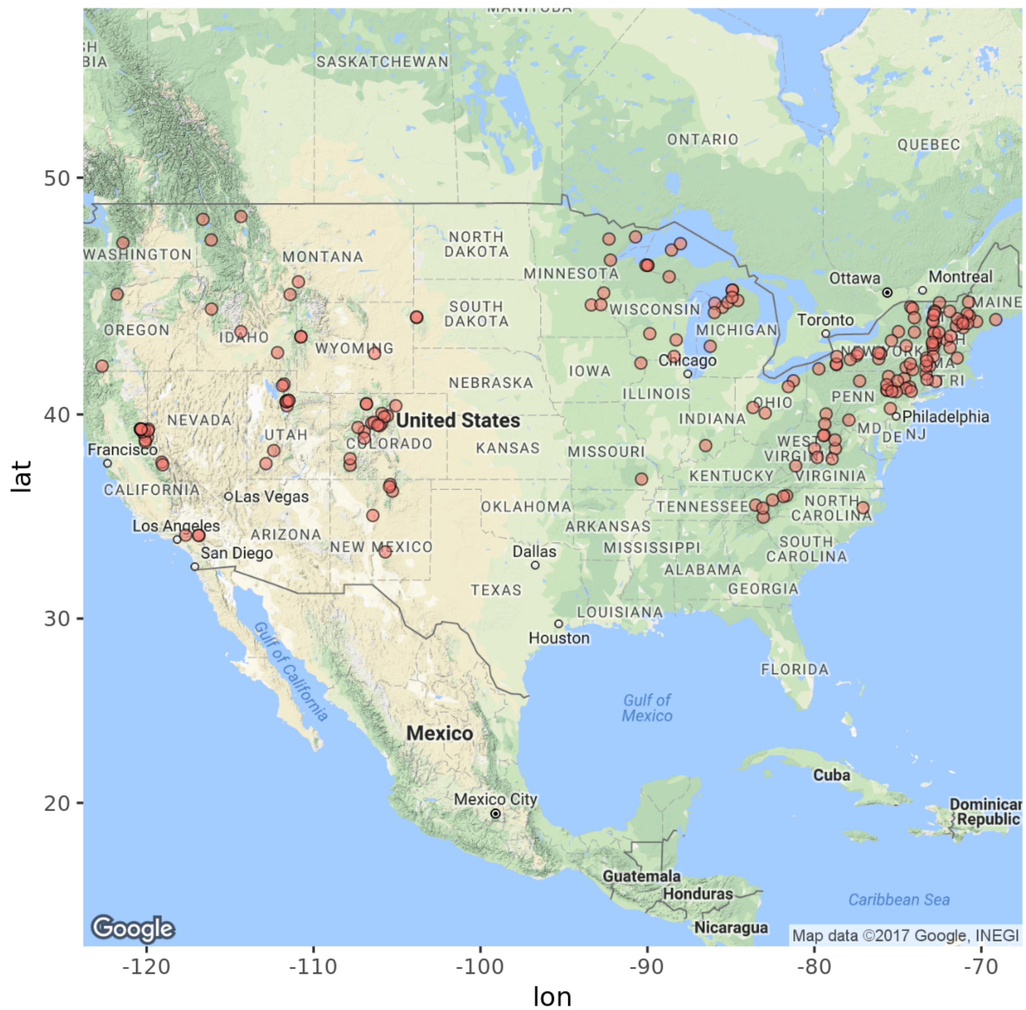


Figure A.7: NSAA Resort Regions



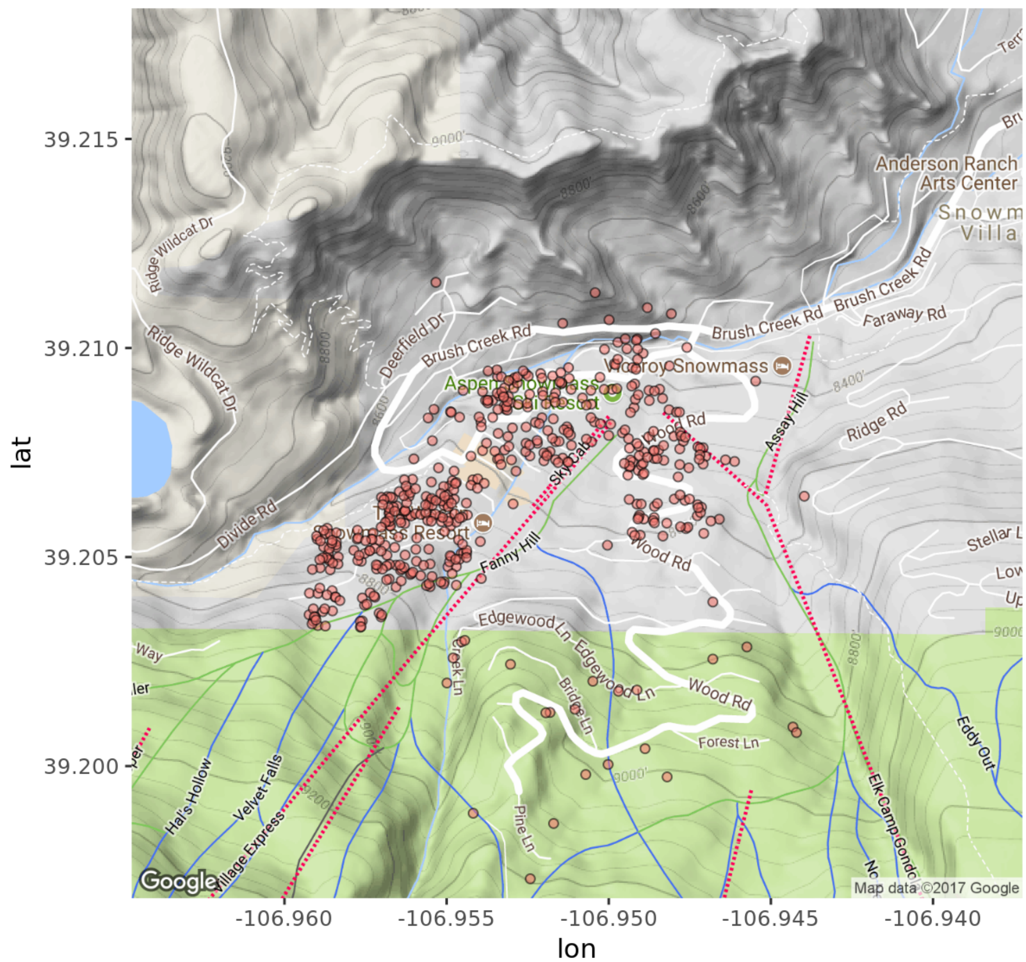
Note: Figure A.7 presents the regions across the U.S. as defined by the NSAA (NSAA, 2018). These are the regions specified in equation A.4.

Figure A.8: Spatial Distribution of Resorts Throughout the United States



Note: Figure A.8 presents the spatial distribution of the 219 resort markets considered in this study.

Figure A.9: Spatial Distribution of Airbnb Properties in Aspen, CO



Note: Figure A.9 presents the spatial distribution of short term rental properties within a 10km buffer near Aspen, Colorado.

APPENDIX B

SUPPLEMENTAL MATERIALS FOR CH. 3

B.1 Additional Tables

Table B.1: Results of Different Clustered Standard Errors

Clustered. SE:	(1) Property	(2) Market	(3) State×WoS
Snowpack	0.01242***	0.01242***	0.01242***
	(0.0006)	(0.0039)	(0.0036)
Snowpack^2	-0.00004***	-0.00004*	-0.00004**
	(0.000006)	(0.00002)	(0.00002)
Property j FE	Yes	Yes	Yes
Day-of-sample FE	Yes	Yes	Yes
# of Clusters	33,636	94	908
Observations	6,610,513	6,610,513	6,610,513
McFadden ρ^2	0.29	0.29	0.29
BIC	6,770,282.87	6,770,282.87	6,770,282.87
F-stat (Wald: IV)	204.02***	204.02***	204.02***

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Note: I explore various levels of clustering to address possible correlation across observations in the sample. Column 1 is the most generous where correlation is assumed to be zero across properties. Column 2, what is used in our primary analysis, clusters standard errors at the market-level. This assumes that observations within a market are correlated, but independent across markets. Column 3 uses state×week-of-sample to cluster observations. I introduce the interaction to ensure a sufficient number of clusters from 13 with state only, to 908 with state×week-of-sample (Wooldridge, 2006; Abadie et al., 2017).

