A Market for Snow: Modeling Winter Recreation Patterns Under Current and Future Climate

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Abstract

Throughout the winter months across the globe, mountain communities and snow-enthusiasts alike anxiously monitor ever-changing snowpack conditions. We model the behavioral response to this climate amenity by pairing a unique panel of 12 million short-term property rental transactions with daily local weather, daily local snowpack, and daily local snowfall in every major ski resort market across the United States. Matching the spatial and temporal variation in the level of the amenity with that of related market transactions, we derive market-specific demand elasticities, explicitly accounting for substitution, to model recreation patterns throughout a typical season. Lastly, we combine downscaled projections of local snowpack under future climate scenarios to estimate within and across season trends in visitation during mid and late-century conditions. Our model predicts reductions in snow-related visitation of -40% to -60%, almost twice as large as previous estimates suggest. This translates to a lower-bound on the annual willingness to pay to avoid reductions in snowpack between \$1.23 billion (RCP4.5) and \$2.05 billion (RCP8.5) by the end of the century.

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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. Many rural mountain towns rely on snowpack to provide recreation opportunities that generate a significant portion of their local economic activity (Beaudin and Huang, 2014; White et al., 2016; Rosenberger et al., 2017; Burakowski et al., 2018), but climate change threatens these opportunities by reducing the supply of precipitation, increasing average temperatures, and shortening the length of the snow season (Feng and Hu, 2007; Burakowski et al., 2008; Burakowski and Magnusson, 2012; Dawson and Scott, 2013). 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 primarily focused on changes in the length of the ski season (extensive margin) to estimate changes in recreation behavior under different climate scenarios. Doing so implicitly makes the assumption that there is no behavioral response to marginal changes in the *amount of snowpack* during the season. We show that failing to account for changes in visitation throughout the season (intensive margin) may lead to substantial underestimation of the impacts of climate change on winter recreation. Moreover, efforts aimed at maintaining season length, such as artificial snow-making, do not fully address the underlying behavioral response to changes in mountain snowpack that are predicted by climate models.

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

To quantify potential changes in winter recreation under future climate scenarios, a researcher must first establish (or make assumptions about) a behavioral response that will map changes in snowpack to changes in resort visitation. Many existing studies have relied upon strong assumptions to generate this relationship, such as assuming that visitation is only a function of season length (Loomis and Crespi, 1999; Scott et al., 2007; Falk and Vanat, 2016; Rosenberger et al., 2017; Wobus et al., 2017). Damages, as measured by lost revenues, can then be mitigated by simply increasing investments in snow-making capacity to maintain minimum operating levels of snowpack at the resort. While this is a reasonable starting point, a known limitation is its ability to capture the behavioral response to marginal changes in resort snowpack that occur throughout the season (Falk, 2010; Gilaberte-Búrdalo et al., 2014; Damm et al., 2017; Scott et al., 2019; Steiger et al., 2019; Steiger and Scott, 2020). Other research has explored this limitation by looking at how skiers substitute across resorts in response to climate variability, concluding that geographical substitution can, in fact, help to bolster aggregate demand in the industry (Englin and Moeltner, 2004; Rutty et al., 2015a,b, 2017; Steiger et al., 2020). We develop a method to estimate a damage function that accommodates substitution such that increases (decreases) in visitation are predicted on days with higher (lower) than average snowpack, providing a flexible damages curve that mirrors the true nature of recreation decisions.

Short-run changes in snowpack provide a key source of variation for identifying the relationship between recreation demand and snowpack as recreation decisions are often made in response to short-run fluctuations in weather conditions (Connolly, 2008; Dundas and von Haefen, 2019; Chan and Wichman, 2020). Unfortunately, market transactions that match the frequency of short-run shocks in mountain snowpack have been largely unavailable. Studies have instead used market data that is aggregated geographically (county or larger), temporally (monthly or larger), or both. Limited availability of high-frequency market transactions has also led prior work to quantify damages by comparing differences in visitation between high-snow and low-snow years ("inter-season") (Steiger, 2011; Butsic et al., 2011; Burakowski et al., 2018). Such 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 (Busse et al., 2015; Deryugina and Hsiang, 2017; Burakowski et al., 2018; Kahn et al., 2019).

We addresses this inconsistency in the resolution of available data by compiling a panel of high-frequency daily market transactions (individual short-term property rentals) together with daily snowpack and weather to estimate the effect of changes in mountain snowpack on visitation. We use daily resort-level visitation to isolate the demand response to marginal changes in snowpack from other confounding factors that influence demand and then draw comparisons to a more coarse monthly-level approach to illuminate the advantages of using daily data in this setting.[2]

Several studies have also used within-season variation in visits and weather, but have been limited to a single season and only a few resorts (Morey, 1984; Englin and Moeltner, 2004).[3] We find evidence of substantial heterogeneity in snowpack elasticities across states,

[2]The use of high-frequency data to estimate demand on the margin has been shown to be important in other contexts, too. For example, Levin et al. (2017) show that failing to account for high-frequency purchases in the gasoline market drastically underestimates the demand response to changes in prices. We find this is true in our context as well and draw these comparisons in the appendix for the interested reader.

[3]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.

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 behavioral response characterized as the elasticity of overnight stays (Falk, 2010).[4] We model both daily and monthly decisions and test for differences between the resulting elasticities. In our setting, we find that elasticity estimates derived using monthly data are less precise and smaller than those derived using daily data, likely due to the inability of the monthly model to control for unobservable variation that is correlated with resort visitation.

We contribute to an emerging literature that uses short-run variation in climate amenities *and* the demand response to predict damages in the contemporary and under future climate scenarios (Chan and Wichman, 2020; Dundas and von Haefen, 2019). We make three primary contributions: 1) we develop a method to estimate 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 states that have a large ski resort and show that significant heterogeneity exists across states; and 3) we estimate the within and across year variation in the contemporaneous value of snowpack and simulate local economic damages under two future warming scenarios, RCP4.5 and RCP8.5.[5] We find that ski resorts could face annual reductions in local snow-related revenues of -40% to -60% (on average) by the end of the century (2080). When this response

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

[5]RCP4.5 and RCP8.5 are Representative Concentration Pathways (RCPs) used by the Intergovernmental Panel on Climate Change (IPCC) as modeled in Meinshausen et al. (2011). The RCPs represent possible global futures and warming responses concentrations and emissions of greenhouse gases. RCP4.5 can be thought of as an intermediate, or more-likely, scenario representing the combination of moderate reductions in emissions and moderate climate responses to those emissions. Whereas RCP8.5 is a more extreme case of higher emissions and climate response and is considered a less-likely but still possible outcome.

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).[6] Across the U.S., partial annual damages total to between \$1.64 billion (RCP4.5) and \$2.36 billion (RCP8.5).

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. Conditional on these controls, impacts on visits are identified from daily 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 dependent variable ($revenue$) using the inverse hyperbolic sine (ihs) and allowing revenue to take a value of 0. The use of the ihs transformation is particularly useful for our application, where our dependent variable follows a log-normal distribution and we are interested in estimating the effect of a change from \$0 in revenue to the asking price of the property. When modeling the move away from 0 while retaining them in the data, the ihs transformation provides intuitive interpretation of the results in the form of percent changes, mirroring that of a traditional $log - log$ specification without the need to implement more ad hoc transformations such as $log(x + n)$ where n is a scalar to move x away from 0 (Bellemare and Wichman, 2020;

[6] These damage estimates, when measured in dollars, should only be considered *partial* estimates of the total damages to activities related to winter recreation, as they do not account for expenditures on other activities directly or indirectly linked to ski resort visitation.

Aihounton and Henningsen, 2021).[7] The general form of our estimating equation is:

$$ihs(revenue)_{it} = \beta log(snowpack)_{rt} + \boldsymbol{Z}'_{rt}\boldsymbol{\delta} + \boldsymbol{X}'_{rt}\boldsymbol{\eta} + \psi_{im} + \varepsilon_{it}. \quad (1)$$

This specification estimates the relationship between daily revenues for property i on each day t and the natural logarithm of *snowpack* in market r on each day t. The elasticity parameter, β, quantifies the effect of a change in mountain snowpack on revenue. The vector $\boldsymbol{Z}$ 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 *holiday week*, a categorical variable *weekday*, and a linear and quadratic of daily *mean temperature*. Also included in $\boldsymbol{X}$ is the total amount of new snow that has fallen in the five days leading up to a trip and, to model substitution behavior and a skier's outside option, the average amount of snowpack at the nearby resorts (those within 100km).[8] The relationship between these characteristics in $\boldsymbol{X}$ 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 or leading up to a U.S. federal holiday.[9] The categorical variable *weekday* provides a unique indicator variable for each day of the week Sunday through Saturday. The parameter ψ is a property-by-month-of-sample

[7] Throughout this paper we report the coefficient as estimated. To recover consistent percent changes one could transform the coefficients presented here using $exp(\beta) - 1$, which is approximately equal to β when β is small.

[8] We examine a wide range of buffers, 50km up to 200km, to estimate sensitivities in classifying nearby resorts. The coefficient on $log(snowpack)$ is robust to the choice of buffer, but smaller than when no nearby resorts are included in the estimation. These results can be found in the appendix.

[9] 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.

fixed effect that captures property-specific determinants of revenue and their trends across the study period. The error term ε is the remaining variation in revenue that is unexplained by the model.

Our model assumes that changes in mountain 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-term property rental market. For example, we assume that variation in the snowpack that occurs across the four Saturdays in a given 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 between *snowpack* and an indicator variable indicating the resident state of the resort:

$$
\begin{aligned}
ihs(revenue)_{it} = & \underbrace{\sum_{s} \beta_s \ log(snowpack)_{rt}[State = s]}_{\substack{\text{State-specific} \\ \text{Elasticities}}} \\
& + \boldsymbol{Z'_{rt}\delta} + \boldsymbol{X'_{rt}\eta} + \psi_{im} + \varepsilon_{it}. \qquad (2)
\end{aligned}
$$

This allows us to examine heterogeneity in the damage function by recovering an estimate of state-specific responses to the climate amenity *snowpack*. The coefficient of interest, β, has the following interpretation: a 1 percent increase (decrease) in *snowpack* causes a β percent change in expected *revenue*. An important feature of our method is the direct relevance of 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 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.

Our primary analysis focuses on the state-level elasticities derived from equation 2. This specification pairs well with the resolution and composition of other data necessary to estimate damages to recreation in the contemporary and under future climate scenarios that yield projections of future snowpack conditions. We examine a variety of alternative functional forms and levels of aggregation in the appendix.[10]

3 The Data

We estimate the behavioral response to changes in mountain snowpack using a panel of 12 million daily observations of rental property bookings on the Airbnb platform (AirDNA, 2017). The data include more than 1.4 million properties and 410 million bookings spanning the contiguous United States. Owners of these properties have the option of listing their property as available or blocking bookings during certain periods for their own use. When a property is rented, it is recorded as reserved and the date of the reservation (booking) is

[10]While informative, these alternate specifications do not lend themselves to incorporating parameters given by climate projections and are not easily linked to integrated assessment modeling framework or to studies of the damages related to changes in snowpack.

Table 1: Statistics from the panel of properties and weather underlying the analysis.

Statistic	Mean	St. Dev.	Min	25%	75%	Max
Revenue (2019$ USD)	86.62	257.46	0	0	0	4,990
Snowpack (in.)	41.36	31.82	1	16	59.55	225
Snowfall (< 24hrs)	0.81	2.35	0	0	0.2	48
Number of Days in Season	163.67	31.27	13	158	173	253
Reserved	0.17	0.38	0	0	0	1
Reservation Lead-time	67.40	69.07	1	20	87	364
Holiday Week	0.11	0.31	0	0	0	1
Mean Temp (F)	30.22	11.18	−17.09	23.05	38.43	71.49
Distance to Resort (km)	4.76	2.99	0.006	2.14	7.59	9.99
Bedrooms	2.47	1.24	1	2	3	7
Bathrooms	2.14	1.08	0	1	3	8
Obs. 12,515,691						

recorded. We identify all properties located within 10km of one of the 236 ski resorts in the United States. We construct an empirical sample of over 60 thousand unique properties within this radius, resulting in over 12 million observed property-day bookings.[11] We observe daily transactions from August 2014 through May 2017—three complete ski seasons. 67 resorts fall within 20km of one or more other resorts. 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 for all 236 resorts from August 2005 through May 2017 (OnTheSnow.com, 2017). These amenities are as reported by the ski resort on each day and directly matches the information that a tourist see on a given day. We recover two measures: 1) snowpack, the depth of the snow as reported by the resort each day; and 2) snowfall, the amount of new snow that has fallen within the last 24 hours at each resort. We classify snowfall into bins of 3 inches and group every observation over 15 inches into the largest bin. We include additional measurements of days during a

[11] We examine the sensitivity of our damage function to the choice of a 10km threshold and find estimates are consistent. See appendix for additional data descriptions.

booking window to capture changes in conditions using a rolling sum of the most recent five days leading up to a stay, which captures a broader window that matches the timing of trip decisions. 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.

