A Recreation Demand Model for Mountain Snowpack

Bryan Parthum
U.S. EPA
parthum.bryan@epa.gov*

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Abstract

Mountain snowpack is a major driver of participation in outdoor winter recreation and is greatly threatened by climate change. To quantify the consumer welfare underlying this climate amenity, I estimate structural parameters in the utility functions of alpine skiers and recover the marginal willingness to pay for mountain snowpack in each resort market. Regional variation in the MWTP for snowpack ranges from \$1.38/inch in the Midwest to \$4.24/inch in the Northeast. On a day with average snowpack at the average resort, consumer surplus from mountain snowpack equals \$80/skier. Daily market shares are used to recover substitution patterns, providing further insight into how skiers move across markets based on changes in mountain snowpack. I find that substitution is larger in the Mountain-West states, suggesting that these skiers 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.

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*Corresponding author: parthum.bryan@epa.gov; U.S. EPA, Office of Policy, National Center for Environmental Economics.
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1 Introduction

Mountain snowpack—the amount of packed, dense snow on the ground—is a major driver of participation in outdoor winter recreation (Hamilton et al., 2007; Shih et al., 2009; Falk, 2010; Damm et al., 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 et al., 2015a; Steiger et al., 2020) or by linking observed (revealed) consumer 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

[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 et al., 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.

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 et al., 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 et al., 2009). These values range anywhere from $14 for a day of skiing (Morey, 1985), to $277

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

(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 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 et al., 2018; Steiger et al., 2019).

Site substitution is a well-known and important phenomenon to consider when modeling recreation behavior (Peterson et al., 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,b), and the Northeastern US (Dawson and Scott, 2013), but remains an area of necessary research (Unbehaun et al., 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.

2 Empirical Framework

In the spirit of the recreation demand literature (Hanemann, 1984; Bockstael et al., 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—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 A1).

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):

[3] I discuss trip-level estimation first. Market-level is discussed in section 5.

$U^i_{jt} = V^i_{jt} + \varepsilon^i_{jt}$, 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:

$$P^i_{jt} = Prob(V^i_{jt} + \varepsilon^i_{jt} > 0), \tag{1}$$

resulting in the standard logit choice probabilities:

$$P^i_{jt} = \frac{1}{1 + exp(-V^i_{jt})}. \tag{2}$$

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 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 A3, A4, and A5).

4 The Model

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

$$U^i_{jt} = -\lambda price_j + \boldsymbol{\beta}' snowpack_{rt} + \boldsymbol{X}'_{rt}\boldsymbol{\phi} + \boldsymbol{Z}'_j\boldsymbol{\gamma} + \Omega_t + \theta_r + \varepsilon_{jt}. \tag{3}$$

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 $\boldsymbol{X}$.

[4] I also estimate a non-parametric binned regression model, discussed in section 4.3.

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, 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 et al., 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 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, person i's utility function becomes:

$$U^i_{jt} = \delta_j + \boldsymbol{\beta'} snowpack_{rt} + \boldsymbol{X'}_{rt}\boldsymbol{\phi} + \Omega_t + \theta_r + \varepsilon_{jt} \tag{4}$$

where

$$\delta_j = -\lambda price_j + \boldsymbol{Z'_j}\boldsymbol{\gamma} + \xi_j. \tag{5}$$

[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.

I estimate equation 4 using a standard logit specification, recovering the β's and the vector of parameters associated with the alternative specific constants 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 5. To allow for correlation across observations, I cluster standard errors at the level of the market (Wooldridge, 2006; Abadie et al., 2017).[7] I estimate equation 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.

4.1 The Endogenous Price of a Trip

The price characteristic in equation 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 4) that subsumes the endogenous price. In the second regression (equation 5), I use a 2SLS approach that is common in the industrial organization literature (Berry et al., 1995; Nevo, 2001; Bayer et al., 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.

[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 et al. (2017).

[7] I examine correlation structures at the property, market, and state levels. Those results and discussion can be found in the appendix (Table A1). Significance is robust to alternative clustering—I choose market-level for the primary analysis.