Table B.2: Marginal Utilities from Trip Decisions (Contd. from Table 3.1)

	(1) National Average	(2) West-East Regions	(3) NSAA Regions
Weekly Snowfall	-76.8167***	-75.8032***	-72.7571***
	(4.42007)	(4.41590)	(4.42725)
Weekly Snowfall^2	24.6878***	24.6754***	27.7108***
	(2.91943)	(2.91925)	(2.89935)
New Snow 1"-3"	0.00991***	0.00971**	0.00469
	(0.00380)	(0.00380)	(0.00380)
New Snow 3"-6"	0.03108***	0.03075***	0.04140***
	(0.00480)	(0.00480)	(0.00479)
New Snow 6"-9"	-0.00465	-0.00369	-0.03613***
	(0.00767)	(0.00767)	(0.00762)
New Snow 9"-12"	0.01412	0.01625	0.02708**
	(0.01143)	(0.01142)	(0.01143)
New Snow 12"-15"	0.03575**	0.03572**	0.02777*
	(0.01438)	(0.01437)	(0.01427)
New Snow 15"+	-0.11925***	-0.11490***	-0.07928***
	(0.01392)	(0.01391)	(0.01377)
Temperature	134.869***	138.680***	224.504***
	(20.4386)	(20.4222)	(20.2170)
Temperature^2	-28.4468***	-28.9883***	-22.9429**
	(10.8402)	(10.8460)	(10.9288)
Market Size	62.6419	49.9075	78.1899
	(55.8591)	(55.9710)	(55.9961)
Market Size^2	30.6767	47.1165*	-10.1123
	(27.8445)	(28.1546)	(28.3001)
Snowpack Outside Option	-294.178***	-266.350***	60.7485*
	(31.7884)	(32.3183)	(33.5216)
Snowpack Outside Option^2	-69.3880***	-74.2635***	-138.305***
	(18.9525)	(19.0039)	(19.2005)
Weekly Snowfall Outside Option	36.5520***	34.3089***	34.4416***
	(5.48513)	(5.49552)	(5.50445)
Weekly Snowfall Outside Option^2	-37.9710***	-36.2836***	-10.6445***
	(3.97956)	(3.97491)	(3.97820)
Temperature Outside Option	-243.839***	-234.195***	-324.261***
	(20.5960)	(20.5793)	(20.3095)
Temperature Outside Option^2	-110.698***	-110.660***	-108.231***
	(10.7968)	(10.8026)	(10.8360)
Property j FE	Yes	Yes	Yes
Day-of-sample FE	Yes	Yes	Yes
Clustered. SE	Market	Market	Market
Observations	6,610,513	6,610,513	6,610,513
McFadden ρ^2	0.2857	0.29143	0.2857
BIC	6,770,282.87	6,770,005.61	6,760,126.80

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Table B.3: Summary Statistics for Trip-level Data

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Panel A: First-step							
Reserved	6,610,951	0.29	0.45	0	0	1	1
Price	6,610,951	323.45	114.86	66.11	247.80	375.97	1,824.98
Snowpack	6,610,951	42.92	31.57	0.16	16.67	61.47	190.00
New Snow	6,610,951	0.85	2.42	0	0	0.3	48
Weekly Snowfall	6,610,951	5.77	11.22	0	0	6.8	198
Mean Temperature	6,610,951	30.06	10.76	−16.31	23.04	38.05	63.87
Total Available Properties	6,610,951	1,961.12	1,547.51	21	550	3,034	5,780
Snowpack Outside Option	6,610,951	41.56	28.59	0.48	16.13	55.03	188.50
Weekly Snowfall Outside Option	6,610,951	5.10	7.82	0.00	0.07	6.56	78.75
Temperature Outside Option	6,610,951	30.94	10.25	−10.63	24.35	38.66	63.87
Panel B: 2SLS Second-step							
ASC (δ_j)	33,636	−3.70	1.22	−7.95	−4.55	−2.95	3.16
Price	33,636	325.92	120.13	66.11	246.38	383.13	1,824.98
Bedrooms	33,636	2.52	1.29	1	2	3	19
Bathrooms	33,636	2.19	1.12	0	1	3	8
Max-guests	33,636	6.98	3.33	1	4	9	50
Super-host	33,636	0.18	0.39	0	0	0	1
Number of Photos	33,636	19.21	10.89	1	12	24	170
Distance (m)	33,636	4,604.85	2,985.49	10.80	1,882.60	7,414.41	9,988.37
Entire Home	33,636	0.92	0.27	0	1	1	1
Private Room	33,636	0.07	0.26	0	0	0	1
Total Days Available	33,636	199.56	107.39	12	125	270	696
Median Home Value	33,636	370,275.80	122,890.40	67,900	278,400	465,200	715,300
Price-IV	33,636	325.91	65.77	115.48	285.55	380.61	492.19
BLP-IV (beds)	33,636	2.52	0.31	1.00	2.36	2.76	3.67
BLP-IV (baths)	33,636	2.19	0.26	1.00	2.04	2.33	3.07
Schedule-IV	33,636	0.20	0.22	0.00	0.03	0.33	0.97

Table B.4: Summary Statistics for Trip-level Data by Region

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Panel A: Mountain-West							
Reserved	5,659,751	0.30	0.46	0	0	1	1
Price	5,659,751	335.21	114.91	109.76	258.25	387.44	1,824.98
Snowpack	5,659,751	47.49	31.73	0.23	20.42	65.25	190.00
New Snow	5,659,751	0.91	2.53	0	0	0.4	48
Weekly Snowfall	5,659,751	6.24	11.75	0	0	7.5	198
Mean Temperature	5,659,751	30.55	10.50	−9.87	23.76	38.46	63.87
Total Available Properties	5,659,751	2,241.42	1,496.64	21	943	3,374	5,780
Snowpack Outside Option	5,659,751	46.05	28.44	0.48	20.14	56.81	188.50
Weekly Snowfall Outside Option	5,659,751	5.51	8.18	0.00	0.11	7.23	78.75
Temperature Outside Option	5,659,751	31.61	9.89	−7.84	25.04	39.16	63.87
Panel B: Central-East							
Reserved	951,200	0.24	0.43	0	0	0	1
Price	951,200	253.48	86.05	66.11	199.00	293.60	1,281.05
Snowpack	951,200	15.70	8.61	0.16	10.00	18.64	60.00
New Snow	951,200	0.45	1.53	0	0	0	30
Weekly Snowfall	951,200	3.00	6.71	0	0	3	120
Mean Temperature	951,200	27.16	11.76	−16.31	19.46	35.35	61.74
Total Available Properties	951,200	293.33	259.20	21	98	411	1,046
Snowpack Outside Option	951,200	14.86	5.98	3.41	10.40	18.00	49.06
Weekly Snowfall Outside Option	951,200	2.68	4.44	0	0	3.5	69
Temperature Outside Option	951,200	26.96	11.38	−10.63	19.35	34.82	61.74

Table B.5: Summary Statistics for Market-level Data

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Market Share	5,973	0.0005	0.0010	0.0000	0.0000	0.0004	0.0086
Price	5,973	265.00	70.69	100.99	215.41	319.22	482.05
Snowpack	5,973	29.61	23.75	1.00	12.19	41.11	166.14
log(Snowpack)	5,973	3.17	0.69	0.69	2.58	3.74	5.12
Weekly Snowfall	5,973	3.97	7.28	0.00	0.00	4.73	99.41
Mean Temperature	5,973	28.70	11.55	−9.87	21.24	36.97	63.87
Price Outside Option	5,973	310.36	22.85	250.74	290.96	328.21	367.53
Snowpack Outside Option	5,973	41.71	20.57	9.95	25.70	58.81	143.24
Weekly Snowfall Outside Option	5,973	5.10	5.09	0.00	1.35	7.09	32.11

B.2 Logit, PPML, and LPM

Table B.6: Results from Logit, PPML, and LPM

	(1) Logit	(2) PPML	(3) LPM
Panel A: Marginal Utilities			
Snowpack	0.01242***	0.00610**	0.00178***
	(0.00392)	(0.00218)	(0.00052)
Snowpack^2	-0.00004*	-0.00002*	-0.000007*
	(0.00002)	(0.00001)	(0.000003)
Price (2SLS)	−0.00526***	−0.00280***	−0.00081***
	(0.00077)	(0.00039)	(0.00012)
Property j FE	Yes	Yes	Yes
Day-of-sample FE	Yes	Yes	Yes
Clustered. SE	Market	Market	Market
Observations	6,610,513	6,610,513	6,610,513
McFadden ρ^2	0.28	0.16	0.29
BIC	6,770,282.87	8,257,517.81	6,760,126.80
F-stat (Wald: IV)	204.02***	241.60***	410.90***
Panel B: Marginal Willingness to Pay			
Snowpack	$2.40	$2.23	$2.24
	[2.38, 2.43]	[2.22, 2.24]	[2.22, 2.26]
Snowpack^2	-$0.01	-$0.01	-$0.01
	[-0.01, -0.01]	[-0.01, -0.01]	[-0.01, -0.01]

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01
Krinsky-Robb 95% confidence intervals in brackets

Note: I explore to what degree the specification of logit, Poisson Pseudo-Maximum Likelihood, and linear probability models influence the policy-relevant metric of willingness to pay. While marginal utilities are not directly comparable (MIXL and logit are represented as standard odds ratios), I find no distinguishable difference in the resulting MWTP.