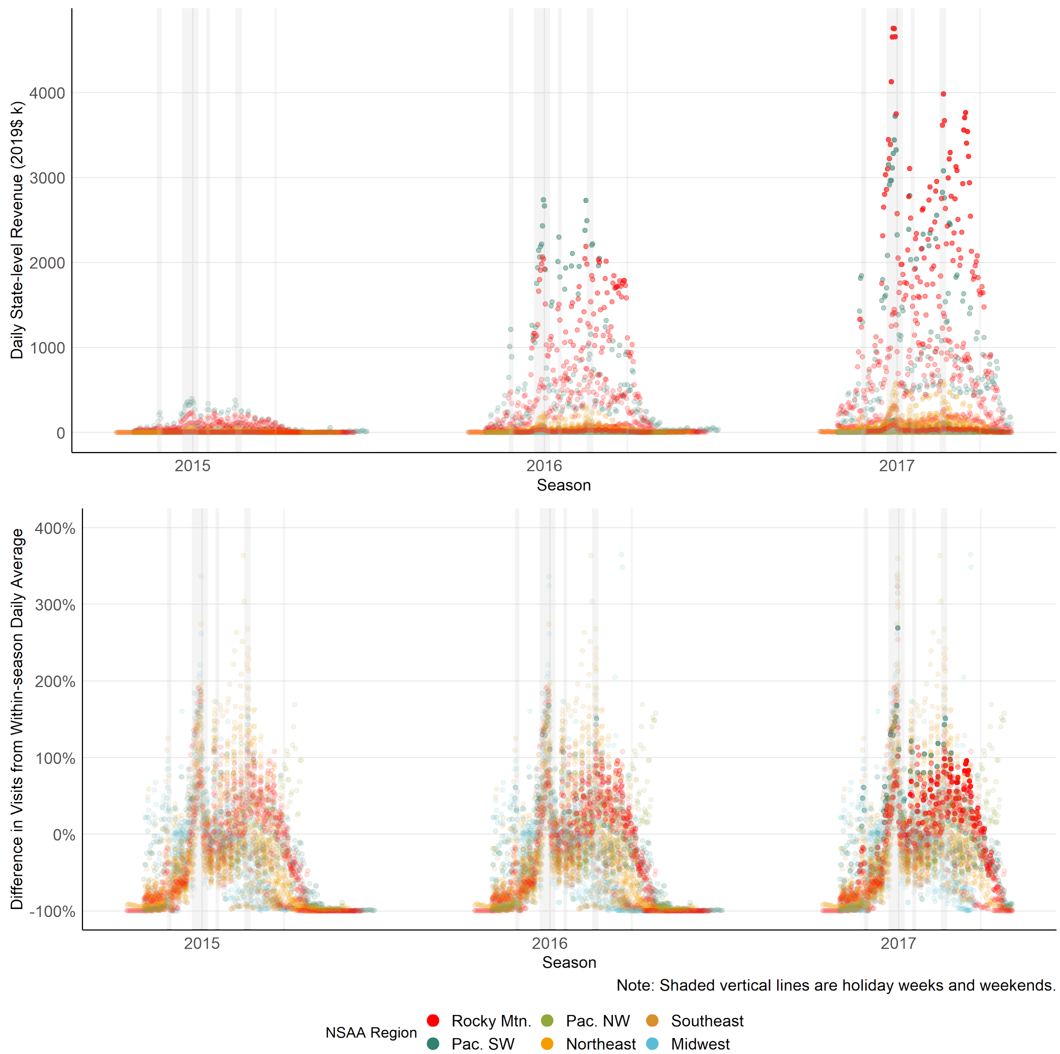
Table 1 provides summary statistics for the data used in our analysis. Daily revenue ranges from \$0 to \$5k.[12] The climate amenity snowpack ranges from 0 to 225 inches, which reflects the depth of snowpack on the ground as measured at the resort each day in the sample. These two variables, revenue and snowpack, are the primary variables of interest. Figure 1 illustrates the dynamic nature of the property panel that motivates our choice of controls in the model. The sample of observed property rentals is changing across the study period, which motivates our implementation of a robust set of controls to capture both time-varying and time-invariant characteristics of the sample. Those controls are described more thoroughly in Section 2.

To generate expectations of future snowpack, we collect locally downscaled climate projections from the suite of Coupled Model Intercomparison Project (CMIP5) models in 1/8-degree resolution across the U.S. (Reclamation, 2013).[13] These projections offer monthly snow-water-equivalent levels for historical (1950-1999) and projected (2020-2100) RCP4.5 and RCP8.5 scenarios. We compute resort-specific historical averages and calculate the

[12] All dollar values provided in this paper are measured in real terms using 2019 U.S. dollars (\$).

[13] The area covered by 1/8th degree of resolution varies by location but, for example, translates to approximately 6 miles wide by 8 miles high over the central Rocky Mountains in Colorado. These distances get smaller as one moves further north, and larger as one moves further south.

Figure 1: Daily revenue (top) and within season deviations (bottom) from the panel of properties



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 28 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 28 states and the number of overnight stays.

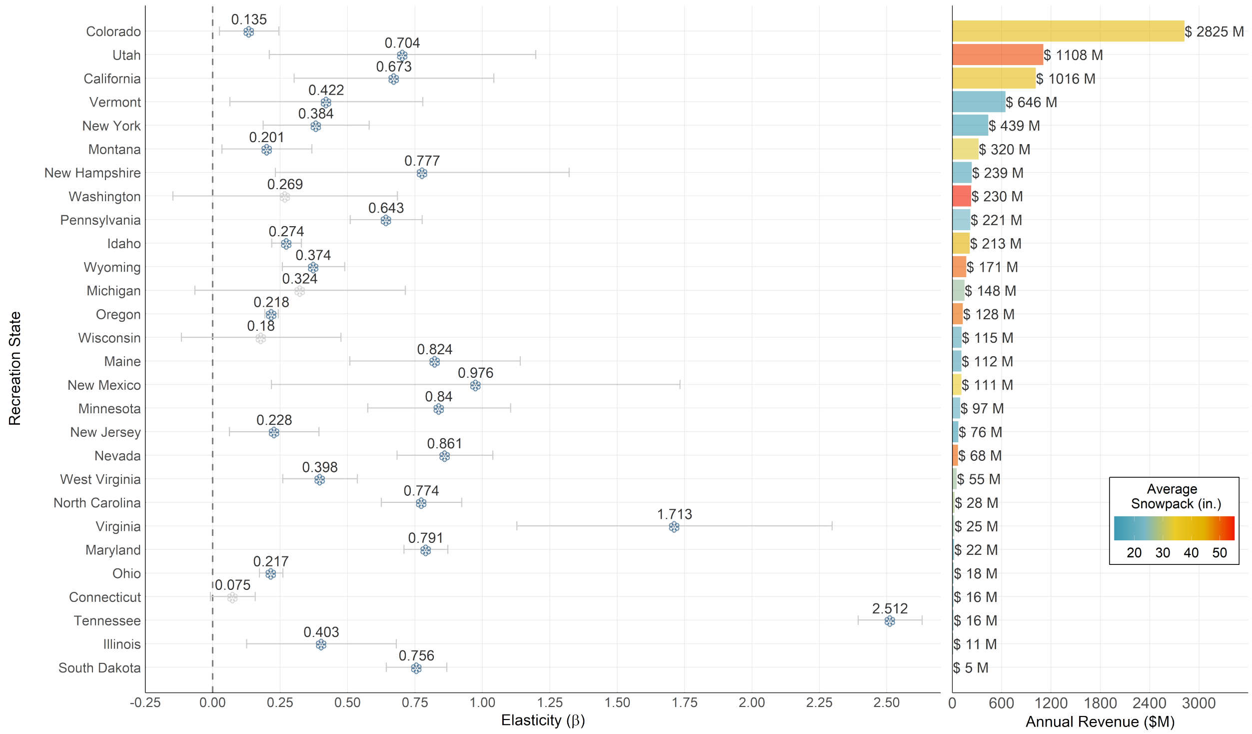
Our research design, which relies on plausibly random variation in snowpack within a season, provides several advantages in the literature on the recreational demand for snow. Previous approaches have been limited to cross-sectional data or coarse panels (spatially, temporally, or both), limiting their ability to control for unobservable characteristics underlying each market. The data we collect here allows for a rich set of controls while maintaining important variation in the climate amenity. The remaining variation (within market and month of sample) provides the identifying source for estimating state-specific behavioral responses to marginal changes in snowpack.

4 The Behavioral Response to Snowpack

We estimate the state-specific behavioral response to mountain snowpack in the form of elasticities—the β parameters in equation 2—that represent the slope of the damage function in each state. We report these results in Figure 2 (left panel) along with their 95% confidence intervals. These estimates reveal substantial heterogeneity between states, with the elasticity of snowpack ranging from 0.075 in Connecticut to 2.512 in Tennessee. We find that some states like Colorado have large snow-related revenue streams ($2.83 billion annually, Figure 2 right panel), but are less responsive to marginal changes in mountain snowpack ($\beta = 0.135$). State-specific elasticities do not systematically vary with mean snowpack, suggesting each state and market has unique underlying characteristics that drive this variation.[14]

[14] We test this in the appendix by regressing the β's on average snowpack. We find no evidence that average snowpack is driving the variation in the state-specific elasticities.

Figure 2: State-specific elasticities (left) and the average annual revenue in the data (right).



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 targeted damage functions that accommodate resort and state-specific characteristics, both of which are correlated with recreation decisions. This is important given the considerable heterogeneity expressed in regional projections of mountain snowpack. Previous estimates of the behavioral response are either assumed to be zero (i.e., skiers *only* respond on the extensive margin of season length), or fixed across geographic regions (i.e., all elasticities are equal across the study area).

5 Damages in Low Snowpack Years

Using observed (within-sample) snowpack patterns from 2005-2017 at resort r on calendar day d (day-of-year), we create an average seasonal trend in snowpack, $\overline{snow_{rd}}$. This allows us to recover a percent deviation from average snowpack for each day in the sample.[15] Snowpack deviation, $\Delta snow$, for resort r on day-of-year d in season y is:

$$\Delta snow_{rdy} = \frac{snow_{rdy}}{\overline{snow_{rd}}}. \tag{3}$$

Similarly, we use observed daily revenue from the short term property market from 2014-2017 to create an average seasonal trend in revenue $\overline{revenue_{rd}}$. The revenue response from daily fluctuations in snowpack builds on equation 3 by incorporating the elasticity of snowpack in each state s to estimate the change in expected revenues:

$$\Delta revenue_{rdy} = \beta_s \times \overline{revenue_{rd}} \times \Delta snow_{rdy}. \tag{4}$$

This allows revenue on each observed day to be higher (lower) than the average revenue when observed snowpack is higher (lower) than the average snowpack on that day, scaled by how responsive skiers are to snowpack in that state (β_s).

The convention in the existing literature is to model damages deterministically, first quantifying revenues in a regular season and then constructing scenarios to apply those daily

[15] For example, if on a particular day at a particular resort, the snowpack was 70 inches and the average on that day-of-year for that same resort was 100 inches, the snowpack deviation would be 0.7, or 70% of the historical average. Alternatively, if the snowpack on that same day was 120 inches, the snowpack deviation would be 1.2, or 120% of the historical average.

revenue calculations to shorter ski seasons. By contrast, the method developed in this paper relies on flexible estimates of the relationship between variation in revenues and variation in snowpack throughout the season. Modeling the behavioral response accounts for the marginal effects of higher/lower snowpack throughout the season as well as for temporal substitution (a form of adaptation). Rather than assuming that damages will only result from changes in the number of days that a resort is operating, we model the full set of changes in resort visitation throughout the season in response to changes in snowpack.

We compare our damage function to those derived from the shortened seasons by trimming the length of each season (resort-specific) based on the observed annual deviation from long-run trends in snowpack. This relationship is estimated by regressing the average annual snowpack at each resort on its season length (days). Our estimates suggest that for each 1 percent decrease in average snowpack, season length is reduced by 0.19 percent. For example, if in a given year a resort received 90 percent of its average snowpack observed in the sample (2005-2017), the length of that resort's season was shortened by $(100 - 90) \times 0.19$, or 2 percent. We distribute this reduction equally between the start and the end of the season (1 percent from the beginning of the season and 1 percent from the end of the season). We recognize that this approximation might not capture reductions in season length that may be conditional on the timing of snowfall throughout the season.[16] This is done at the resort-level, such that resort openings and closures are specific to each individual resort.

It is important to recognize that losses in season length can be partially addressed with artificial snowmaking. When estimating the flexible damage function derived in this

[16]See Table E1 in the appendix for a full discussion of these results and how we develop the illustrative comparison described here.

paper, we focus on the mass of the snowpack distribution at levels above where snowmaking would typically be applied. We therefore assume snowmaking can fully offset the potential reductions in the length of the season. If artificial snowmaking is not able to maintain the length of the season (Steiger and Mayer, 2008; Scott et al., 2019; Steiger and Scott, 2020), then the losses estimated by trimming the season will be overstated and the losses estimated using our more flexible within-season damage function will be understated.[17]