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 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:

$$price_j = \boldsymbol{Z_k'}\Pi_1 + \Pi_2\Upsilon_j + \boldsymbol{Z_j'}\Gamma + \theta_r + \upsilon_j. \tag{6}$$

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 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 provides a complete comparison of the three approaches.

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 A1). 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:

$$\begin{aligned} U^i_{jt} =& \delta_j + \sum_m \beta_m snowpack_{rt}[region = m] \\ & + \beta_2 snowpack^2_{rt} + \boldsymbol{X'_{rt}\phi} + \Omega_t + \theta_r + \varepsilon_{jt}, \end{aligned} \tag{7}$$

where $\delta_j = -\lambda price_j + \boldsymbol{Z'_j\gamma} + \xi_j$. The only difference between equations 4 and 7 is the addition of the interaction between snowpack and region.

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:

$$\begin{aligned} U^i_{jt} = \delta_j + \sum_b \beta_b snowpack_{rt}[bin = b] \\ + \beta_2 snowpack^2_{rt} + \boldsymbol{X'_{rt}} \boldsymbol{\phi} + \Omega_t + \theta_r + \varepsilon_{jt}, \end{aligned} \tag{8}$$

where $\delta_j = -\lambda price_j + \boldsymbol{Z'_j}\boldsymbol{\gamma} + \xi_j$. Similar to the regional specification in equation 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:

$$\begin{aligned} U^i_{jt} = \delta_j + \sum_m \sum_b \beta_{bm} snowpack_{rt}[region = m][bin = b] \\ + \beta_2 snowpack^2_{rt} + \boldsymbol{X'_{rt}} \boldsymbol{\phi} + \Omega_t + \theta_r + \varepsilon_{jt}, \end{aligned} \tag{9}$$

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 5) when exploring heterogeneity in the marginal utility of snowpack.

4.4 Results of Trip-level Estimation

I find that skiers have large and statistically significant preferences for deeper snowpack (Table 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 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). 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 2). I do find substantial regional variation, ranging from \$1.38 in the Midwest to \$4.24 in the Northeast. As mentioned earlier,

[8] Results for all attributes in the model can be found in the Appendix (A2).

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 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 1). 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.

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:

$$\omega_{jt} = -\lambda_i price_{jt} + \beta_i log(snowpack)_{jt} + \boldsymbol{X'}_{jt}\boldsymbol{\phi} + \Psi_j + \Omega_y + \theta_h + \xi^i_{jt}. \tag{10}$$

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).

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:

$$s_{jt} = \frac{exp(\omega_{jt})}{1 + \sum_j exp(\omega_{jt})}. \tag{11}$$

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 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 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:

$$\eta_{jkt} = \frac{\partial s_{jt}}{\partial x_k} \frac{x_k}{s_j}. \tag{12}$$

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:

$$\eta_{jk} = \begin{cases} \dfrac{\beta_x x_k}{1-\sigma_m}(1-(1-\sigma_m)s_k - \sigma_m s_{k|m}) & \text{if } j = k; j,k \in m \\ \dfrac{\beta_x x_k}{1-\sigma_m}((1-\sigma_m)s_k + \sigma_m s_{k|m} & \text{if } j \neq k; j,k \in m \\ \beta_x x_k s_k & \text{if } j \neq k; j \in m; k \notin m \end{cases} \tag{13}$$

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 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.

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.

Tables

Table 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 4 and the 2SLS estimate of *price* from 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 4 are in the appendix (Table A2). Full results for the 2SLS estimates for equation 5 are in table 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 7).

Table 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	-\$0.002
	[-0.01, -0.01]	[-0.01, -0.01]	[-0.002, -0.002]

Krinsky-Robb 95% confidence intervals in brackets

Note: MWTP are calculated using the ratio of the marginal utilities in table 1 such that $MWTP = \beta/\lambda$. Empirical distributions of MWTP are calculated using the Krinsky-Robb approach (Krinsky and Robb, 1986).