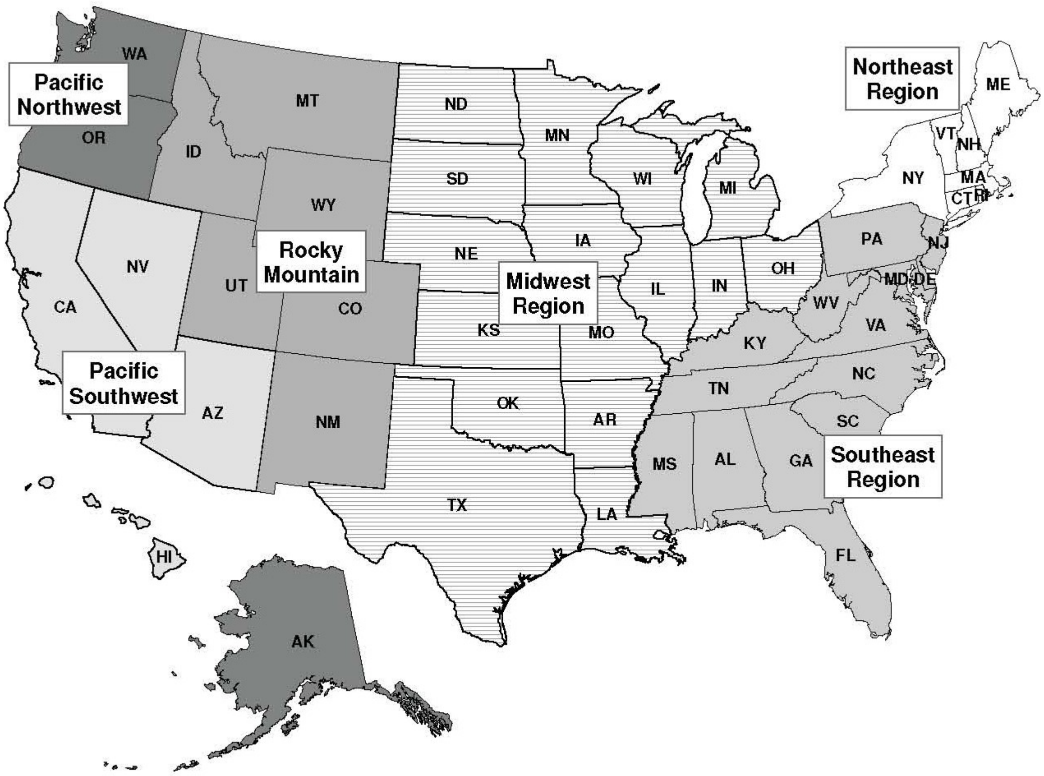
Table B.7: MWTP from Ken Train's Heating Data

	(1) MIXL	(2) Logit	(3) PPML	(4) LPM
Contract Length	-0.21***	-0.15***	-0.15***	-0.12***
	(0.01)	(0.02)	(0.02)	(0.02)
Local Company	2.13***	1.99***	2.05***	1.72***
	(0.09)	(0.17)	(0.20)	(0.17)
Well-known Company	1.51***	1.30***	1.41***	1.01***
	(0.07)	(0.12)	(0.15)	(0.10)
Time-of-Day Rate	9.30***	8.78***	8.76***	8.82***
	(0.12)	(0.14)	(0.16)	(0.11)
Seasonal Rate	9.35***	9.25***	9.31***	9.18***
	(0.13)	(0.13)	(0.17)	(0.09)

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Note: Using the heating data from the *mlogit* package (Train and Croissant, 2012), I explore to what degree the specification of logit, Poisson Pseudo-Maximum Likelihood, and linear probability models influence the policy-relevant metric of willingness to pay. While marginal utilities are not directly comparable (MIXL and logit are represented as standard odds ratios), I find little distinguishable difference (all but contract length are not statistically different between the models) in the resulting MWTP. MWTP is estimated using the delta method and the command wtp.gmnl (Sarrias and Daziano, 2017).

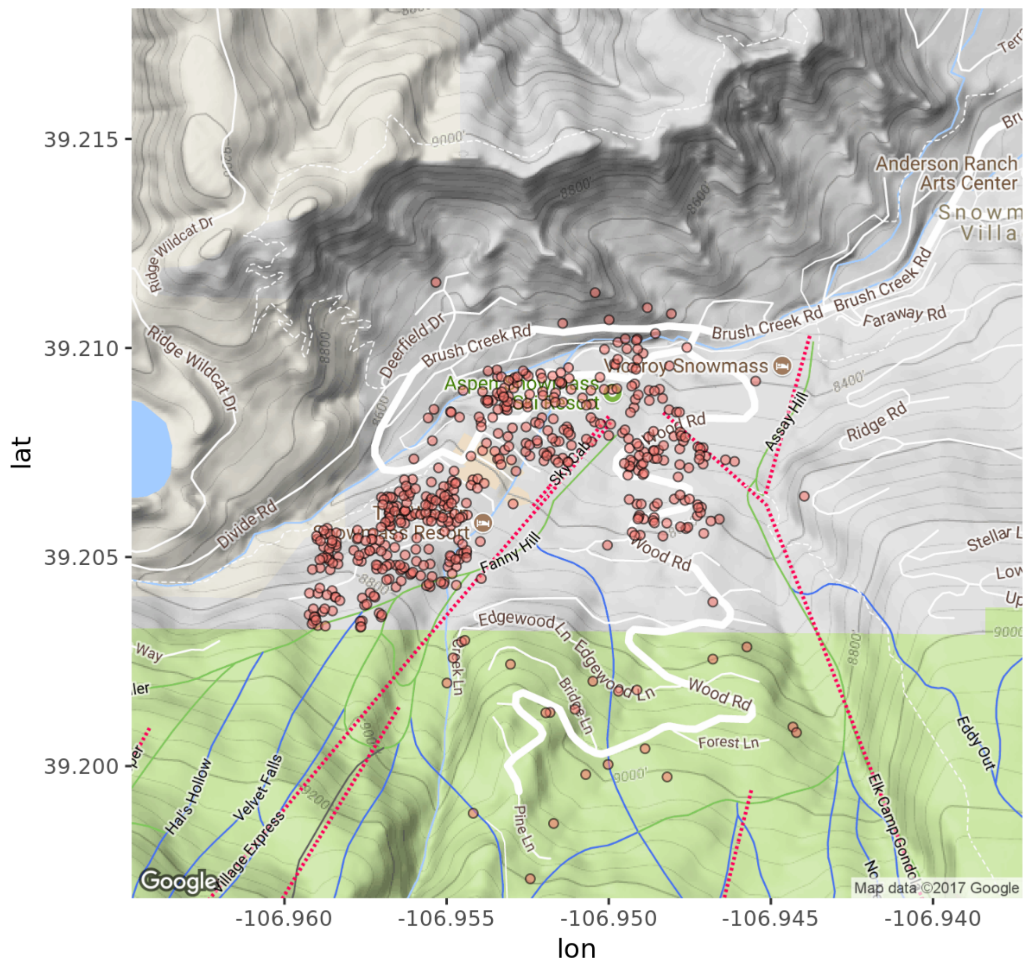
Figure B.1: NSAA Resort Regions



B.3 Additional Figures

Note: Figure A.7 presents the regions across the U.S. as defined by the NSAA (NSAA, 2018). These are the regions specified in equation A.4. I combine California, Nevada, Oregon, and Washington to be a combined NSAA region called "West-coast".

Figure B.2: Spatial Distribution of Airbnb Properties in Aspen, CO



Note: Figure A.9 presents the spatial distribution of short term rental properties within a 10km buffer near Aspen, Colorado.

APPENDIX C

SUPPLEMENTAL MATERIALS FOR CH. 4

C.1 The Survey

Water Quality in the Upper Sangamon River Survey

This survey will collect information for research being conducted at the University of Illinois. The research will study how people value changes to water quality in a nearby watershed resulting from changes in agriculture practices. You will not be asked to provide your name or address and your participation and answers to this survey will be completely anonymous.

Participation is voluntary and will take approximately 10 minutes

You should only complete this survey if you are over 18 years old. Please complete the survey to the best of your ability. You may choose not to answer specific questions or discontinue the survey at any time.

Your participation in this survey is very important. You might not benefit directly from participation, but the information from this survey will help policy makers, economists, and watershed managers choose how and how much to improve water quality in your area. We will be happy to provide you with a copy of the final report at your request.