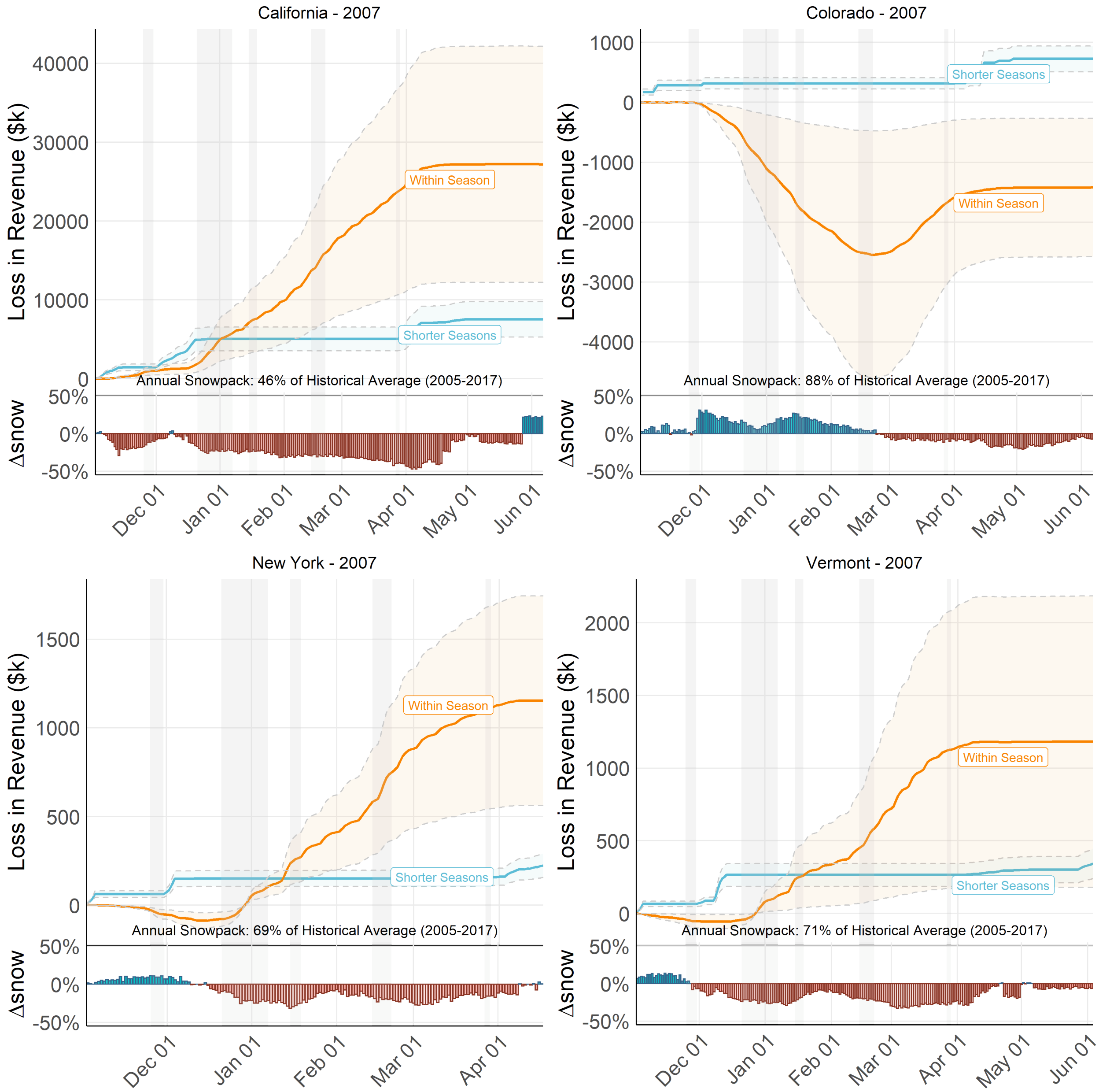
Figure 3 plots within-season damage functions for four states in 2007—a lower than average year for snowpack across the U.S.—along with 95% confidence intervals as predicted using the econometric uncertainty in the model.[18] Our approach demonstrates that these within-season effects are critical for estimating revenue losses from low snowpack days and years. For example, when seasonal trends in visitation occur, such as around the Christmas or Spring Break holidays (shaded in gray), large deviations in snowpack (equation 3) will generate large deviations in expected revenue (equation 4). Increased demand on days with better-than-average snowpack can compensate for lost revenues on days with lower-than-average snowpack, explicitly accounting for temporal substitution throughout the season.

In 2007, California, New York, and Vermont had much lower snowpack during peak visitation periods during the season (holidays are shaded in gray) that accelerated the growth rate (slope) of the damage function. Colorado had better-than-average snowpack during these peak visitation days, resulting in our damage function predicting net gains for Colorado,

[17]The opening and closing of resorts is resort-specific based on that resort's observed snowpack. It is possible for some states to have a continuous opening or closing of resorts within it, resulting in a state's *Shorter Seasons* damage function to be constantly changing throughout the season. It is also possible for a state to have all resorts open resulting in that state's *Shorter Seasons* damage function to be fixed at a given level (flat with a slope equal to zero).

[18]The same figure for the year 2012 can be found in the appendix.

Figure 3: State-level damage functions using observed within-sample snowpack in 2007.



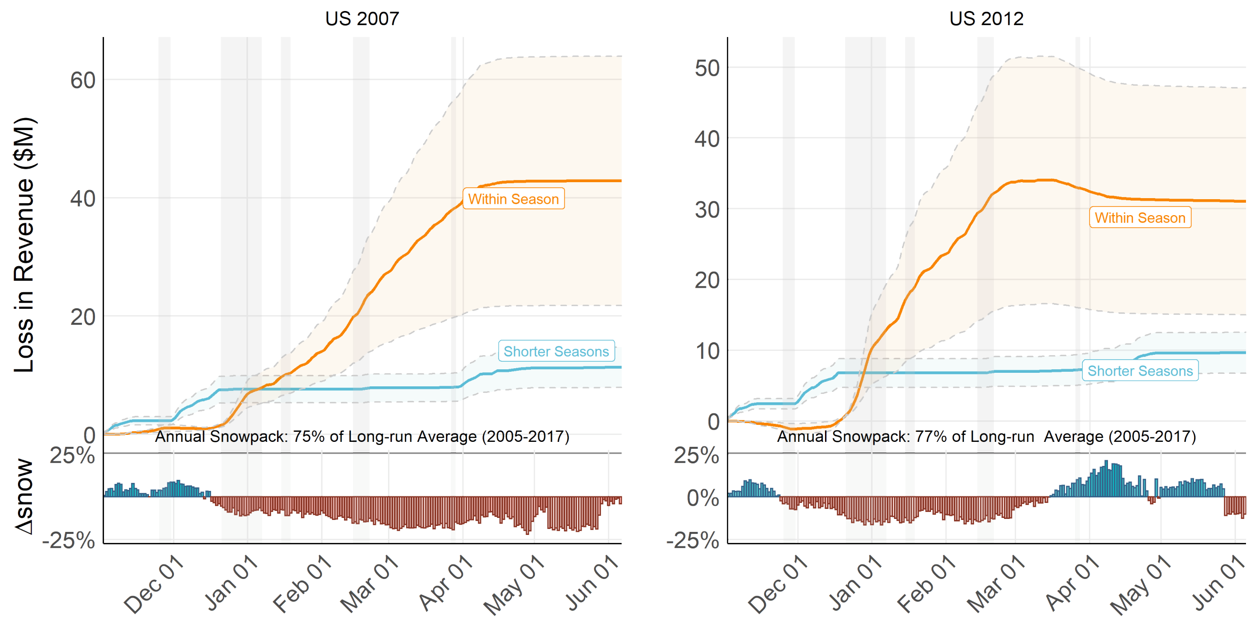
despite having a lower-than-average annual snowpack (88 percent of its long-run average). The flexible nature of our damage function captures the spatial and temporal patterns of substitution that are expected to occur in response to differential trends in snowpack during peak visitation periods.

The comparison between the present (within-season) approach and established methods reveals two important differences: 1) our damage function captures the response to changes in snowpack on the margin, consistent with how we would expect recreation decisions to be made and 2) in cases when the shorter seasons method would predict positive damages, by accounting for the timing of snowpack it is possible for a resort or state to actually have net gains even when snowpack was lower than average for the year (e.g., Colorado in 2007). Moreover, using established season-length methods provides little information about when damages accrue throughout the season, which is a necessary feature of a damage function when estimating relationships between time-varying demand and time-varying amenity levels.

The *Shorter Seasons* damage function is analogous to the approach typically used to estimate damages under future climate scenarios. Efforts to maintain season length, such as investments in artificial snowmaking, could help to reduce the accumulation of damages that arises from losses on the extensive margin. However, the damages we estimate on the intensive margin that arise from the behavioral response to marginal changes in snowpack are beyond the scope of typical artificial snowmaking (Steiger and Mayer, 2008; Joksimović et al., 2020). It is not unreasonable to assume that *all* of the damages on the extensive margin could be reduced to near zero through large investments in artificial snowmaking. If the practice of artificial snowmaking expands drastically, then the future costs associated with that technology might depart significantly from those observed today.

On the other hand, the *Within Season* damage function we develop assumes no change in season length and assumes that snowpack levels are maintained above the threshold that would push a resort into early closure. This is the result of reductions in snowpack on a given day under different climate scenarios being only a portion of the overall snowpack—assuming

Figure 4: National (U.S.) damage functions using observed within-sample snowpack in 2007 and 2012.



that resorts at no point are forced to close. Figure 4 applies the methods described above and aggregates daily damages across the U.S. for 2007 and 2012 winter seasons. While 2007 and 2012 received similar snowpack, the timing of snowpack accumulation results in a different trajectory in the damage path. Compared to the method of estimating shorter seasons, it is clear that the timing of snowpack accumulation drives substitution throughout the season and dictates the slope of the resulting damage function.

6 An Application of Elasticities to Future Climate

Using the same within-sample trends for the period 2005-2017, we construct the baseline within-season variation in each state to simulate an average season (the average accumulation of snowpack at each resort throughout the season). We then estimate changes in average expected snowpack under future climate scenarios using the suite of CMIP5 climate models

(Reclamation, 2013), yielding daily snowpack estimates for an average season in the contemporary, and an average season under RCP4.5 and RCP8.5 scenarios. We estimate the annual recreation revenue by modifying equation 3 to replace the observed (contemporaneous) snowpack in year y with the predicted snowpack in an average year $\overline{y}$ under future climate scenarios c:

$$\Delta snow'_{rd\overline{y}c} = \frac{snow'_{rd\overline{y}c}}{\overline{snow_{ry}}}. \tag{5}$$

The response function from deviations in snowpack under future climate is then:

$$\Delta revenue'_{rd\overline{y}c} = \beta_s \times \overline{revenue_{ry}} \times \Delta snow'_{rd\overline{y}c}. \tag{6}$$

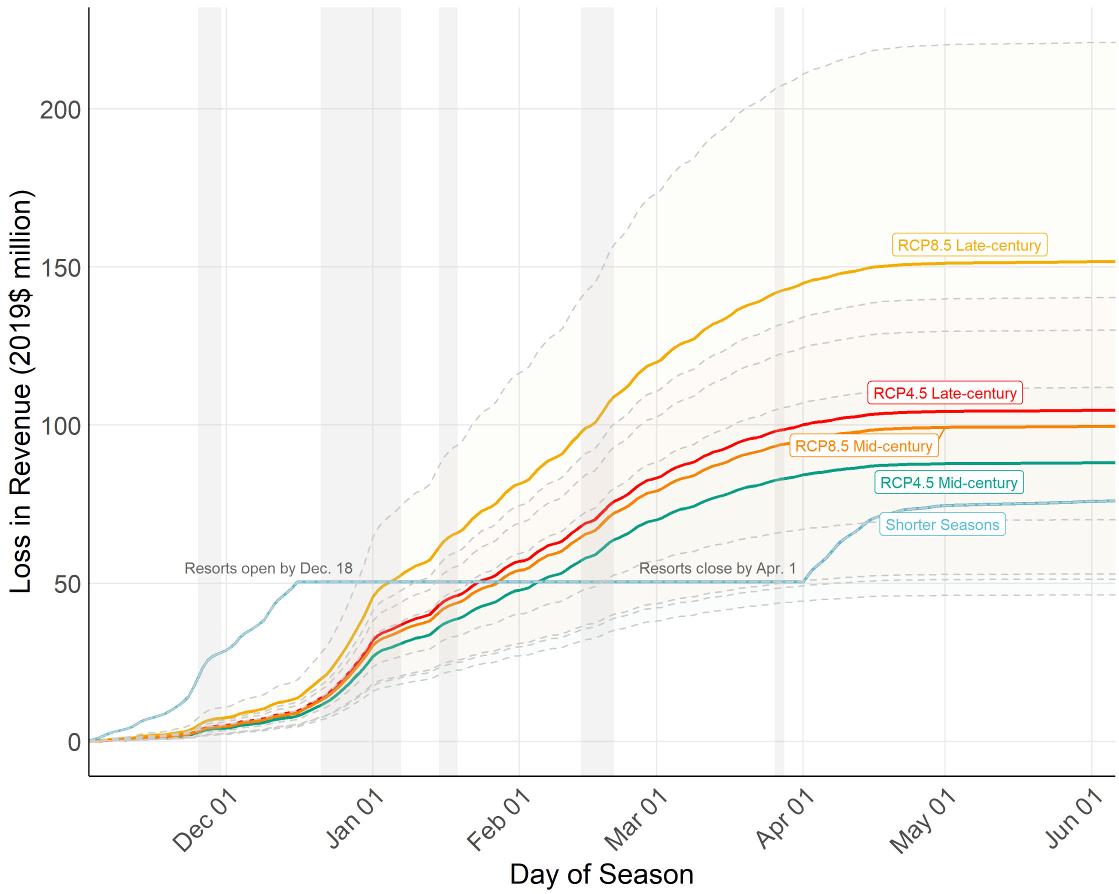
We report the total change in revenue in each climate scenario c:

$$\Delta Revenue_c = \sum_{rd} \Delta revenue'_{rd\overline{y}c} \tag{7}$$

Figure 5 summarizes the results of the simulations and aggregated by equation 7 under each RCP scenario and period.[19] For lost revenues from shorter seasons, we assume that (through the use of artificial snowmaking) resorts are still able to open by the winter holiday rush, December 18th, and can remain open through the end of April. This deviates from our previous method of comparing our damage function to one that relies on shorter seasons

[19] As discussed in Section 2, the damage functions derived in this paper account for substitution across resorts by modeling the snowpack available at resorts within 200km of a given market. That is, our elasticity estimates directly account for differences in weather and snowpack at resorts other than where the skier chooses to visit. To the extent that the relative change in snowpack between a resort and its substitutes falls outside of the range we observe in our sample (larger or smaller), then the estimated elasticities estimated could under—or over—estimate the long-run behavioral response in each market. The damages estimates provided under future climate scenarios require the assumption that the state-specific elasticities of the damage function do not change over time. See appendix F.1 and F.2 for additional discussion.

Figure 5: Accumulation of lost revenues throughout a typical season under future climate.



and adopts the idea that artificial snowmaking can help to bolster the length of the season. These estimates assume no other changes in revenues while the resorts are able to maintain minimum operating level of snowpack (Scott et al., 2007; Steiger, 2011; Dawson and Scott, 2013; Wobus et al., 2017; Steiger and Scott, 2020).