Table 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 4: Market-level Marginal Utilities

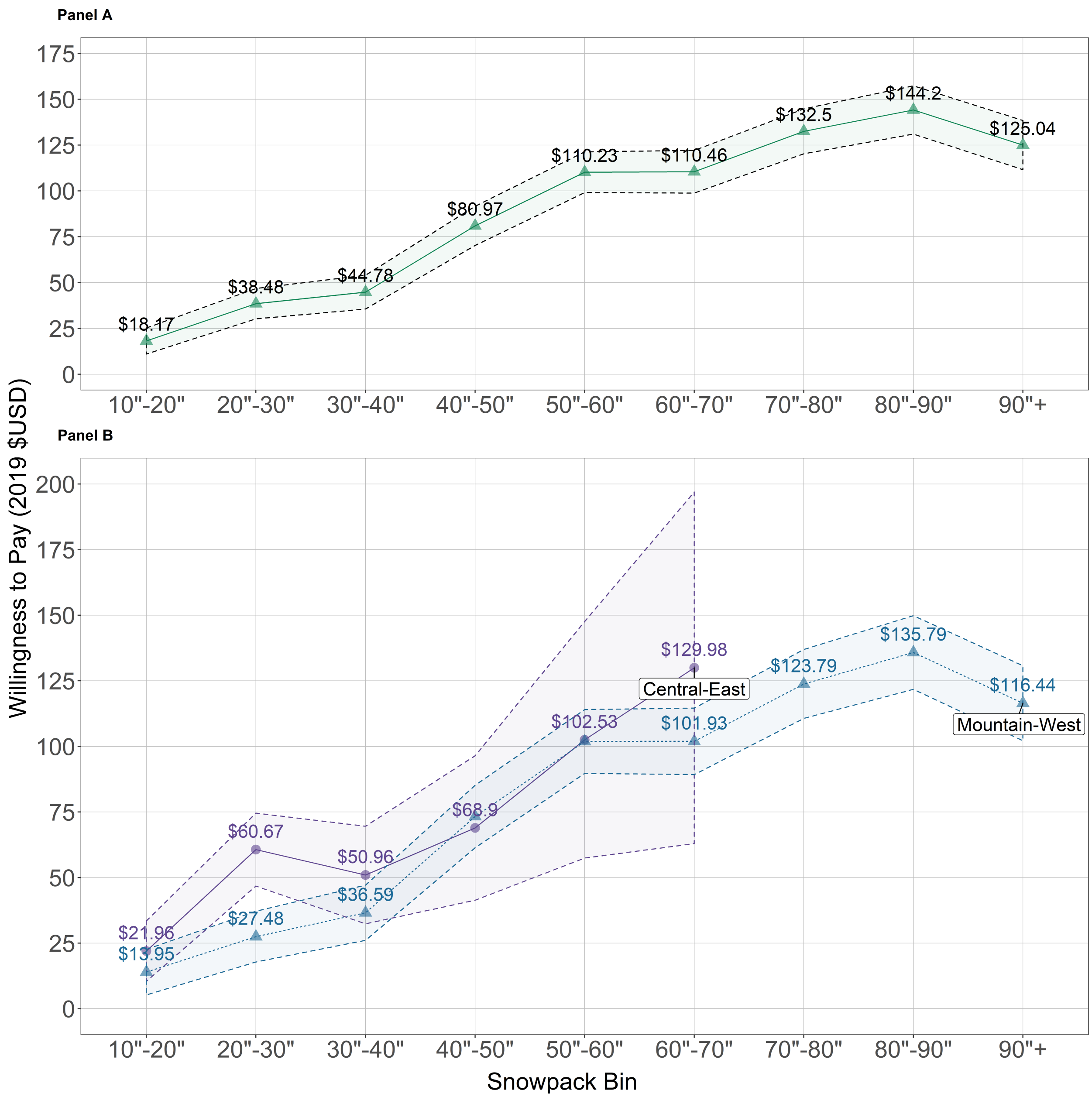
	(1) Mean (λ, β)	(2) Std. Dev
Price	-0.040***	0.023***
	(0.012)	(0.005)
log(snowpack)	0.827***	0.016
	(0.122)	(0.622)
State FE	Yes	
Season FE	Yes	
Holiday FE	Yes	
Clustered. SE	NSAA Region	
Observations	5,937	
F-stat (Wald: IV)	81.02***	

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).