Please keep this information for your records

You should keep this information for your future reference. If you have any questions about this survey research or its results please contact: watersurvey@illinois.edu

If you have any questions about your rights as a research subject, including questions, concerns, complaints, or to offer input, you may call the Office for the Protection of Research Subjects (OPRS) at 217-333-2670 or e-mail OPRS at irb@illinois.edu.

Instructions

This survey measures what people think about changes in local water quality due to local changes in agriculture practices. We are interested in how much you care about features such as: fish species and populations, local problems from water pollution like algal blooms, and the likelihood of reaching targets that have been set to reduce serious water quality problems in the Gulf of Mexico.

The survey has two sections:

1. **In section one** of the survey, you will be asked six questions. In each of those questions, we will ask you to choose between two possible future scenarios and the current situation ("No Change").

2. **In section two** of the survey, there will be some short questions about you so that we can understand what factors affect the way people feel about local water quality.

Remember that all your answers will be completely anonymous.

Background Information

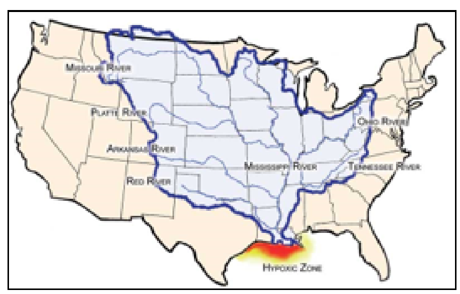
Rivers, streams, and lakes in the U.S. Midwest have been changed by things like farming. The soil and climate in the region provide a great environment for growing crops. However, rain runs off fields and carries bits of soil (sediment) and chemicals from fertilizer and plants (nutrients) into local waters. Runoff of nutrients and sediment causes local problems, reduced fish numbers and sudden growths of green algae that smell bad and can be toxic. Nutrient pollution also creates a big area that is starved of oxygen (the hypoxic zone) in the Gulf of Mexico.

Upper Sangamon River Basin

Locally, proposed changes that reduce nutrient runoff can improve rivers and lakes by providing clearer water and better habitat for fish. Improved water conditions can increase both the number of different **kind**s of fish (species) and **how many** fish there are (population). Some of these fish are game fish that are often fished for by recreational anglers, including bass, creel, and trout. Other types of fish are not directly interesting to people fishing, but they help support healthy homes in rivers and lakes for birds and other wild animals.

Hypoxia in the Gulf of Mexico

The nutrients and sediment that run off lands throughout the U.S. Midwest drain into the Gulf of Mexico. Once in the Gulf, these nutrients create a "dead zone" stretching thousands of square miles around the mouth of the Mississippi River. There are 12 states, including the state of Illinois, who have pledged to reduce the dead zone in the Gulf. Those states have agreed with the U.S. EPA to reduce nutrient flows from their lands by 45% by the year 2040.



Features of Water Quality Improvements

Depending on how it is done, changes in water quality can have different results. The features described below are of interest in this survey. Please read this carefully in order to answer the questions in the survey.

Species of Game Fish	The number of different game fish species found in a typical 100 yards of river in the highlighted section of the river (100 yards is the length of a football field). A high number means you can expect to see many different kinds of game fish.
Population of All Fish	The number of individual fish (from all species, game and non-game) found in a typical 100 yards of river in the highlighted section of the river. A high number means you can expect to see many individual fish. They may be all the same type, or they may be several different types.
Algal Blooms Reduced	The percent reduction in the frequency of algal blooms in the highlighted section of the river. These are typically seen in the ponds and lakes connected to the river. A higher number means you will see fewer algal blooms. For example: 100 means 100 percent reduction so there are no algal blooms, 0 means the number of algal blooms stays exactly the same as it is now.
Nutrient Targets	The likelihood that the Upper Sangamon River area succeeds in reaching its goal of reducing nearly half of the nutrients running down to the Gulf of Mexico by 2040. A higher number means the target is more likely to be reached. For example: 100 means the target is definitely reached; 0 means the target is definitely not reached.
Distance	The distance in miles from you to the cleaned up section of the river. This feature depends on which section of river is cleaned up and where you live.
Annual Cost	The amount of money that your household will have to pay every year to improve the water quality in the Upper Sangamon River. The money will be paid through an increase in annual county fees. If you are a renter, this will be passed on through rent charged by the landlord.

Current Experience

Before you answer the next questions, help us understand your current experience.

How often have you seen algal blooms in the rivers near you?
- a) Never
- b) Rarely, once every couple of years
- c) Not often, once per year
- d) Sometimes, several times a year
- e) Very often

How many times in the last year have you gone fishing in the Upper Sangamon River?
- a) 0
- b) 1
- c) 2
- d) 3
- e) 4
- f) 5
- g) more than 5

How many times in the last year have you participated in other recreation activities in the Upper Sangamon River Basin? (Boat, swim, bike, walk the trails, etc.)
- a) 0
- b) 1
- c) 2
- d) 3
- e) 4
- f) 5
- g) more than 5

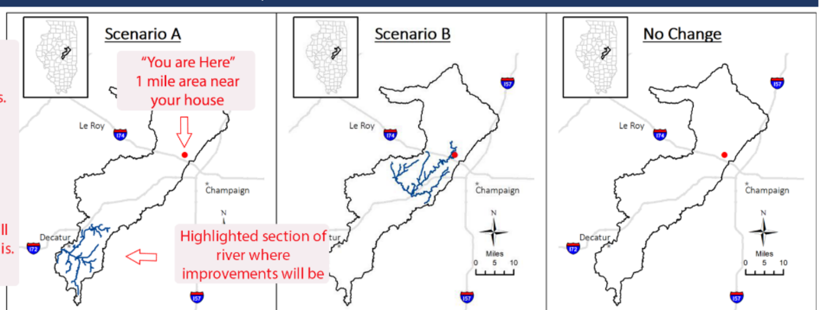
Question Number 1

Example Card

1) There are three scenarios.

2) Choose the one you like most.

3) The third option will always be "No Change." This means evrything will stay the way it currently is.



	Scenario A	Scenario B	No Change
Game Fish Species	Species: 3	Species: 1	Species: 1
Fish Population	Population: 30	Population: 75	Population: 30
Algal Blooms Reduced	25%	0%	0%
Nutrient Target Met	100%	75%	0%
Distance from Home	28 miles	1 miles	-
Annual Cost	$25	$125	$0

Average number of species every 100 yards of river

Average number of fish every 100 yards of river

Reduction in algal blooms

Likelihood of reaching nutrient target

Distance from your house to the section of river

Annual fee required to make improvements

If Scenarios A and B are the ONLY options besides No Change. Which would you choose?

Things to Remember

For the purposes of this survey you should assume that every possible future scenario:

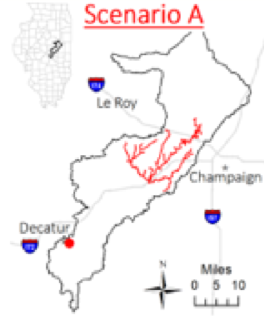
- will ONLY affect the highlighted area of the river
- will NOT result in additional changes such as fishing or visiting regulations
- will NOT result in a change in agricultural acreage or profits
- WILL be paid for by an annual increase in county fees

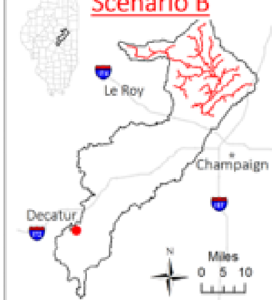
Experience from previous similar surveys is that people often say they would be willing to pay more money for something than they actually would. For example, in one study, 80% of people said they would buy a product, but when a store actually stocked the product, only 43% of people actually bought the new product. It is important that you make each of your upcoming selections like you would if you were **actually** facing these exact choices in reality. Note that paying for environmental improvement means you would have less money available for other purchases.

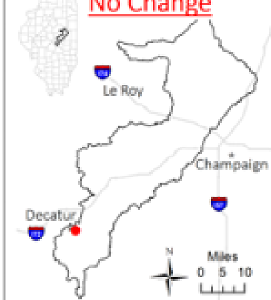
Ready, set, choose.

Remember, each of the six questions is separate and independent from the previous questions. For every question, Scenarios A and B are the ONLY options besides the "No Change." Which would you choose?

If scenarios A and B were the only options besides No Change, which would you choose?







	Scenario A	Scenario B	No Change
Game Fish Species	2	5	1
Fish Population	75	50	30
Algal Blooms Reduced	25%	0%	0%
Nutrient Target Met	75%	50%	0%
Distance from Home	23 miles	39 miles	-
Annual Cost	$5	$15	$0

If you are unsure about scenarios A or B, or would not actually spend the money, please choose No Change.