An important take-away from Figure 5 is that damages resulting from the behavioral response to marginal changes in snowpack throughout the season quickly outpace damages from conventional methods that uses increases in artificial snowmaking to maintain season length. This is true even after imposing the strong assumption that there will be no changes in season length under future climate and damages are only attributable to the intensive margin within a season. This directly follows from the overwhelming evidence outlined in our analysis in section 4, which indicates that recreational visitors respond to marginal changes in resort snowpack.

6.1 A Simulated Decade of Revenues from Snowpack

Building on the previous exercise, we simulate a decade of ski seasons under future climate scenarios. We do this using projected future reductions in snowpack from the CMIP5 climate modeling suite for each of the 13 years of observed snowpack at each resort. For this simulation, we add the revenue from estimated daily lift ticket sales (NSAA, 2018) to the that of the overnight accommodations—the average per-bedroom expense on short term property rentals (observed) multiplied by the estimated number of overnight stays (NSAA, 2018).[20]

Figure 6 summarizes the results of the simulated decade under the contemporary and late-century snowpack.[21] We report the average *total* revenues that are attributable to snowpack in each year y of scenario c:

$$Revenue_{yc} = \sum_{rd}(\beta_s \times \overline{revenue_{rd}} \times snow_{rdyc}) \tag{8}$$

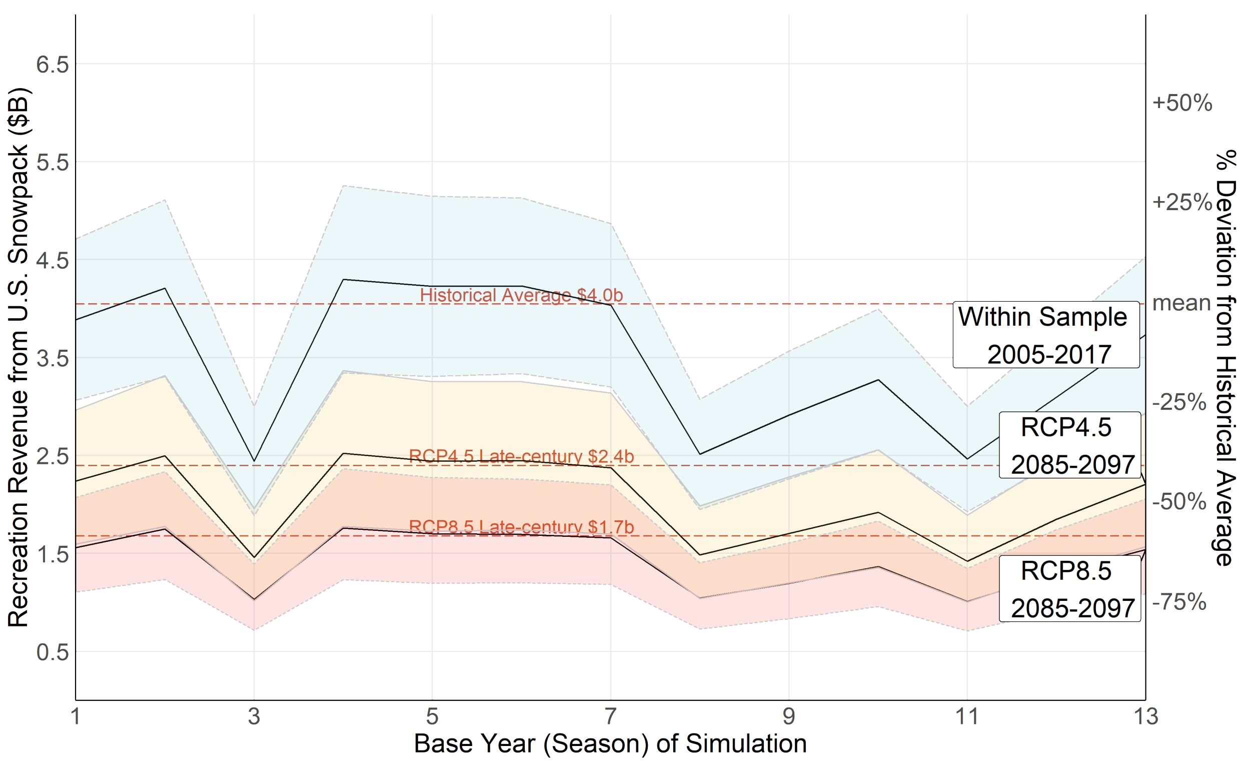
The three scenarios represented in Figure 6 are: 1) an average decade in the contemporary (within-sample); 2) an average decade under RCP4.5 by late-century; and 3) an average decade under RCP8.5 by late-century. Values represent the total recreation value of snowpack across the 28 states (left axis) and its deviation from historical averages (right

[20] A full description of the underlying revenues and state-level simulations can be found in the appendix.
[21] Additional figures for RCP4.5 and RCP8.5 can be found in the appendix.

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 2080.

The year-to-year variation and deviation from the historical mean can be seen using the axis on the right side of the figure. 90% confidence intervals are also reported for each simulation that reflect the combined variation across the suite of CMIP5 models and the uncertainty in the econometric model used to estimate the elasticity parameter (the standard error of β). 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 an average of around \$2.5 billion (\$1.9 to \$2.8 within the 90% confidence interval) in annual revenue, which approaches the range predicted by mid-century climate

Figure 6: National (U.S.) revenues from snowpack over contemporaneous and future decades.

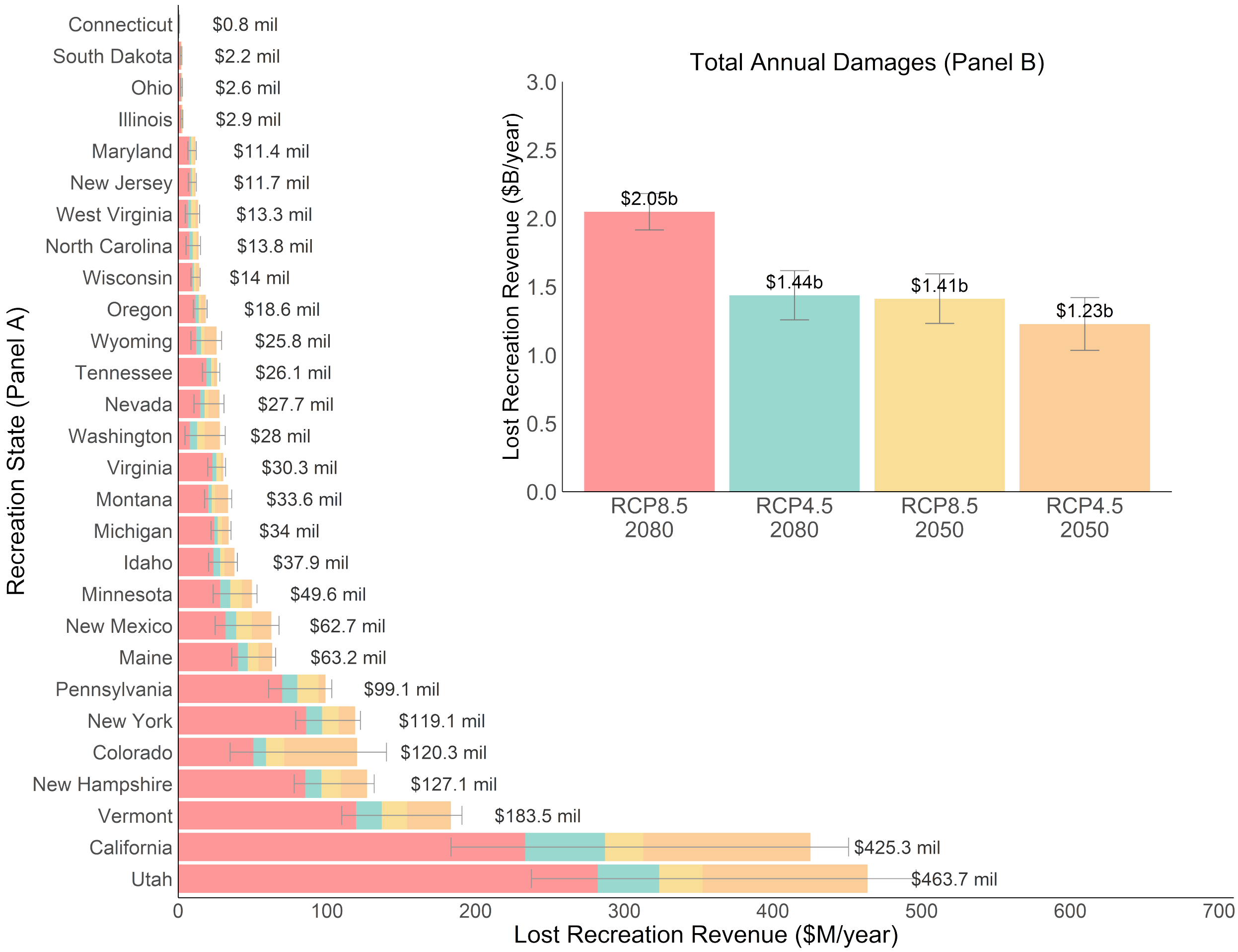


models for RCP8.5. Under RCP4.5 and RCP8.5 (respectively), these estimates indicate that total recreation revenue could fall to between -35% and -50% by mid-century and -40% to -60% by late-century. Revenue in the year with the highest snowpack during the mid-century period is approximately equivalent to the lowest snowpack year in the contemporaneous period. By the late-century period, the highest snowpack year in our simulation will generate merely half of the economic activity observed during the worst year in our contemporary sample.

The difference between each line in Figure 6 captures the annual economic damages across the U.S. We report the average difference over the 13 years in Figure 7. Panel A summarizes the expected annual losses in each state for each RCP scenario and period (mid- and late-century). The 90% confidence intervals, again, represent the combined variation across the suite of CMIP5 models and the econometric uncertainty in our model. 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 U.S. under both RCP scenarios and periods.

Average annual damages under RCP8.5 2080 range from $1 million in Connecticut (a 5 percent reduction in revenue from current levels) to $464 million in Utah (a 42 percent reduction in revenue). As mentioned, these estimates reflect the lost recreation revenue from snowpack using only the revenue from overnight stays and daily lift ticket sales. There are certainly other expenditures directly and indirectly linked to changes in snowpack in each market. For example, expenditures on ski rental equipment or related service industries are not captured in these values. Our estimates of lost revenues provide a lower bound on

Figure 7: State-specific and national damages from climate change under future snowpack conditions.



consumer surplus. The willingness to pay for snowpack among recreational visitors may greatly exceed the value that is captured in revenue impacts.

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; and 3) the state's predicted change in snowpack under future climate scenarios. California, for example, has large existing levels of snow recreation (over $1 billion each year) in addition to a large elasticity of snowpack ($\beta = 0.673$) and is also predicted to lose a substantial percentage of the average annual snowpack (-55% to -75%). Other states, such as Colorado, might have much higher annual revenue streams (over \$2.82 billion), but are less responsive to changes in the snowpack ($\beta = 0.135$), and are also predicted to have smaller shocks in average annual snowpack given future climate conditions (-30% to -50%).

7 Discussion

While many factors influence a person's decision of when and where to go ski, one of the strongest determinants, mountain snowpack, relies almost entirely on climate to deliver it. Warmer average temperatures and changing climate will inevitably lead skiers to make alternative recreation decisions, not only due to shorter seasons and closures, but throughout the season as snowpack fails to sufficiently accumulate. Increases in the availability of data from short-run housing markets have created opportunities for more accurate modeling of these recreation decisions as a function of exogenous climate amenities.

We provide estimates that focus on resort-level variation in snowpack to identify the implicit price of snow in the short-term property rental market. While much of the activity in our sample is directly tied to snowfall at the nearby mountain resort, there are certainly other sources of demand. Activities for which demand is orthogonal to variation in snowpack, as would be the case for cross-country skiing or sledding, then our results also capture the implicit price of the full set of activities related to snowpack in a given market. The demand for activities that are orthogonal to variation in snowpack—a mountain festival or holiday travel—will not be captured. Market-by-time (in our case, property-by-month-of-sample) fixed effects capture the dynamics related to housing price changes or changes in the supply of short-term property rentals or hotel properties in a given market. Additionally, our estimates capture changes in revenue associated with lower levels of snowpack. To the extent that owner costs such as cleaning, maintenance, and depreciation depend on changes in snowpack, revenue impacts may differ from impacts on profits. We note that while the majority of management costs will likely not depend on variation in snow, property depreciation and costs related to plow or other services might be lower in a future with lower snowfall.

The estimates provided in this study use variation in short-term property rental revenue in response to changes in snowpack to capture the implicit price of the climate amenity. In Figures 5 and 6, we assess the effects of reduced snowfall on resort visitation by adjusting our estimates to incorporate the additional non-lodging costs of a visit (lift ticket cost). Here, we assume that the implicit price function is constant across the different components of the cost of a visit. While this is not an assumption that we can test in this study, it lends itself to a test of future work using the travel cost method or from resort-specific lift ticket sales.

In this study, we make three key contributions to the understanding of human recreation decisions and the behavioral response to marginal changes in climate amenities: 1) we develop a method for deriving a flexible damage function parameterized by elasticities for a climate amenity that varies at high spatial and temporal frequencies; 2) we recover state-specific snowpack elasticities in all major ski resort markets across the U.S. 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 ski resorts could face annual reductions of -40% to -60% of snow-related revenue by the end of the century (2080). This is nearly double the magnitude of existing estimates that use only the length of season to estimate changes in visitation—implicitly making the assumption that the behavioral response to changes in mountain snowpack is equal to zero. When our method—mapping recreation behavior continuously throughout the season—is applied to existing expenditures on lift-tickets and overnight stays, we estimate damages across the U.S. between \$1.23 billion (RCP4.5) and \$2.05 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, 2021).[22] Further exploration into how skiers choose to substitute across markets will be an important next step in uncovering wintertime recreation patterns and behavior to account for the full suite of damages due to a changing climate.