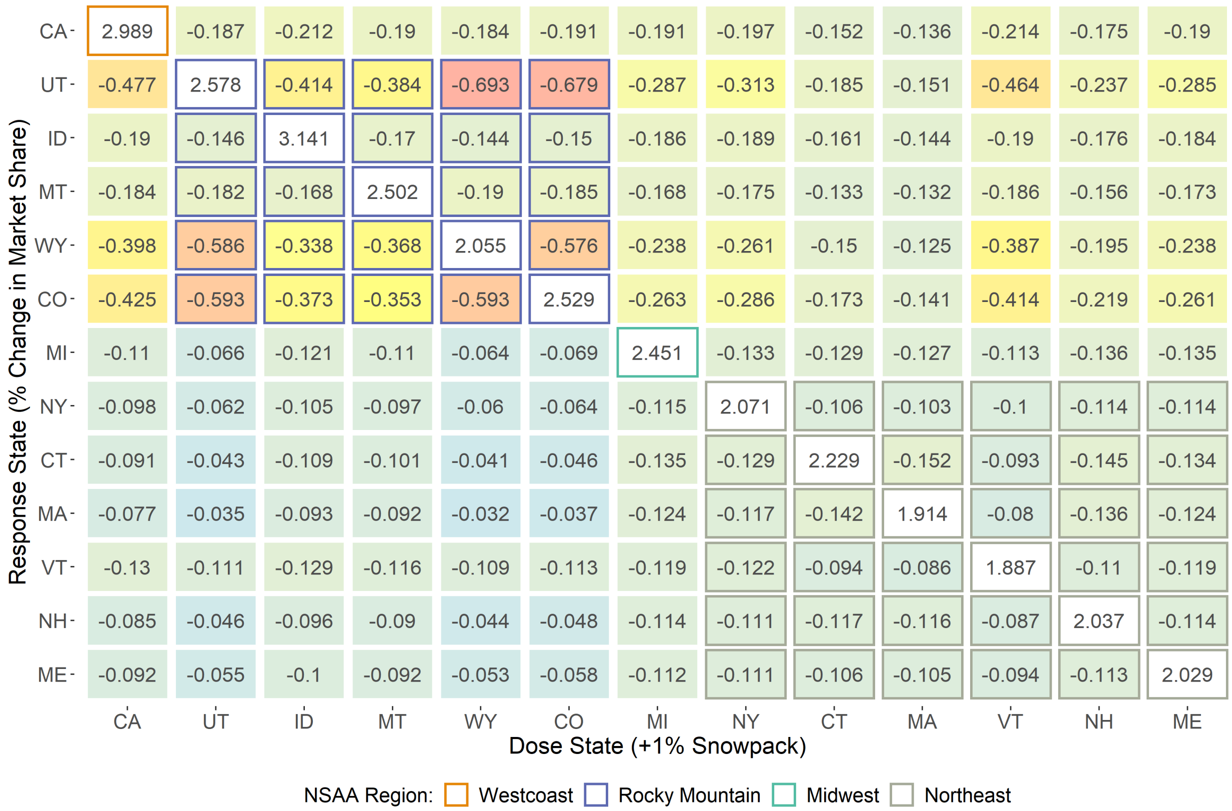
402 # Figures

Figure 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 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.

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Appendices for "A Recreation Demand Model for Mountain Snowpack")

A Additional Tables

Table A1: Results of Different Clustered Standard Errors

	(1)	(2)	(3)
Clustered. SE:	Property	Market	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 A2: Marginal Utilities from Trip Decisions (Contd. from Table ??)