Almost Finished

Now we are going to ask a few quick questions about you, and then you will be finished.

1. Do you consider where you live to be rural?
   a. Yes
   b. No

2. Think about your household's total income each year. What category does it fall into?
   a. Less than $25,000 per year
   b. $25,000 - $34,999 per year
   c. $35,000 - $49,999 per year
   d. $50,000 - $74,999 per year
   e. $75,000 - $99,999 per year
   f. $100,000 - $149,999 per year
   g. $150,000 - $199,999 per year
   h. More than $200,000 per year

3. Do you own your home?
   a. Yes
   b. No

4. Do you or your family farm or do work related to agriculture?
   a. Yes
   b. No

5. What is your age group?
   a. 18-29 years old
   b. 30-44 years old
   c. 45-64 years old
   d. Over 65 years old

6. What is your gender?
   a. Female
   b. Male
   c. Other

7. What is your race?
   a. White
   b. African American
   c. Hispanic or Latino
   d. American Indian, or Alaska Native
   e. Other

8. What is your highest level of education?
   a. Less than high school
   b. High school / GED
   c. Some college
   d. Two-year college degree
   e. Four-year college degree
   f. Graduate degree

9. How many years have you lived in central Illinois?
   a. 0 to 5 years
   b. 5 to 10 years
   c. 10 to 20 years
   d. 20 to 30 years
   e. More than 30 years

10. How familiar are you with the water quality issues discussed in this survey?
    a. 0 – not familiar at all
    b. 1 – somewhat familiar
    c. 2 – familiar
    d. 3 – very familiar
    e. 4 – very familiar and involved

11. Do you ever go fishing in the Sangamon River?
    a. 0 - No, never
    b. 1 - Sometimes, once per year
    c. 2 - Yes, several times per year

12. Do you ever go hiking or recreating near the Sangamon River?
    a. 0 - No, never
    b. 1 - Sometimes, once per year
    c. 2 - Yes, several times per year

13. Please add any comments, questions, or concerns that you would like us to know about.

C.2 Summary Statistics

Table C.1: Summary Statistics

	(1) Respondents	(2) mean	(3) min	(4) max
Rural	343	0.53	0	1
Works in Agriculture	343	0.16	0	1
Male	343	0.32	0	1
White	343	0.78	0	1
Homeowner	343	0.56	0	1
Age				
18 - 29	343	0.25	0	1
30 - 44	343	0.33	0	1
45 - 64	343	0.3	0	1
>65	343	0.12	0	1
Household income ($k)				
$<$ $25,000	343	0.24	0	1
$25,000 - $34,999	343	0.16	0	1
$35,000 - $49,999	343	0.16	0	1
$50,000 - $74,999	343	0.2	0	1
$75,000 - $99,999	343	0.13	0	1
$100,000 - $149,999	343	0.07	0	1
$150,000 - $199,999	343	0.02	0	1
$>$ $200,000	343	0.01	0	1
Education				
Less than high school	343	0.04	0	1
High school / GED	343	0.24	0	1
Some college	343	0.27	0	1
Two-year degree	343	0.11	0	1
Four-year degree	343	0.22	0	1
Graduate degree	343	0.12	0	1
Years of Residency				
0-5 years	343	0.06	0	1
5-10 years	343	0.04	0	1
10-20 years	343	0.17	0	1
20-30 years	343	0.2	0	1
>30 years	343	0.53	0	1
Minutes to Complete	343	10.49	3.52	321.82

Note: Experience categories range from 0 (never go) to 5 (more than 5 times per year). Water Quality Issues relates to their current understanding of the water quality concerns in the watershed, and ranges from 0 (not aware of any) to 4 (very aware and involved). Algal Blooms refers to the respondents current experience with algal blooms, and ranges from 0 (never see them) to 4 (very often, all the time).

Table C.2: Differences between Survey Respondents and U.S.Census (2019)

	(1) Respondents	(2) Census	(3) Difference
Works in Agriculture	0.15 (0.00)	0.05 (0.03)	-0.10*** (0.01)
Male	0.32 (0.00)	0.50 (0.04)	0.18*** (0.01)
White	0.77 (0.00)	0.94 (0.10)	0.16*** (0.02)
Homeowner	0.57 (0.00)	0.75 (0.16)	0.18*** (0.03)
Age			
18 - 29	0.22 (0.23)	0.18 (0.04)	-0.05 (0.04)
30 - 44	0.30 (0.31)	0.23 (0.04)	-0.07 (0.06)
45 - 64	0.36 (0.35)	0.38 (0.04)	0.02 (0.06)
> 65	0.12 (0.20)	0.21 (0.05)	0.09** (0.04)
Household income ($k)			
< $25,000	0.06 (0.10)	0.12 (0.17)	0.07* (0.03)
$25,000 - $34,999	0.01 (0.03)	0.07 (0.03)	0.07*** (0.01)
$35,000 - $49,999	0.15 (0.24)	0.13 (0.08)	-0.02
$50,000 - $74,999	0.20 (0.31)	0.20 (0.06)	0.00 (0.06)
$75,000 - $99,999	0.22 (0.31)	0.18 (0.07)	-0.04 (0.06)
$100,000 - $149,999	0.18 (0.27)	0.17 (0.07)	-0.00 (0.05)
$150,000 - $199,999	0.18 (0.22)	0.07 (0.05)	-0.11*** (0.04)
> $200,000	0.01 (0.02)	0.04 (0.04)	0.04*** (0.01)
Education			
Less than high school	0.22 (0.29)	0.06 (0.04)	-0.16*** (0.05)
High school/GED	0.12 (0.27)	0.35 (0.09)	0.23*** (0.05)
Some college	0.21 (0.22)	0.24 (0.04)	0.03 (0.04)
Two-year degree	0.08 (0.21)	0.09 (0.02)	0.01 (0.04)
Four-year degree	0.19 (0.20)	0.16 (0.07)	-0.03 (0.04)
Graduate degree	0.18 (0.33)	0.08 (0.07)	-0.10 (0.06)
Zip Codes	42	42	42

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Note: Comparisons are provided between the 2017 American Community Survey (ACS) 5-year zip code level data and the sample in the choice experiment. Averages are across the 42 zip codes in the study area. Our sample is largely representative of the region, with a few differences. Our sample is more likely to work in agriculture; however, this is likely because of the broad wording of the question where we asked respondents if they or their family performed work related to agriculture, and results are consistent with this. Our sample is more likely to be female, less likely to be white, and less likely to be a homeowner. The age of respondents is representative of the U.S. Census, with fewer above the age of 65. Our sample has similar income and education levels.

Table C.3: Differences between Respondents in Rural and Urban Areas

	(1) Rural	(2) Urban	(3) Difference
Works in Agriculture	0.19 (0.39)	0.12 (0.33)	-0.06 (0.04)
Male	0.32 (0.47)	0.32 (0.47)	-0.00 (0.05)
White	0.81 (0.40)	0.74 (0.44)	-0.07 (0.05)
Homeowner	0.60 (0.49)	0.52 (0.50)	-0.08 (0.05)
Age			
18 - 29	0.24 (0.43)	0.27 (0.44)	0.03 (0.05)
30 - 44	0.36 (0.48)	0.29 (0.46)	-0.07 (0.05)
45 - 64	0.28 (0.45)	0.32 (0.47)	0.04 (0.05)
$>$ 65	0.12 (0.32)	0.12 (0.32)	0.00 (0.03)
Household income ($k)			
$<$ $25,000	0.20 (0.40)	0.28 (0.45)	0.08* (0.05)
$25,000 - $34,999	0.19 (0.39)	0.14 (0.34)	-0.05 (0.04)
$35,000 - $49,999	0.17 (0.38)	0.16 (0.36)	-0.02 (0.04)
$50,000 - $74,999	0.19 (0.39)	0.20 (0.40)	0.02 (0.04)
$75,000 - $99,999	0.14 (0.35)	0.13 (0.34)	-0.01 (0.04)
$100,000 - $149,999	0.09 (0.29)	0.05 (0.22)	-0.04 (0.03)
$150,000 - $199,999	0.02 (0.13)	0.03 (0.17)	0.01 (0.02)
$>$ $200,000	0.01 (0.10)	0.01 (0.11)	0.00 (0.01)
Education			
Less than high school	0.03 (0.18)	0.04 (0.21)	0.01 (0.02)
High school/GED	0.27 (0.44)	0.21 (0.41)	-0.06 (0.05)
Some college	0.31 (0.46)	0.22 (0.42)	-0.08* (0.05)
Two-year degree	0.08 (0.27)	0.14 (0.35)	0.07** (0.03)
Four-year degree	0.22 (0.42)	0.22 (0.42)	0.01 (0.05)
Graduate degree	0.09 (0.29)	0.16 (0.36)	0.06* (0.04)
Years of Residency			
0-5 years	0.04 (0.19)	0.09 (0.29)	0.06** (0.03)
5-10 years	0.04 (0.19)	0.04 (0.21)	0.01 (0.02)
10-20 years	0.15 (0.36)	0.18 (0.39)	0.03 (0.04)
20-30 years	0.25 (0.43)	0.15 (0.36)	-0.10** (0.04)
$>$ 30 years	0.52 (0.50)	0.53 (0.50)	0.01 (0.05)
Experience			
Recreational Fishing	0.76 (1.36)	0.43 (1.08)	-0.32** (0.13)
Hiking/Biking Trails	1.34 (1.63)	1.03 (1.46)	-0.31* (0.17)
Water Quality Issues	1.90 (1.27)	1.71 (1.21)	-0.18 (0.13)
Algal Blooms	1.90 (1.27)	1.71 (1.21)	-0.18 (0.13)
Minutes to Complete	11.14 (24.32)	9.76 (7.42)	-1.38 (1.99)
Respondents	182	161	343