[22] 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, 2021).

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Appendices for "The Recreation Response to Marginal Changes in Mountain Snowpack and Implications for a Changing Climate"

In the following sections, we provide an expanded discussion of our empirical framework (section A), a description of the data (section B), details on alternative specifications (section C), and complete derivations of the underlying damage functions used in our simulations (section D). Sections E and F provide additional tables and figures that support our main findings, in addition to analyzing the sensitivity of our main findings to various samples and specifications.

A 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 ($revenue$) 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) damage function:

$$ihs(revenue)_{it} = \underbrace{\sum_{s} \beta_s \; log(snowpack)_{rt}[State = s]}_{\substack{\text{State-specific} \\ \text{Elasticities}}}$$
$$+ \boldsymbol{Z'_{rt}\delta} + \boldsymbol{X'_{rt}\eta} + \psi_{im} + \varepsilon_{it}. \tag{A.1}$$

The β_s in our model can be explicitly defined as:

$$\beta_s = \frac{\partial ihs(revenue)_s}{\partial log(snowpack)_s}. \tag{A.2}$$

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

$$Implicit\ Revenue_s = \beta_s \times \frac{\overline{Revenue_s}}{\overline{Snowpack}_s}. \tag{A.3}$$

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.3 is also the first part of equation A.4:

$$Rev_s^{snow} = \underbrace{\beta_s \times \frac{AR_s}{HS_s}}_{\substack{\text{Implicit} \\ \text{Revenue}}} \times CS_s. \tag{A.4}$$

The average annual revenue AR (the numerator in equation A.4) is the average annual estimate of demand for lift tickets and overnight stays from equation A.5:

$$\begin{aligned} Annual\ Revenue_s = & \underbrace{Visits_s \times Price_s^{lift\ ticket}}_{\text{Daily Visits}} \\ & + \underbrace{Overnight\ Stays_s \times Price_s^{bed}}_{\text{Overnight Stays}} \end{aligned} \tag{A.5}$$

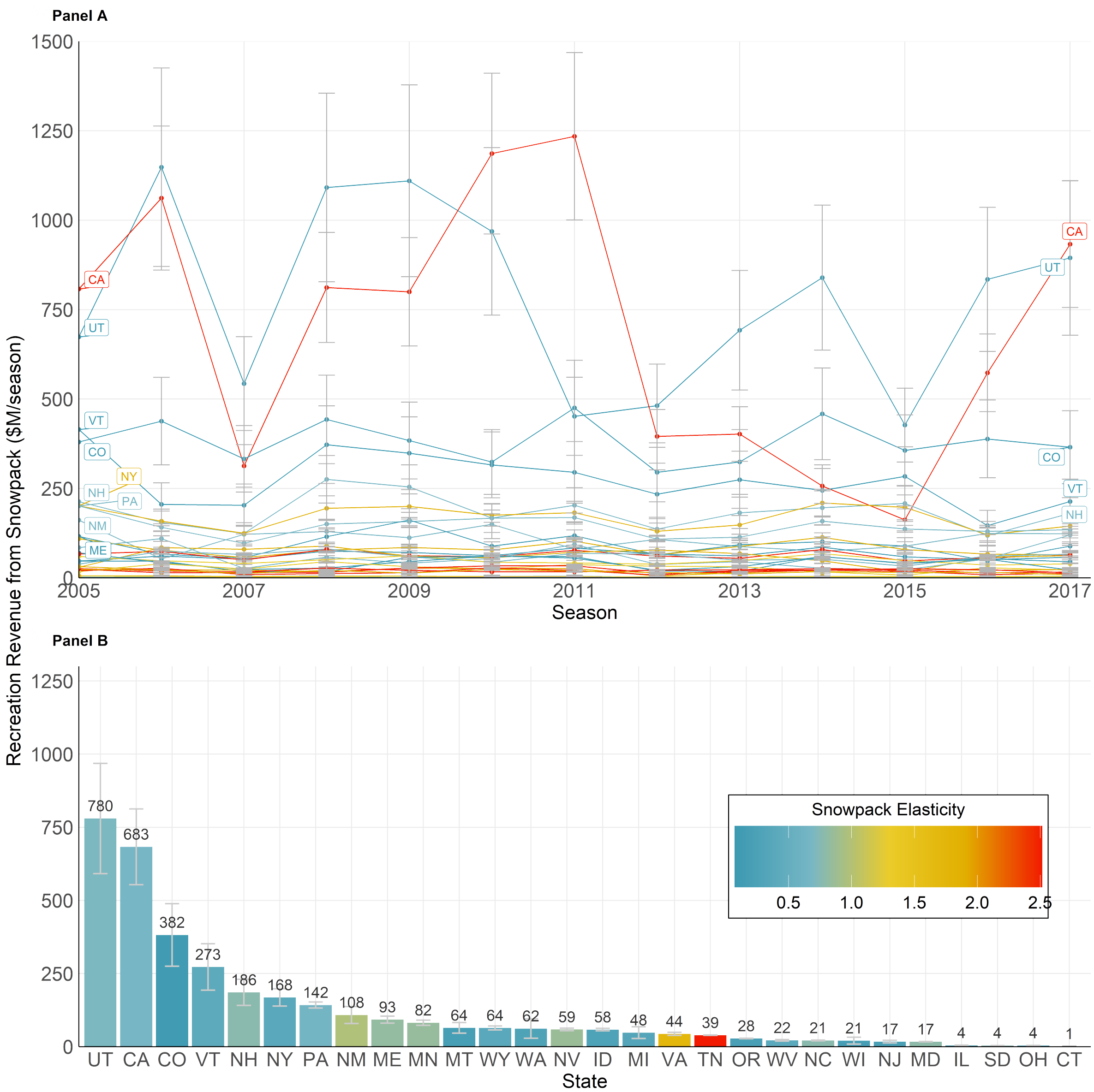
The average annual revenue term in equation A.5 consists of two components: 1) daily visits, defined as the average annual number of visits in each state multiplied by the average price of a lift ticket in state s; and 2) overnight stays, defined as the average annual number of overnight stays multiplied 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:

$$Rev_s^{snow} = \beta_s \times \frac{AR_s}{HS_s} \times HS_s = \beta_s \times AR_s. \tag{A.6}$$

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. Figure A.1 the year-to-year recreation revenue from snowpack for each of the 28 states in our sample from the 2005 to 2017 operating seasons (Panel A) alongside their average annual recreation revenue predicted by our damage function (Panel B).

Figure A.1: Annual state-level recreation revenue from snowpack from 2005-2017.



B 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 data include 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 236 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 damage 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 sample of properties is changing over time. Every month of sample the set of properties that are available are updated. While month-to-month the change in the sample is relatively minor, the change across years is noteworthy. Because the sample is changing, we implement a robust set of controls that control for both time-varying characteristics of the sample and time-invariant characteristics. Those controls are described more thoroughly in section 2.

The climate amenities, *snowpack* and *snowfall*, are acquired from a website (OnTheSnow.com, 2017) that provides daily reports for all 236 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 236 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 that are 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.

C Alternative Specifications and Discussion

The general form of our estimation framework is equation 1 which estimates a national average damage function using all markets in the sample. This specification omits the interaction between *snowpack* and an indicator for each state. Column 1 of Table C1 summarizes these results and presents the average damage function for all resort markets—providing a baseline estimate for the parameter of interest β. To estimate regional heterogeneity in the damage function, we introduce regional interaction terms with *snowpack* to recover the snowpack elasticity specific for each region k:

$$\begin{aligned} ihs(revenue)_{it} = &\sum_k \beta_s \; log(snowpack)_{rt}[Region = k] \\ &+ \boldsymbol{Z'_{rt}\delta} + \boldsymbol{X'_{rt}\eta} + \psi_{im} + \varepsilon_{it}. \end{aligned} \tag{C.1}$$

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 F.4.

Columns 2 and 3 in Table C1 summarize the underlying heterogeneity in the damage function identified using equation C.1. Column 2 presents the interaction between *snowpack* and two general regions, Central-East and Mountain-West. Column 3 presents the interaction

Table C1: Regional comparisons in average elasticity estimates.

	(1) National Average	(2) Two Regions West-East	(3) NSAA Regions
log(Snowpack)	0.223**		
	(0.09)		
log(Snowpack) × Mtn.-West		0.208**	
		(0.093)	
log(Snowpack) × Cent.-East		0.488***	
		(0.072)	
log(Snowpack) × Pac. NW			0.477***
			(0.087)
log(Snowpack) × Pac. SW			0.627***
			(0.182)
log(Snowpack) × Rocky Mtn.			0.172**
			(0.075)
log(Snowpack) × Midwest			0.330**
			(0.131)
log(Snowpack) × Northeast			0.477***
			(0.087)
log(Snowpack) × Southeast			0.772***
			(0.190)
Prop. × Month of Sample FE	✓	✓	✓
Weekday FE	✓	✓	✓
Clu. SE: Market	✓	✓	✓
Observations	12,515,691	12,515,691	12,515,691
Adjusted R^2	0.396	0.396	0.396

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

between *snowpack* the six regions as determined by the NSAA regions. Coefficients reported in this table have the same interpretation as our state-specific elasticities. For example, the national average β is 0.223. This implies that for every 1 percent reduction in mountain snowpack, revenues will decline by 0.223 percent. 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*.

C.1 Heterogeneity in average elasticities and property characteristics

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:

$$
\begin{aligned}
ihs(revenue)_{it} = & \sum_{c} \beta_s \ log(snowpack)_{rt}[C = c] \\
& + \boldsymbol{Z'_{rt}\delta} + \boldsymbol{X'_{rt}\eta} + \psi_{im} + \varepsilon_{it}. \qquad \text{(C.2)}
\end{aligned}
$$

Here, C represents variables defining property characteristics. Table C2 summarizes the results of equation C.2. In column 1 we include the results of the main specification, equation 1. Column 2 of table C2 introduces an interaction between *snowpack* and full-time

Table C2: Comparison of elasticities across types of properties and their characteristics.

	(1) Full Sample	(2) Full Time Rentals	(3) Distance From Resort	(4) Other Characteristics
log(Snowpack)	0.223**	0.098**	0.212**	0.108*
	(0.097)	(0.041)	(0.095)	(0.063)
log(Snowpack) × Rental		0.384**		
		(0.169)		
log(Snowpack) × < 2km			0.078	
			(0.049)	
log(Snowpack) × km				0.009
				(0.007)
log(Snowpack) × Beds				0.067**
				(0.030)
log(Snowpack) × Baths				-0.078**
				(0.039)
log(Snowpack) × Max Guests				0.014
				(0.013)
Prop. × Month of Sample FE	✓	✓	✓	✓
Weekday FE	✓	✓	✓	✓
Clu. SE: Market	✓	✓	✓	✓
Observations	12,515,691	12,515,691	12,515,691	12,515,691
Adjusted R^2	0.396	0.396	0.396	0.396

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

rentals (properties that are always available for the public to rent, i.e., 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, owners maintain a personal schedule (blackout days) that is unaffected by demand shocks (i.e., owners who occasionally occupy their property likely do so when the snow conditions are most desirable). 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 average elasticities are uniform across the 10km buffer and properties with more beds and fewer bathrooms are more desirable when *snowpack* is high.

C.2 Nonlinear damage functions in snowpack levels

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

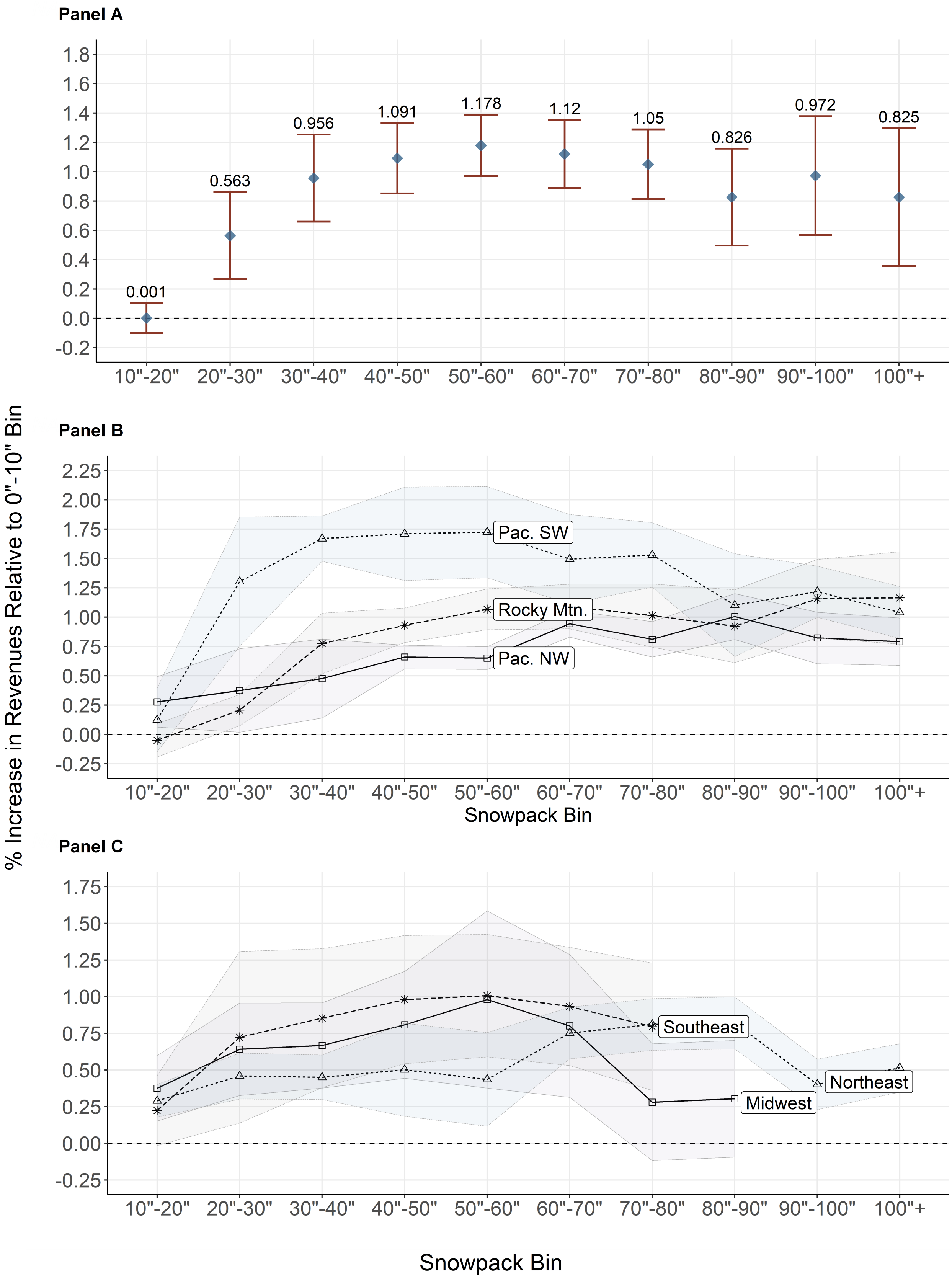
$$\begin{aligned} ihs(revenue)_{it} = & \sum_{d} \beta_s \; log(snowpack)_{rt}[Snowpack = d] \\ & + \boldsymbol{Z'_{rt}}\boldsymbol{\delta} + \boldsymbol{X'_{rt}}\boldsymbol{\eta} + \psi_{im} + \varepsilon_{it}. \end{aligned} \tag{C.3}$$