	(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 A3: 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 A4: 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 A5: 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 Logit, PPML, and LPM

Table A6: Results from Logit, PPML, and LPM

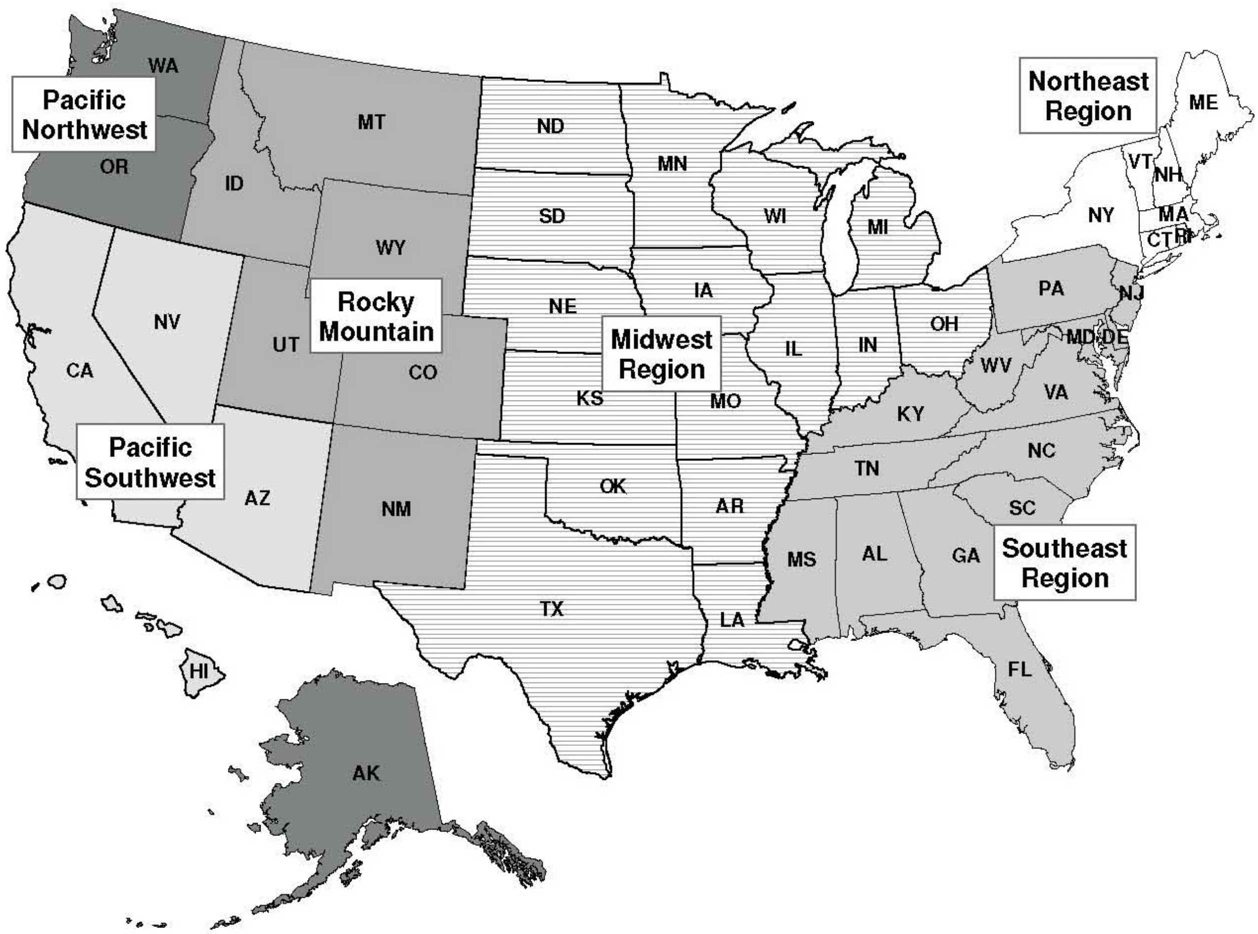
	(1) Logit	(2) PPML	(3) LPM
Panel A: Marginal Utilities			
Snowpack	0.01242***	0.00610**	0.00178***
	(0.00392)	(0.00218)	(0.00052)
Snowpack^2	-0.00004*	-0.00002*	-0.000007*
	(0.00002)	(0.00001)	(0.000003)
Price (2SLS)	-0.00526***	-0.00280***	-0.00081***
	(0.00077)	(0.00039)	(0.00012)
Property j FE	Yes	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.