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

C.3 Rural and Urban Preferences

Table C.4: Differences in MWTP Between Rural and Urban Respondents

Mean MWTP Coefficients	(1) Full Sample	(2) Rural	(3) Urban
Distance (miles)	-0.67***	-0.87***	-0.77***
	(0.15)	(0.23)	(0.21)
Fish Species	4.73**	2.65	5.62**
	(1.48)	(1.79)	(1.77)
Fish Population	0.17**	0.05	0.23**
	(0.06)	(0.07)	(0.08)
Algal Blooms (%)	0.77***	0.80***	0.77***
	(0.11)	(0.13)	(0.15)
Nutrient Target	0.95***	1.11***	0.79***
	(0.13)	(0.16)	(0.14)
Status Quo (No Program)	-69.49***	-50.92***	-10.53
	(14.78)	(12.93)	(12.22)
SD of Random Parameters			
Distance (miles)	92.57***	5.57	104.78***
	(18.69)	(15.47)	(21.48)
Fish Species	1.06***	1.16***	1.38***
	(0.26)	(0.34)	(0.32)
Fish Population	6.58***	10.47***	10.38***
	(2.12)	(2.79)	(1.96)
Algal Blooms (%)	0.35**	0.25*	0.50***
	(0.09)	(0.11)	(0.10)
Nutrient Target	0.85***	1.08***	0.67***
	(0.16)	(0.21)	(0.17)
Cost	0.85***	1.11***	0.85***
	(0.13)	(0.18)	(0.15)
Status Quo (No Program)	1.42***	1.28***	1.50***
	(0.23)	(0.18)	(0.28)
Observations (Respondents)	2058 (343)	1092 (182)	966 (161)
Log-likelihood	-1717.19	-899.63	-786.11
AIC	3506.38	1871.26	1644.22
McFadden ρ^2	0.15	0.16	0.16
LR χ^2_{63}	62.90		

Standard errors in parentheses   *p<0.1; **p<0.05; ***p<0.01

Note: Column 1 provides the results of the WTP-space model for the pooled (full) sample. Column 2 and 3 divide the sample into rural and urban respondents. The likelihood ratio test in column 1 tests for joint similarities between rural and urban respondents. We fail to reject that MWTP values are jointly the same.

C.4 Correlation Coefficients

Table C.5: Correlation Coefficients in Primary Models

Panel A: Full Sample							
	Status Q.	Distance	Fish Spe.	Fish Pop.	Algal	Nutrient	Cost
Status Q.	1						
Distance	0.006	1					
Fish Spe.	-0.631	0.489	1				
Fish Pop.	0.236	-0.103	-0.658	1			
Algal	-0.169	0.142	-0.392	0.792	1		
Nutrient	-0.541	0.486	0.304	0.067	0.526	1	
Cost	0.085	-0.078	-0.438	0.627	0.537	0.438	1
Panel B: Rural							
	Status Q.	Distance	Fish Spe.	Fish Pop.	Algal	Nutrient	Cost
Status Q.	1						
Distance	-0.591	1					
Fish Spe.	-0.253	-0.572	1				
Fish Pop.	-0.017	-0.054	-0.150	1			
Algal	-0.264	0.848	-0.691	0.238	1		
Nutrient	-0.202	0.463	-0.188	-0.006	0.614	1	
Cost	0.260	-0.018	-0.251	0.200	0.286	0.613	1
Panel C: Urban							
	Status Q.	Distance	Fish Spe.	Fish Pop.	Algal	Nutrient	Cost
Status Q.	1						
Distance	-0.390	1					
Fish Spe.	-0.222	-0.080	1				
Fish Pop.	-0.122	0.337	0.245	1			
Algal	0.047	0.376	-0.352	0.815	1		
Nutrient	-0.533	0.621	0.156	0.039	-0.111	1	
Cost	0.219	0.082	0.240	0.424	0.219	0.467	1

Note: Correlation coefficients are recovered from the primary model in Table 4.2 (Panel A) and the rural and urban samples in Table C.4 (Panel B). As expected, correlations between parameters are large for many of the attributes providing strong evidence that an attribute-correlated model is appropriate.

C.5 Certainty Adjustments

Table C.6: MWTP with Certainty Adjustments

	(1) Full Sample	(2) Adjustment 1	(3) Adjustment 2
Distance (miles)	-0.67***	-0.76***	-0.67*
	(0.15)	(0.18)	(0.28)
Fish Species	4.73**	3.34	-7.61
	(1.48)	(1.89)	(4.78)
Fish Population	0.17**	0.14	0.09
	(0.06)	(0.07)	(0.13)
Algal Blooms (%)	0.77***	0.89***	0.75*
	(0.11)	(0.15)	(0.30)
Nutrient Target	0.95***	1.06***	0.63*
	(0.13)	(0.16)	(0.26)
Status Quo (No Program)	-69.49***	-8.90	196.67***
	(14.78)	(12.31)	(56.60)
Observations (Respondents)	2058 (343)	2058 (343)	2058 (343)
Log-likelihood	-1717.19	-1762.15	-1433.89
AIC	3506.38	3596.29	2939.78
McFadden ρ^2	0.15	0.13	0.29

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Note: Column 1 presents the results from our primary specification (Table 4.2). Column 2 makes a certainty adjustment that recodes any "not very certain" follow-up questions to the status quo option. Column 3 makes a certainty adjustment that recodes any "not very certain" and "somewhat certain" follow-up questions to the status quo option. This can be interpreted as moving from less restrictive (column 1) to more restrictive (column 3). MWTP values become more noisy (larger standard errors) in columns 2 and 3. However, MWTP for improvements in Algal Blooms and reaching the Nutrient Target are still large and significant. The MWTP for distance is also robust to certainty adjustments. As discussed in Penn and Hu (2020), the most restrictive assumptions regarding certainty adjustments (column 3) are believed to underestimate the true MWTP—overcorrecting for hypothetical bias.

C.6 Preference-space Results

Table C.7: Preferences-Space Models and Marginal Utilities

Mean Marg. Util.	(1) Full Sample	(2) ASC Het.	(3) Rural	(4) Urban
Distance (miles)	-0.0124***	-0.0134***	-0.0119**	-0.0135***
	(0.0026)	(0.0028)	(0.0038)	(0.0040)
Fish Species	0.0500	0.0495	0.0091	0.0908*
	(0.0271)	(0.0279)	(0.0395)	(0.0402)
Fish Population	0.0031**	0.0032**	0.0013	0.0048**
	(0.0010)	(0.0011)	(0.0014)	(0.0015)
Algal Blooms (%)	0.0143***	0.0149***	0.0125***	0.0171***
	(0.0015)	(0.0016)	(0.0021)	(0.0023)
Nutrient Target	0.0167***	0.0170***	0.0172***	0.0170***
	(0.0015)	(0.0016)	(0.0022)	(0.0022)
Cost	0.0163***	0.0165***	0.0150***	0.0191***
	(0.0021)	(0.0022)	(0.0029)	(0.0033)
Status Quo (No Program)	-0.7933***	-0.2811	-1.1083***	-0.4291
	(0.1980)	(0.2626)	(0.2755)	(0.2963)
Status Quo × Rural		-0.5295		
		(0.2880)		
Status Quo × Aware of Water Issues		-0.3753		
		(0.2223)		
SD of Ran. Param.				
Distance (miles)	0.024***	0.027***	0.03***	1.50**
	(0.006)	(0.005)	(0.007)	(0.28)
Fish Species	0.160**	0.174**	0.225**	0.024*
	(0.055)	(0.06)	(0.09)	(0.009)
Fish Population	0.007***	0.007***	0.006*	0.009**
	(0.002)	(0.002)	(0.003)	(0.003)
Algal Blooms (%)	0.017**	0.017***	0.021***	0.012**
	(0.002)	(0.003)	(0.003)	(0.004)
Nutrient Target	0.016***	0.016***	0.017***	0.015***
	(0.002)	(0.12)	(0.003)	(0.003)
Status Quo (No Program)	1.70***	2.12***	1.300*	2.17***
	(0.32)	(0.43)	(0.54)	(0.47)
Status Quo × Rural		1.78***		
		(0.41)		
Status Quo × Aware of Water Issues		0.167		
		(0.34)		
Obs. (Respondents)	2058 (343)	2058 (343)	1092 (182)	966 (161)
Log-likelihood	-1739.9212	-1730.2633	-913.4013	-807.9063
AIC	3535.8424	3550.5267	1882.8027	1671.8127
McFadden ρ^2	0.14	0.15	0.14	0.16
LR χ^2_{63}	37.23			

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Note: The likelihood ratio test in column 1 tests for joint similarities between rural and urban respondents (columns 3 and 4). We fail to reject that preferences are jointly the same. For all preference-space regressions, the coefficient on cost is assumed fixed. All other parameters are assumed to be distributed normal.