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

$$ihs(revenue)_{it} = \sum_{d}\sum_{k} \beta_{dk}\ log(snowpack)_{rt}[Snowpack = d][Region = k] \\ + \boldsymbol{Z}'_{rt}\boldsymbol{\delta} + \boldsymbol{X}'_{rt}\boldsymbol{\eta} + \psi_{im} + \varepsilon_{it}. \tag{C.4}$$

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 C.1 where the β's are relative daily revenues for each snowpack bin (the reference level of revenue is the revenue when *snowpack* falls between 0 and 10 inches). For example, a coefficient estimate of 1.178 (the 50-60 inch bin) indicates that an additional day with snowpack between 50-60 inches results 117.8 percent of revenues relative to a day with 0 to 10 inches, or 17.8 percent more demand. Panel A summarizes the national damage function using binned *snowpack* (equation C.3, and panels B and C summarize the regional binned *snowpack* (equation C.4). In both cases, the damage 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.

Figure C.1: Nonlinear damage functions using binned levels of snowpack.



C.3 The advantages of high-frequency data to estimate behavioral elasticities

As discussed in the introduction of the main text (section 1), 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 damage function (the monthly version of equation 1) and the state-specific damage functions (the monthly version of equation 2). For month m of season y in resort market r this is:

$$ihs(revenue)_{rm} = \beta \log(snowpack)_{rm} + \boldsymbol{X'_{rm}}\boldsymbol{\delta} + \boldsymbol{\Phi}_{rmy} + \varepsilon_{rm}. \tag{C.5}$$

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 vector $\boldsymbol{\Phi_{rmy}}$ is a vector of market, month, and season fixed effects. Table C3 summarizes the results of the national average elasticities resulting from the monthly (column 1) and daily (column

Table C3: Average demand elasticities when using monthly and daily data.

	(1) Daily Data	(2) Monthly Data
log(Snowpack)	0.223**	0.153***
	(0.097)	(0.047)
Market + Month + Season FE		✓
Clu. SE	Market	State
Property × Month of Sample FE	✓	
Weekday FE	✓	
Observations	12,515,691	2,169
Adjusted R^2	0.396	0.608

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

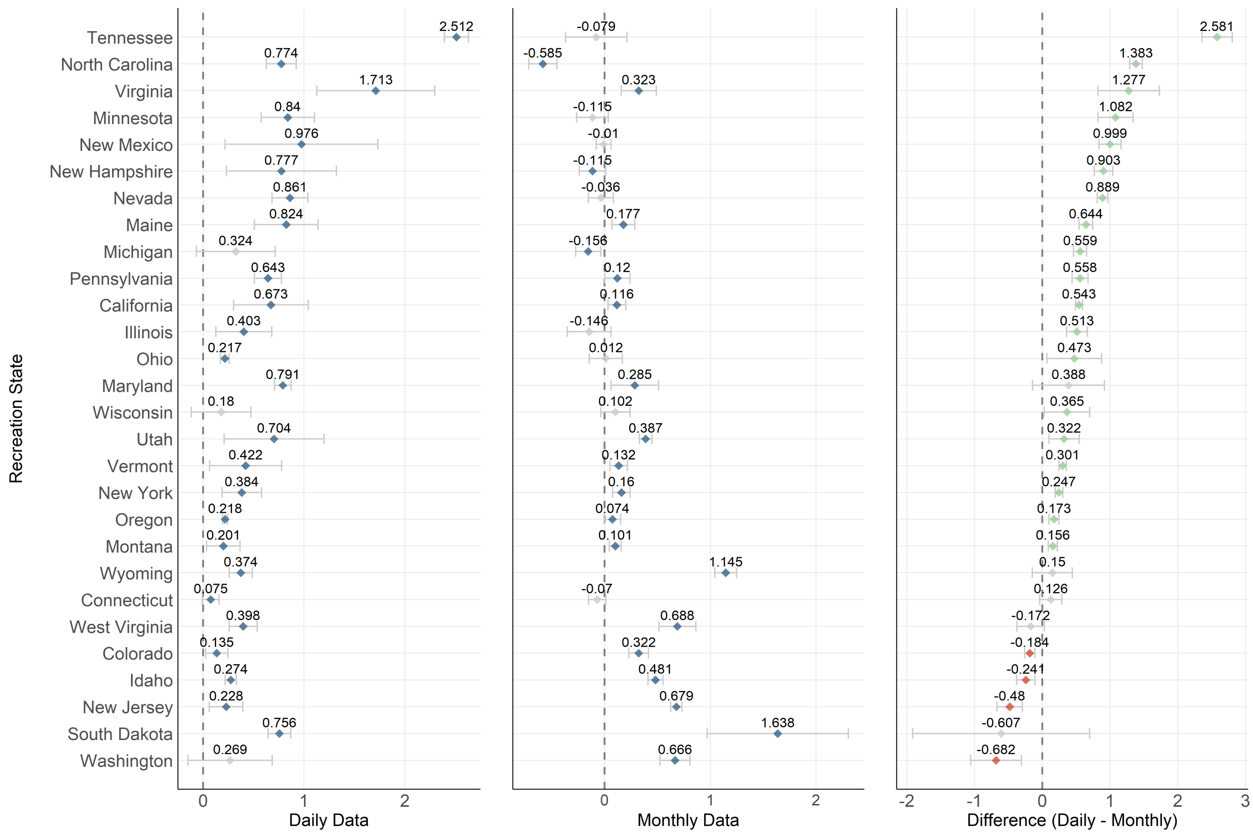
2) specifications. Monthly analyses are the finest (most granular) temporal scale offered in the existing literature. When aggregating our data to the monthly-level, we must relax the high-dimensional set of controls of property-by-month-of-sample fixed effects to separate additive vectors of market, month, and 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).

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

$$\begin{aligned} ihs(revenue)_{rm} = & \sum_{s} \beta_s \; log(snowpack)_{rm}[State = s] \\ & + \boldsymbol{X'_{rm}}\boldsymbol{\delta} + \boldsymbol{\Phi}_{rmy} + \varepsilon_{rm}. \end{aligned} \tag{C.6}$$

Figure C.2 presents the results of equation C.6. Here, we show state-specific elasticities estimated using daily data (left, our primary estimates used throughout this paper), monthly data (center), and the bootstrapped difference between the two (right) from 500 simulations. We find that the average magnitude of the difference ($\beta^{daily} - \beta^{monthly}$) is positive. 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 greater 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. Statistically insignificant coefficients (and their differences) are indicated by a light grey (not filled in) marker.

Figure C.2: Demand elasticities when using monthly and daily data, and their differences.



D The 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. The expenditures we consider here 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 mountain snowpack. 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:

$$AR_s = \underbrace{V_s \times P_s^{pass}}_{\substack{\text{Daily}\\ \text{Visits}}} + \underbrace{OS_s \times P_s^{bed}}_{\substack{\text{Overnight}\\ \text{Stays}}} \tag{D.1}$$

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:

$$Rev_{st}^{snow} = \underbrace{\beta_s \times \frac{AR_s}{HS_s}}_{\substack{\text{Implicit}\\ \text{Revenue}}} \times CS_{st}. \tag{D.2}$$

The first term in equation D.2, 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 D.2, 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 and macroeconomic trends.

The average recreation revenue from snowpack in each state varies significantly across states, ranging from \$1 million in Connecticut to \$780 million in Utah (Figure A.1, bottom 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:

$$\sum_s Rev_{st}^{snow} \tag{D.3}$$

and report the results of equation D.3 in Figures 6 (late century), Figure D.1 (for RCP4.5), and Figure D.2 (for RCP8.5).

Figure D.1: National (U.S.) revenues from snowpack over contemporaneous and future decades under RCP4.5.

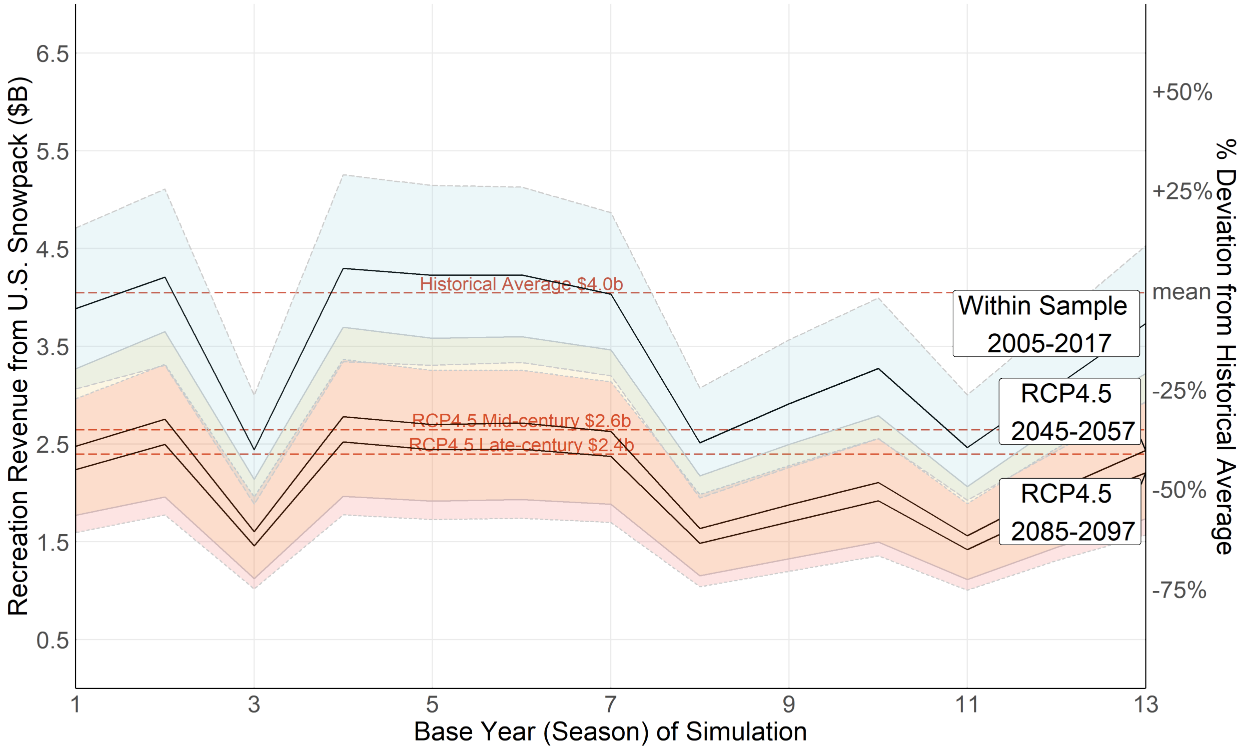
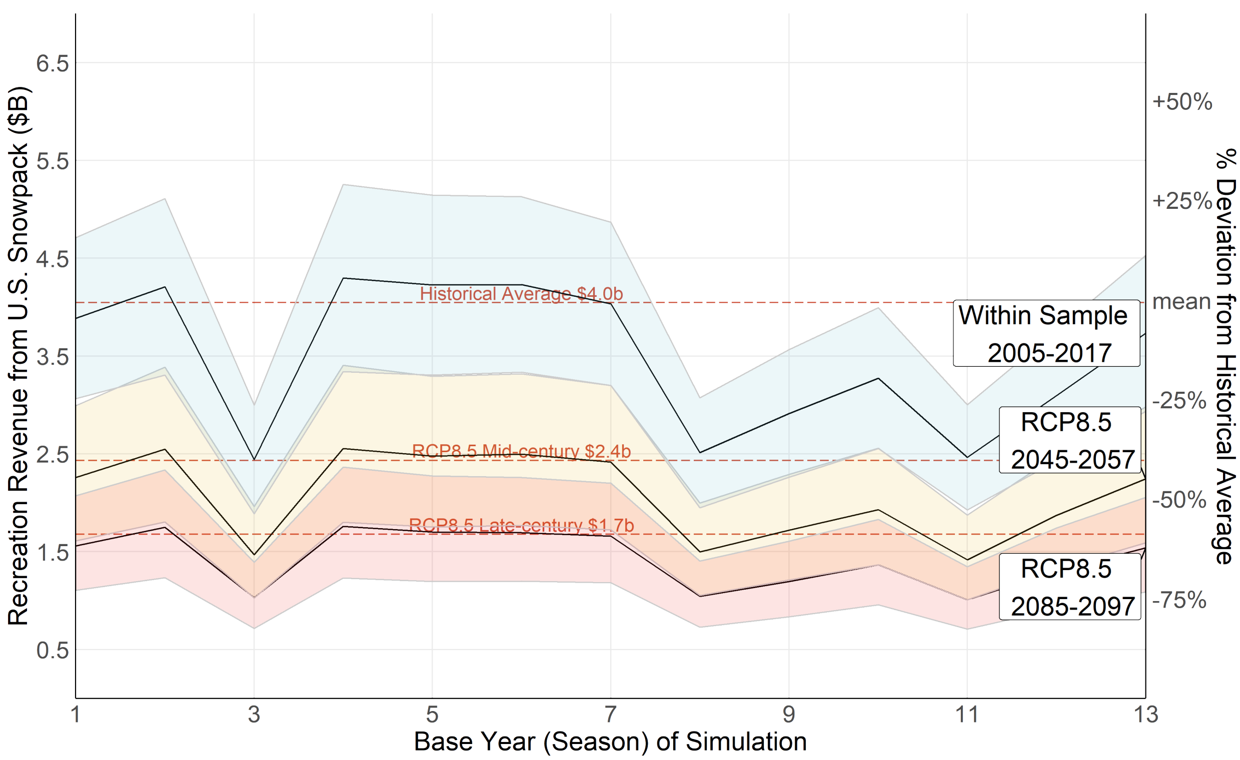


Figure D.2: National (U.S.) revenues from snowpack over contemporaneous and future decades under RCP8.5.