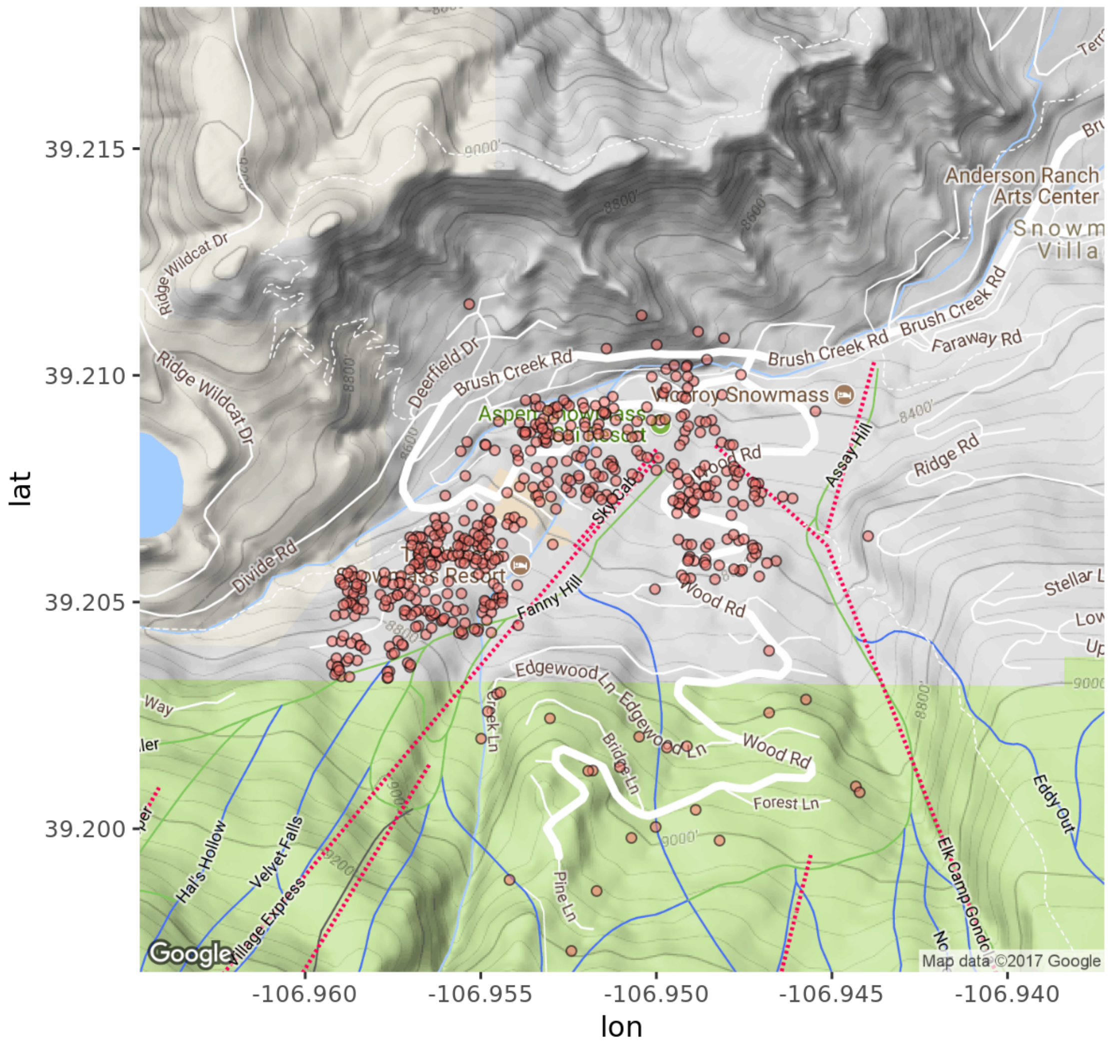
C Additional Figures

Figure A1: NSAA Resort Regions



Note: Figure A1 presents the regions across the U.S. as defined by the NSAA (NSAA, 2018). These are the regions specified in equation 7. I combine California, Nevada, Oregon, and Washington to be a combined NSAA region called "West-coast".

Figure A2: Spatial Distribution of Airbnb Properties in Aspen, CO



560 **Note:** Figure A2 presents the spatial distribution of short term rental properties within a
561 10km buffer near Aspen, Colorado.