Table C.8: MWTP from Preference-Space Models

	(1) Full Sample	(2) ASC Heterogeneity	(3) Rural	(4) Urban
Distance (miles)	-0.76***	-0.82***	-0.80**	-0.71**
	(0.18)	(0.20)	(0.29)	(0.24)
Fish Species	3.06	3.00	0.61	4.77*
	(1.73)	(1.77)	(2.65)	(2.27)
Fish Population	0.19**	0.19**	0.09	0.25**
	(0.07)	(0.07)	(0.10)	(0.10)
Algal Blooms (%)	0.88***	0.90***	0.84***	0.90***
	(0.13)	(0.14)	(0.20)	(0.17)
Nutrient Target	1.02***	1.03***	1.15***	0.89***
	(0.15)	(0.15)	(0.25)	(0.17)
Status Quo (No Program)	-48.54***	-17.04	-74.06***	-22.52
	(11.95)	(15.75)	(19.88)	(15.16)
Status Quo × Rural		-32.10		
		(17.96)		
Status Quo × Aware of Water Issues		-22.75		
		(13.59)		

Standard errors in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: MWTP values are recovered from the preference-space model summarized here. Means and standard errors are estimated using the delta method in the *gmnl* package in R (Sarrias and Daziano, 2017). The coefficient on cost was assumed to be fixed for the population. This allowed us to derive meaningful distributions of MWTP by taking a simple ratio of the mean preference parameters. Results are comparable to the estimates in the WTP-space models in our main analysis (Table 4.2). However, the MWTP produced from the WTP-space models has a tighter distribution around the means with more precise estimates of the mean MWTP for each attribute.

C.7 MIXL, Logit, PPML, and LPM Specifications

Table C.9: Marginal Utilities from Logit, Poisson Pseudo-ML, and LPM

	(1) MIXL	(2) Logit	(3) PPML	(4) LPM
Distance (miles)	-0.0113***	-0.0101***	-0.0056***	-0.0019***
	(0.0024)	(0.0031)	(0.0017)	(0.0005)
Fish Species	0.0414	0.0151	0.0020	0.0037
	(0.0256)	(0.0267)	(0.0145)	(0.0060)
Fish Population	0.0023**	0.0021**	0.0012***	0.0004**
	(0.0009)	(0.0007)	(0.0003)	(0.0001)
Algal Blooms (%)	0.0126***	0.0112***	0.0061***	0.0026***
	(0.0014)	(0.0015)	(0.0008)	(0.0003)
Nutrient Target	0.0149***	0.0115***	0.0064***	0.0026***
	(0.0014)	(0.0011)	(0.0006)	(0.0002)
Cost	0.0159***	0.0154***	0.0084***	0.0034***
	(0.0019)	(0.0023)	(0.0013)	(0.000)
Status Quo	-0.9255**	-0.7932***	-0.6768***	-0.1181***
	(0.2031)	(0.1663)	(0.1200)	(0.0313)
Individual j FE	Yes	Yes	Yes	Yes
Clustered. SE	Individual	Individual	Individual	Individual
Correlated Parameters	No	No	No	No
Obs. (Respondents)	2058 (343)	2058 (343)	2058 (343)	2058 (343)
Log-likelihood	-1,754.2	-3,335.46	-3,931.15	-3,508.40
AIC	3,534.338	7,404.93	8,596.30	7,750.81
ρ^2 and R^2	0.14	0.06	0.01	0.13

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

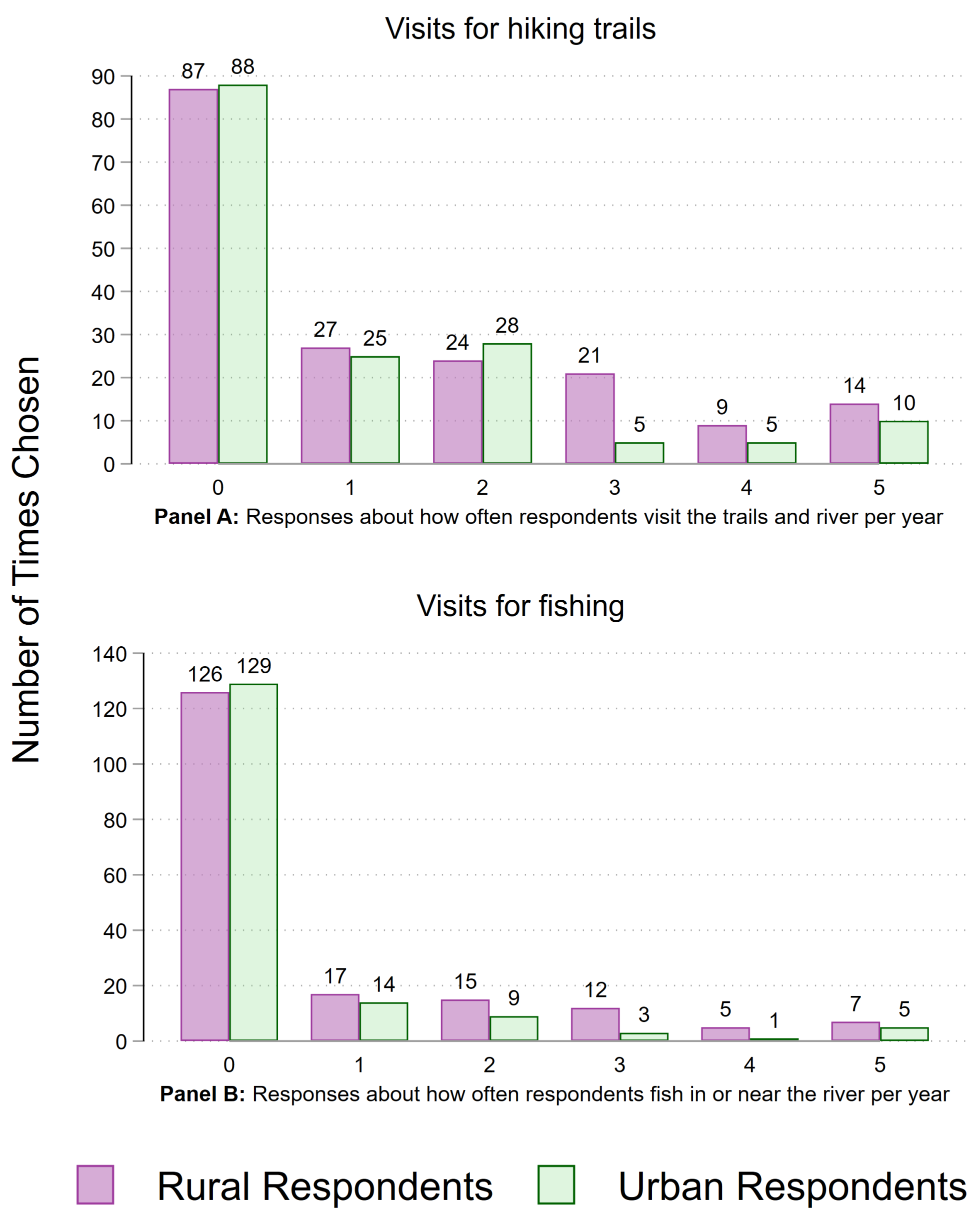
Table C.10: MWTP from Preference-Space Specifications