E Additional Tables

Table E1: Contributions of average snowpack to resort season length and elasticities.

	Season Length		Elasticity (β)	
	(1)	(2)	(3)	(4)
Dependent Var.:	Season Days	log(Season Days)	β	β
	(linear)	(nonlinear)	(linear)	(nonlinear)
Average Snowpack	0.891**		-0.002	-0.290
	(0.295)		(0.003)	(0.517)
log(Average Snowpack)		0.191**		
		(0.069)		
Average Snowpack ^{2}				0.194
				(0.517)
Constant	130.783***	4.389***	0.663***	0.607***
	(9.794)	(0.225)	(0.114)	(0.057)
Observations	434	434	82	82
R^2	0.102	0.087	0.004	0.006

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

Note: To establish the comparison between our damage function and existing damage functions, we estimate the relationship between season length and average snowpack. When estimated linearly in levels (column 1), the coefficients suggest that for every 1 additional inch of average snowpack in a season the season would be extended by 0.89 additional days. There is reason to believe that season length is not linear in snowpack (Wobus et al., 2017) and we estimate a nonlinear relationship in column 2. This column suggests that for every 1 percent reduction in average snowpack at a resort the season will be 0.2 percent shorter. This is the specification we use to estimate reductions in season days in the contemporary as described in section 5.

We also explore if elasticity estimates vary with mean snowpack. We use each state's elasticity estimate (β_{state}) as a dependent variable in a regression on average snowpack in that state. We find no evidence that our elasticity estimates vary with average snowpack, linearly (column 3) or nonlinearly (column 4).

Table E2: The effect of accounting for substitute resorts and nearby snow conditions on average elasticities.

	(1) No Buffer	(2) 50km Buffer	(3) 100km Buffer	(4) 150km Buffer	(5) 200km Buffer
log(Snowpack)	0.290**	0.229**	0.223**	0.225**	0.219**
	(0.137)	(0.104)	(0.097)	(0.112)	(0.109)
Prop. × Month of Sample FE	✓	✓	✓	✓	✓
Weekday FE	✓	✓	✓	✓	✓
Clu. SE: Market	✓	✓	✓	✓	✓
Observations	12,903,718	12,515,691	12,515,691	12,515,691	12,515,691
Adjusted R^2	0.396	0.395	0.396	0.395	0.396

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

Note: To control for the snowpack and weather at nearby (substitute) resorts, we include the conditions at resorts that fall within the specified buffers. These control characteristics are the observed snowpack, snowfall, and temperature at all resorts within the buffer. We maintain the 100km buffer throughout all specifications in the main analysis.

Table E3: Comparison of elasticities between individual and multi-mountain resorts.

	(1) All Resorts	(2) Any Pass	(3) By Pass
log(Snowpack)	0.223**	0.223**	0.266**
	(0.097)	(0.099)	(0.131)
log(Snowpack) × Any Pass		0.197	
		(0.196)	
log(Snowpack) × M.A.X			0.062
			(0.180)
log(Snowpack) × Powder Alliance			0.603***
			(0.166)
log(Snowpack) × Mountain Collective			0.389**
			(0.169)
log(Snowpack) × Rocky Mountain Super Pass			-0.202
			(0.241)
log(Snowpack) × Epic Pass			0.213
			(0.304)
Prop. × Month of Sample FE	✓	✓	✓
Weekday FE	✓	✓	✓
Clu. SE: Market	✓	✓	✓
Observations	12,515,691	12,509,123	12,509,123
Adjusted R^2	0.396	0.396	0.396

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

Note: Of the 236 resorts in our sample, 45 are part of a multi-mountain conglomerate or participate in in-network shares that allow skiers to either visit the mountain for free (sometimes limited in number) or at a reduced rate. Our data contain information on five of these multi-pass during our study period: 1) the Multi Alpine Experience (M.A.X.) pass (18 resorts); 2) the Powder Alliance pass (6 resorts); 3) Mountain Collective (9 resorts); 4) the Rocky Mountain Super Pass (5 resorts), and 5) the Epic pass (7 resorts). We model the effect of belonging to a network of shared mountains by including an interaction between $log(snowpack)$ and an indicator variable that identifies the network that the resort belongs to. Column 1 is our primary specification and assumes the behavioral response is uniform across mountains. Column 2 introduces an indicator that estimates the effect of belonging to *any* of the five passes relative to not belonging to a conglomerate. Column 3 breaks these passes into their own unique behavioral response. The Mountain Collective and Powder Alliance passes show larger than average elasticity estimates (but not statistically different than the overall average elasticity of 0.223), suggesting those skiers are potentially more responsive to snowpack conditions than the average resort.

Table E4: Comparison of average elasticities throughout an average season.

	(1) Main	(2) Semester	(3) Trimester
log(Snowpack) × Beginning	0.223**	0.237***	0.193**
	(0.097)	(0.092)	(0.098)
log(Snowpack) × Middle			0.154***
			(0.041)
log(Snowpack) × End		-0.023	0.142***
		(0.013)	(0.045)
Prop. × Month of Sample FE	✓	✓	✓
Weekday FE	✓	✓	✓
Clu. SE: Market	✓	✓	✓
Observations	12,515,691	12,515,691	12,515,691
Adjusted R^2	0.396	0.396	0.396

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

Note: The controls we use in the primary model are motivated by the fact that there are unobservable time-varying and time-invariant characteristics driving demand throughout the season. In these specifications, we relax the temporal control to examine heterogeneity in the average elasticity parameter β throughout the season. The period is defined in semesters by parsing the season into halves and then again in trimesters by parsing the season into thirds. For the semester specification, we find that the response is nearly uniform between these periods and not statistically different (coefficients of 0.24 (beginning) and 0.22 (end)). For the trimester specification we find slightly stronger relationship between snowpack and revenues in the beginning of the season (0.19) compared to the middle (0.15) and end (0.14). This is consistent with the binned snowpack specification described above where snowpack is thinner early on and accumulates throughout the season such that diminishing marginal returns in the level of snowpack is realized in our estimates. It is also consistent with the idea that people wait for snowpack to improve in expectation of future snowfall and are, therefore, slightly more responsive to changes in snowpack at the beginning of the season. The results are also consistent with the intuition underlying our choice of controls in the model

Table E5: Comparison of elasticities from samples that constrain lead-time reservations.

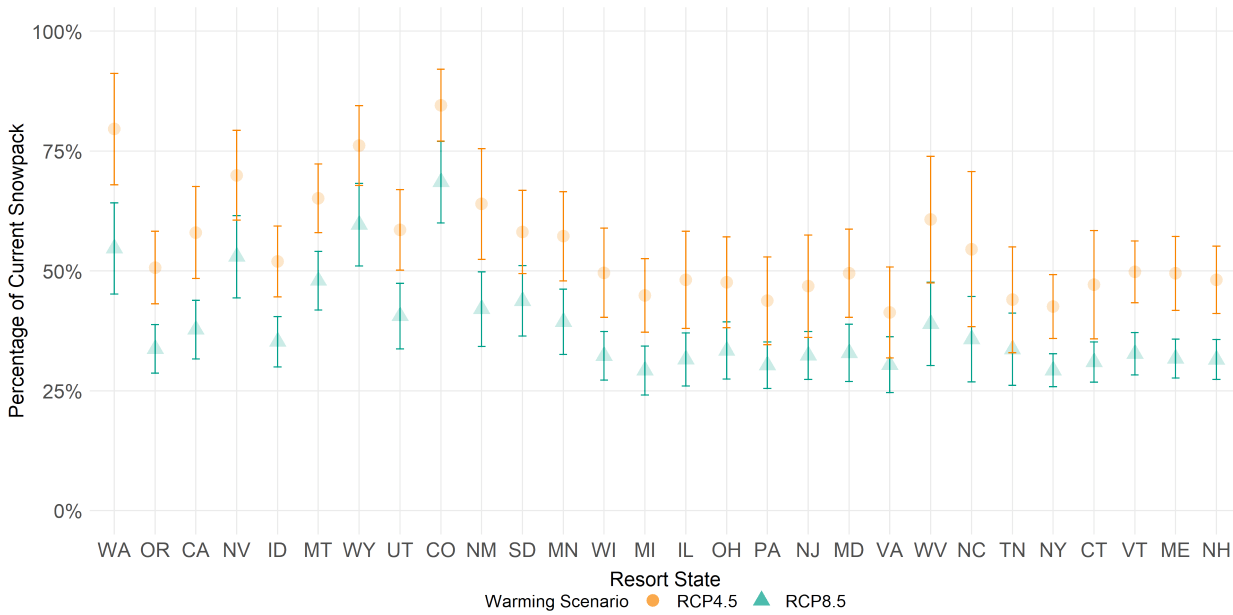
	(1) No Restrictions	(2) ≤ 2 Days	(3) ≤ 5 Days	(4) ≤ 7 Days	(5) ≤ 10 Days
log(Snowpack)	0.223**	0.124***	0.133***	0.140***	0.152***
	(0.097)	(0.003)	(0.006)	(0.010)	(0.016)
Prop. × Month of Sample FE	✓	✓	✓	✓	✓
Weekday FE	✓	✓	✓	✓	✓
Clu. SE: Market	✓	✓	✓	✓	✓
Observations	12,515,691	10,508,614	10,585,114	10,633,522	10,714,418
Adjusted R^2	0.396	0.289	0.266	0.262	0.259

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

Note: We incorporate the timing of the reservation by constraining the sample to those that were reserved less than 2 days in advance of their trip, less than 5 days, less than 7 days, and then again less than 10 days. One hurdle with this approach is that in our data we do not (explicitly) observe cancellations. Without the ability to model the skier's choice to cancel a visit or trip, it is difficult to disentangle the effects of last-minute bookings versus last-minute cancellations. However, the direct effects on revenue should only depend on whether the property was ultimately booked. We find that in the sample of reservations that was made within the constrained advanced booking window is, on average, slightly less responsive to last-minute changes in snowpack. The coefficients on these samples range from 0.124 (2-day sample) to 0.152 (10-day sample).

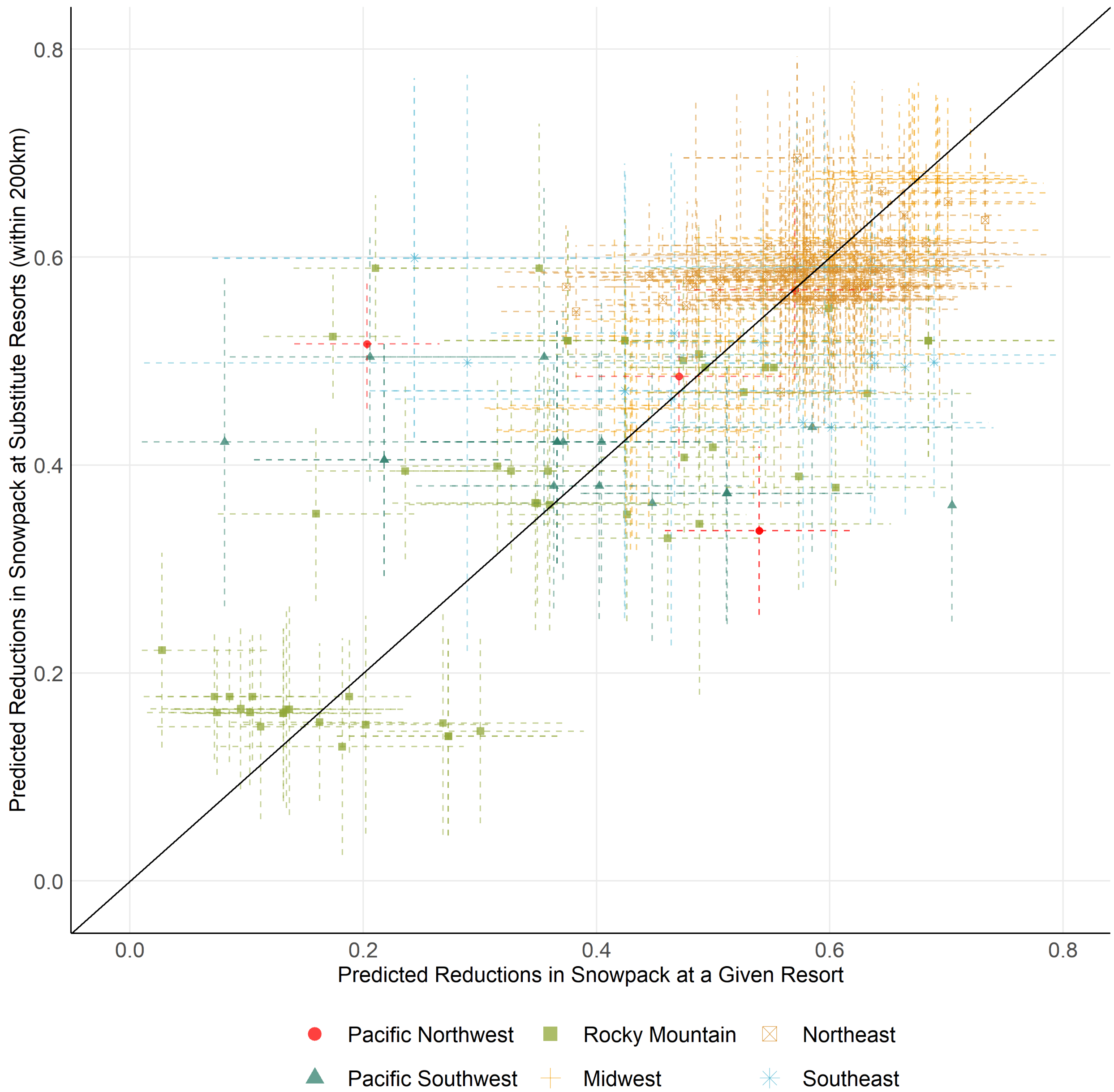
F Additional Figures

Figure F.1: Predicted Snowpack Under Different Warming Scenarios.