	(1) MIXL	(2) Logit	(3) PPML	(4) LPM
Distance (miles)	-0.71***	-0.66***	-0.67**	-0.56**
	(0.17)	(0.22)	(0.24)	(0.19)
Fish Species	2.59	0.98	0.24	1.08
	(1.67)	(1.73)	(1.73)	(1.77)
Fish Population	0.14**	0.14**	0.15**	0.14**
	(0.06)	(0.05)	(0.05)	(0.05)
Algal Blooms (%)	0.79***	0.73***	0.73***	0.76***
	(0.12)	(0.17)	(0.19)	(0.17)
Nutrient Target	0.94***	0.74***	0.76***	0.75***
	(0.13)	(0.17)	(0.15)	(0.13)
Status Quo	-58.01***	-51.46***	-80.42***	-34.03***
	(13.38)	(10.26)	(16.23)	(7.46)

Standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

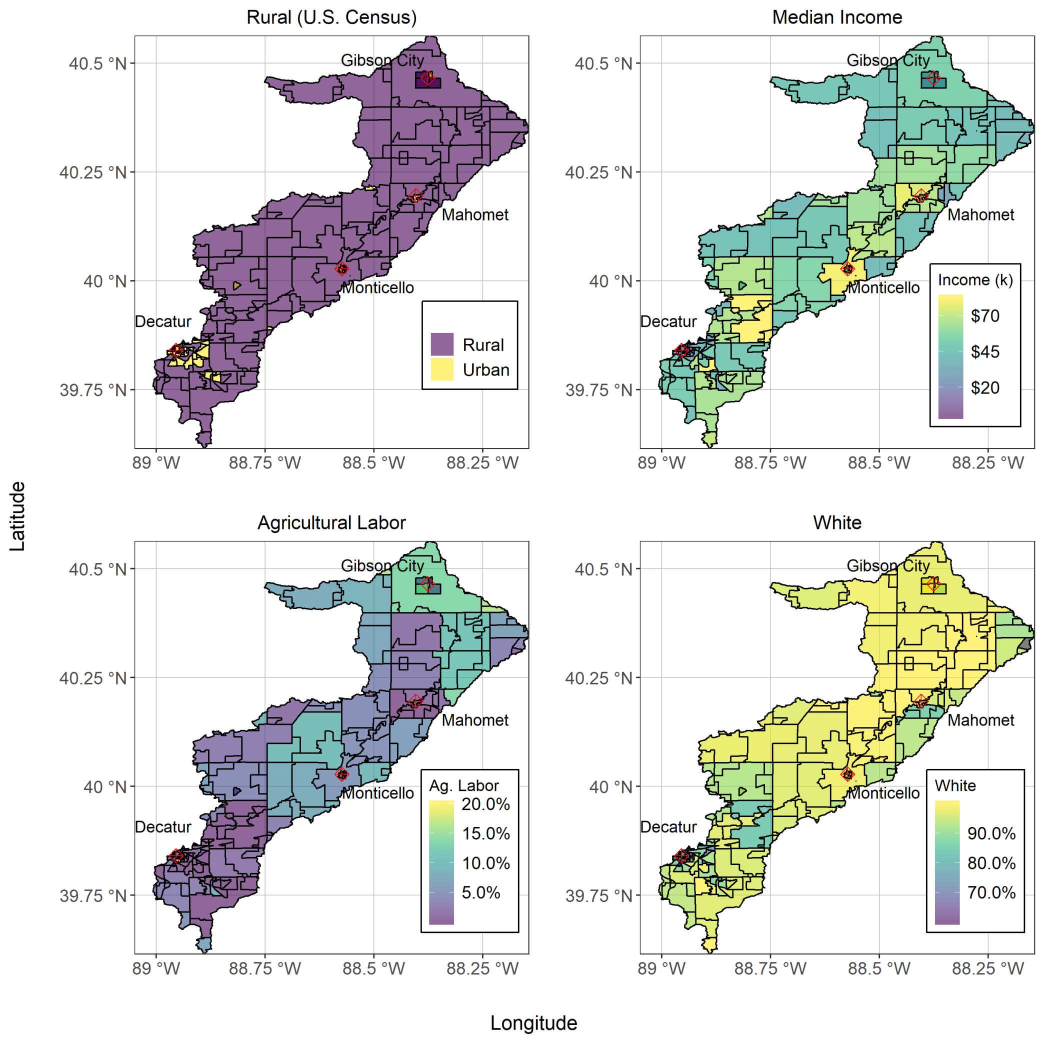
C.8 Additional Figures

Figure C.1: Responses to Questions about Recreation



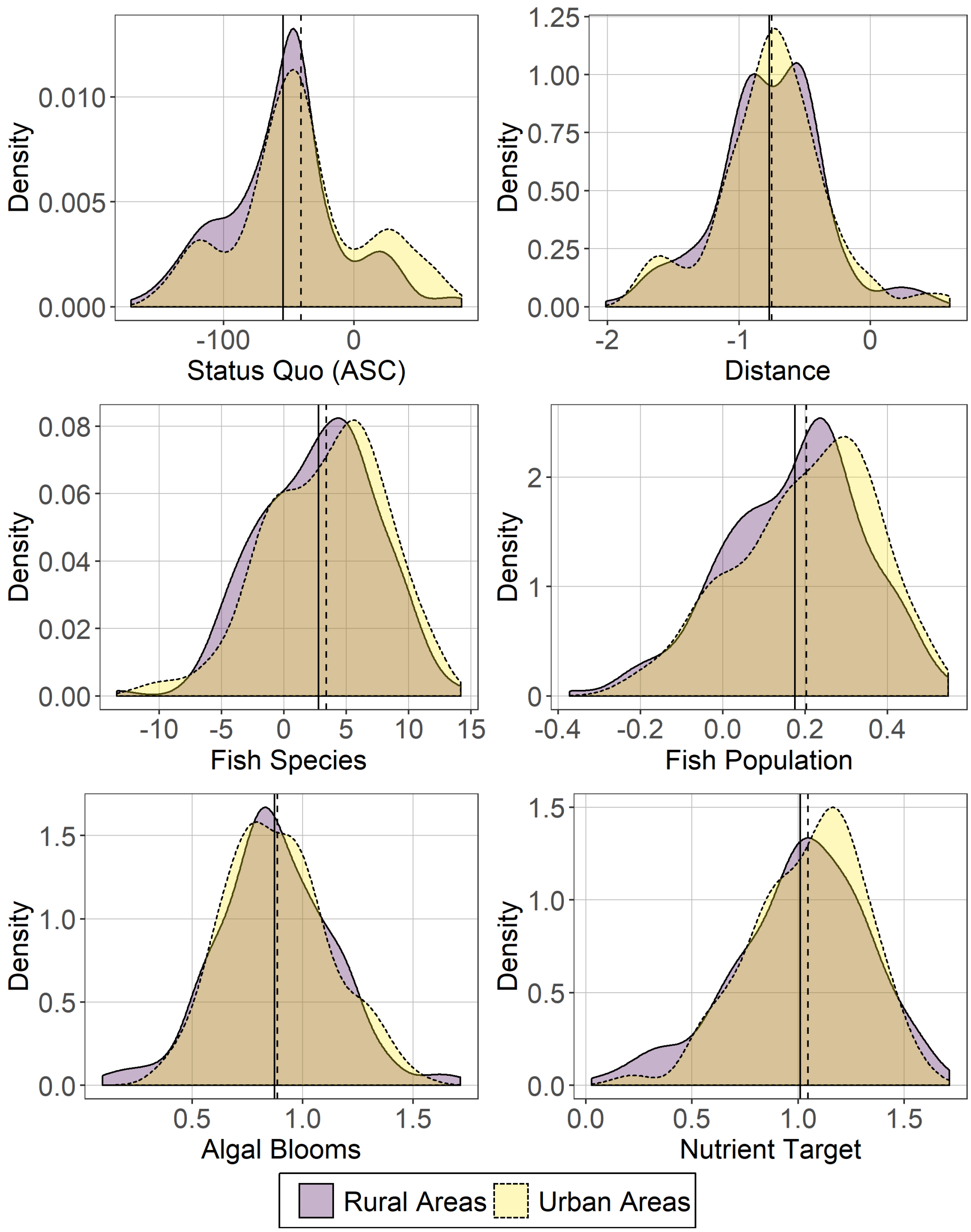
Note: Responses to the post-survey questionnaire about how frequently respondents visit the trails around the Upper Sangamon River each year, and if they participate in recreational fishing. Respondents rarely visit the trails, and even more rarely fish in the river or nearby water.

Figure C.2: Demographics and characteristics plots of the USRB



Note: Data from the American Community Survey (U.S.Census, 2019) are plotted within the watershed. Comparisons between these data and our sample are found in Table C.2.

Figure C.3: Conditional Individual-Specific Means of MWTP



Note: Conditional individual-specific means of MWTP are derived using the *gmnl* package in R (Sarrias and Daziano, 2017). These values are used in the IAM exercise to estimate the spatial distribution of benefits within the watershed.

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