Note: Figure F.1 depicts the mean (point estimates) predicted levels of snowpack under RCP4.5 and RCP8.5 warming scenarios, measured as a percentage of historical snowpack (e.g., an estimate of 75% means an expected loss of 25% from current levels) along with the uncertainty (5^{th} and 95^{th} percentile error bars) across the CMIP5 climate models and resorts within a state. All states in the sample are expected to experience reductions in average snowpack, with relatively similar in magnitudes observed across nearby states (listed from west to east). As discussed in Section 2, the damage functions derived in this paper account for substitution across resorts by modeling the snowpack available at resorts within 200km of a given market. That is, our elasticity estimates directly account for differences in weather and snowpack at resorts other than where the skier chooses to visit. To the extent that the relative change in snowpack between a resort and its substitutes falls outside of the range we observe in our sample (larger or smaller), then the estimated elasticities estimated could under—or over—estimate the long-run behavioral response in each market. The damage estimates provided under future climate scenarios require the assumption that the state-specific elasticities do not change over time. While it is plausible that reductions in snowpack will be uniform if substitution primarily occurs within close proximity to a resort, this assumption could be relaxed with higher resolution or more precise estimates of snowpack reductions and a structural approach that tests the sensitivity of damages using a rich representation of cross-elasticities. The relatively uniform losses across nearby states within a given warming scenario, as shown in Figure F.1, supports the use of time-invariant elasticities. Figure F.2 explores a higher resolution correlation between own and substitute resort snowpack under RCP4.5.

Figure F.2: Predicted Snowpack Under Different Warming Scenarios.



Note: Figure F.2 presents predicted snowpack losses at the resort-level under RCP4.5 at the end of the century (2100). The x-axis spans the range of predicted reductions in snowpack at the resorts in the sample that have at least one substitute resort within 200km (as included and specified in the primary damage functions throughout this paper). The y-axis spans the predicted reductions in snowpack at the substitute resorts (the average of all substitute resorts within 200km). The point estimates represent the mean reductions across the suite of CMIP5 models, along with the uncertainty (5^{th} and 95^{th} percentile dotted lines) in their projections. While some resorts are predicted to experience more—or less—than their nearby substitute resorts (as denoted by the distance from the 45-degree line), after accounting for uncertainty in the CMIP5 projections most resorts experience comparable snowpack losses as their substitute resorts.

Figure F.3: State-level damage functions using observed within-sample snowpack in 2012.

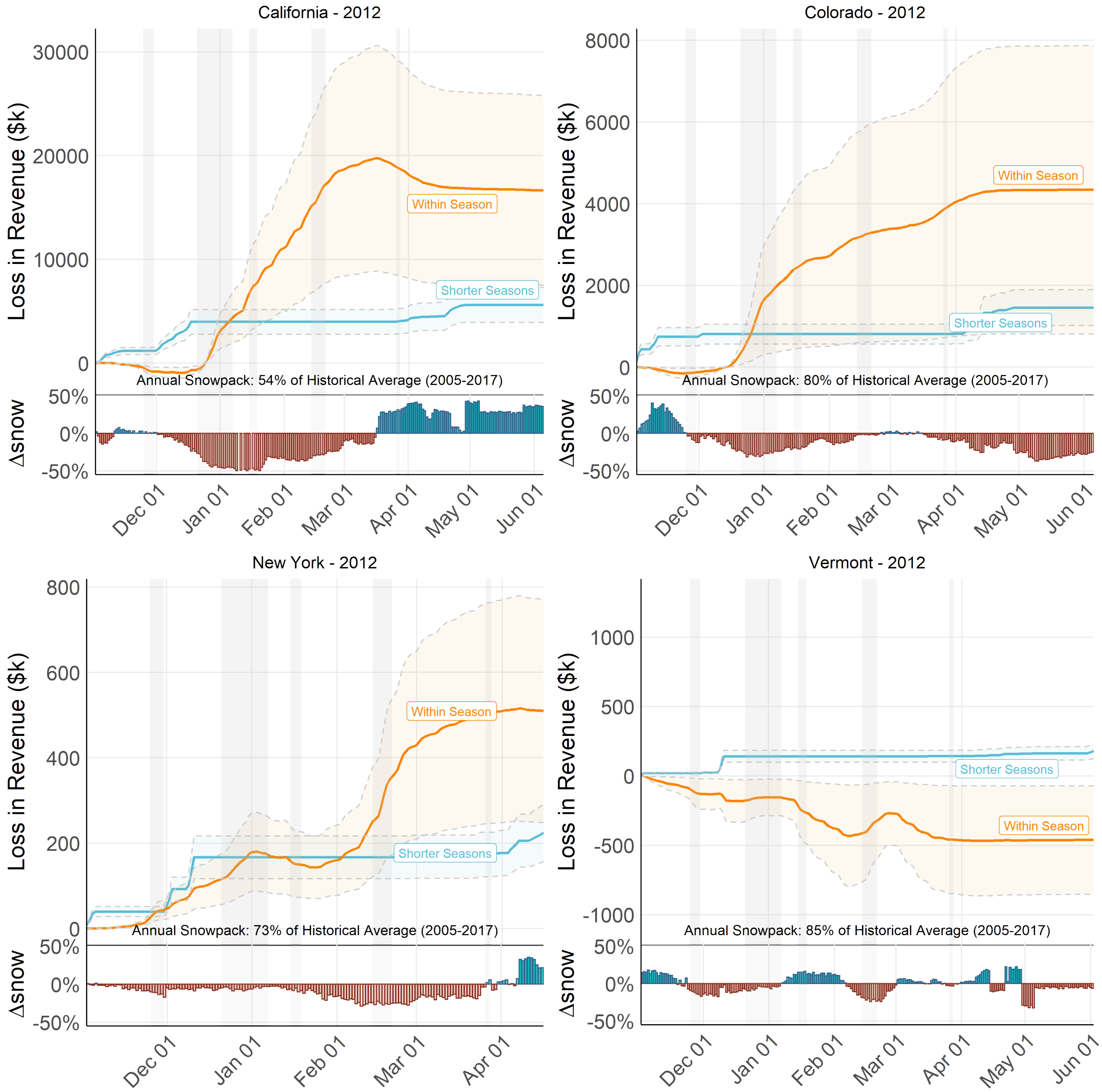
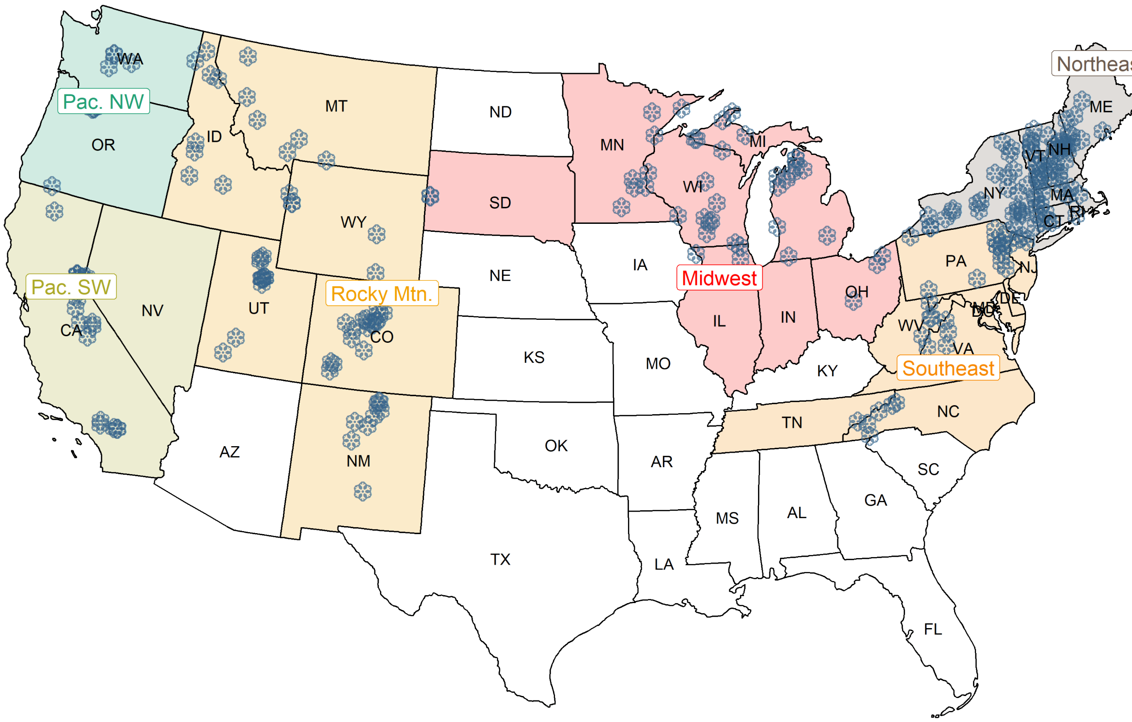
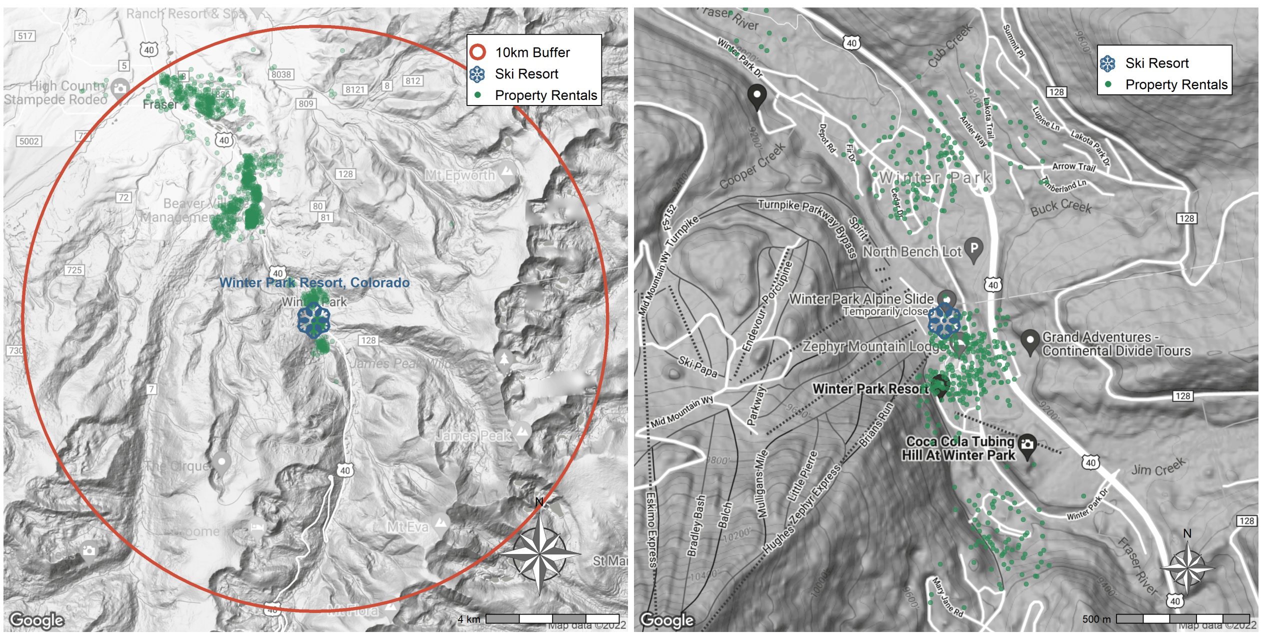


Figure F.4: NSAA Resort Regions and Distribution of Resorts Throughout the United States.



Note: Figure F.4 presents the regions across the U.S. as defined by the NSAA (NSAA, 2018) and the 236 ski resorts included in our sample. These are the regions specified in equation C.1 and elasticity results summarized by NSAA region in Table C1. States not filled in (white) are states without a ski resort in our sample.

Figure F.5: Spatial Distribution of rental properties around Winter Park Resort, Colorado



Note: Figure F.5 presents the spatial distribution of short term rental properties within a 10km buffer around Winter Park Resort, Colorado.