# 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 13 million short-term property rental transactions with daily local weather, daily local snowpack, and daily local snowfall in every major ski 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 snowpack elasticities that explicitly account 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 \$1.64 billion (RCP4.5) and \$2.36 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 in 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 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 accommodate 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; Chan and Wichman, 2018; Dundas and von Haefen, 2019). 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-resolution 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.

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).[2] We find evidence of substantial heterogeneity in snowpack elasticities across states, limiting the external validity of estimates from any particular resort. Other work has used monthly counts of overnight stays and monthly averages of snowpack to estimate the the behavioral response characterized as the elasticity of overnight stays (Falk, 2010).[3] 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

[2]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.

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

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, 2018; 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 major resort markets across the United States (US) 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 climate scenarios, RCP4.5 and RCP8.5. We find that resort markets 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 is applied to expenditures on lift-tickets and overnight stays, the estimated annual damages in each state range from $1 million (Connecticut) to $566 million (California). Across the US, 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 unobservable time-invariant characteristics in each market, while exploiting detailed variation in the level of the climate amenity (*snowpack*). Daily revenue for property $i$ on day $t$ is either 0 (not reserved), or the asking price on that day. To estimate the elasticity between revenue and snowpack, we transform the dependant variable (daily revenue) using the inverse hyperbolic sine (*ihs*) and allowing revenue to take a value of 0 (Bellemare and Wichman, 2020). Our estimating equation is:

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

This specification estimates the relationship between daily revenues for property $i$ on each day $t$ and the natural logarithm of *snowpack* in resort market $r$ on each day $t$. The elasticity parameter, $\beta$, 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*; the relationship between these and revenue is summarized by the parameter vector $\boldsymbol{\eta}$. The indicator for *holiday week* assumes a value of 1 for weekdays and weekends following or leading up to a US federal holiday.[4] The categorical variable *weekday* provides a unique indicator variable for each day of the week Sunday through Saturday. The parameter $\psi$ is

[4]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.

a property-by-month-of-sample fixed effect that captures property-specific revenue trends across the study period. The error term $\varepsilon_{it}$ is the remaining variation in revenue that is unexplained by the model.

This 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 resort market in February of 2016 is driven by variation in weather that is random in relation to the market for overnight stays. Importantly, variation in snowpack is matched with the consumer decisions in this market. $\beta$ 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 $\beta$ for each state $s$, we introduce an interaction between *snowpack* and a dummy variable indicating the resident state of the resort:

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

This allows us to examine heterogeneity in the revenue function by recovering an estimate of state-specific responses to the climate amenity *snowpack*.[5] $\beta$ has the following interpretation:

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

a 1 percentage point increase in *snowpack* causes a $\beta$ percentage point change in expected *revenue*. An important feature of our method is the direct relevance of the resulting coefficient, $\beta$, 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.

# 3 The Data

We estimate the behavioral response to changes in mountain snowpack using a panel of 13 million daily observations of rental property bookings on the Airbnb platform. Our study area comprises the 219 resort markets that contain active Airbnb listings (AirDNA, 2017).[6] 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 as reported by the resort from August 2005 through May 2017 (OnTheSnow.com, 2017). We recover two measures: 1) snowpack, the depth of the snow as reported by the resort each day; and 2) snowfall, the new snow that has fallen within the last 24 hours at each resort. We classify snowfall into bins of 3 inches and group every observation over 15 inches into the largest bin. Daily

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

mean temperature is acquired from Oregon State's PRISM Climate Group (PRISM, 2018). Summary statistics for the bookings, snowpack, and weather variables used in our analysis are in Table 1.

To generate expectations of future snowpack, we collect locally downscaled climate projections from the suite of CMIP5 models in 1/8-degree resolution across the US (Reclamation, 2013). 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 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

Table 1: Summary Statistics

| Statistic | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|
| Revenue ($USD) | 86.62 | 257.46 | 0 | 0 | 0 | 4,990 |
| Snowpack (in.) | 41.36 | 31.82 | 0.00 | 16.00 | 59.55 | 225.00 |
| Snowfall ($<$ 24hrs) | 0.81 | 2.35 | 0 | 0 | 0.2 | 48 |
| Reserved | 0.17 | 0.38 | 0 | 0 | 0 | 1 |
| Reservation Lead-time | 67.40 | 69.07 | 1.00 | 20.00 | 87.00 | 364.00 |
| 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 (m) | 4,769.14 | 2,994.52 | 6.77 | 2,135.41 | 7,589.33 | 9,998.69 |
| Bedrooms | 2.47 | 1.24 | 1 | 2 | 3 | 7 |
| Bathrooms | 2.14 | 1.08 | 0 | 1 | 3 | 8 |
| Obs. 12,903,718 | | | | | | |

us with annual ski resort visitation in each of the 28 states and the number of overnight stays.

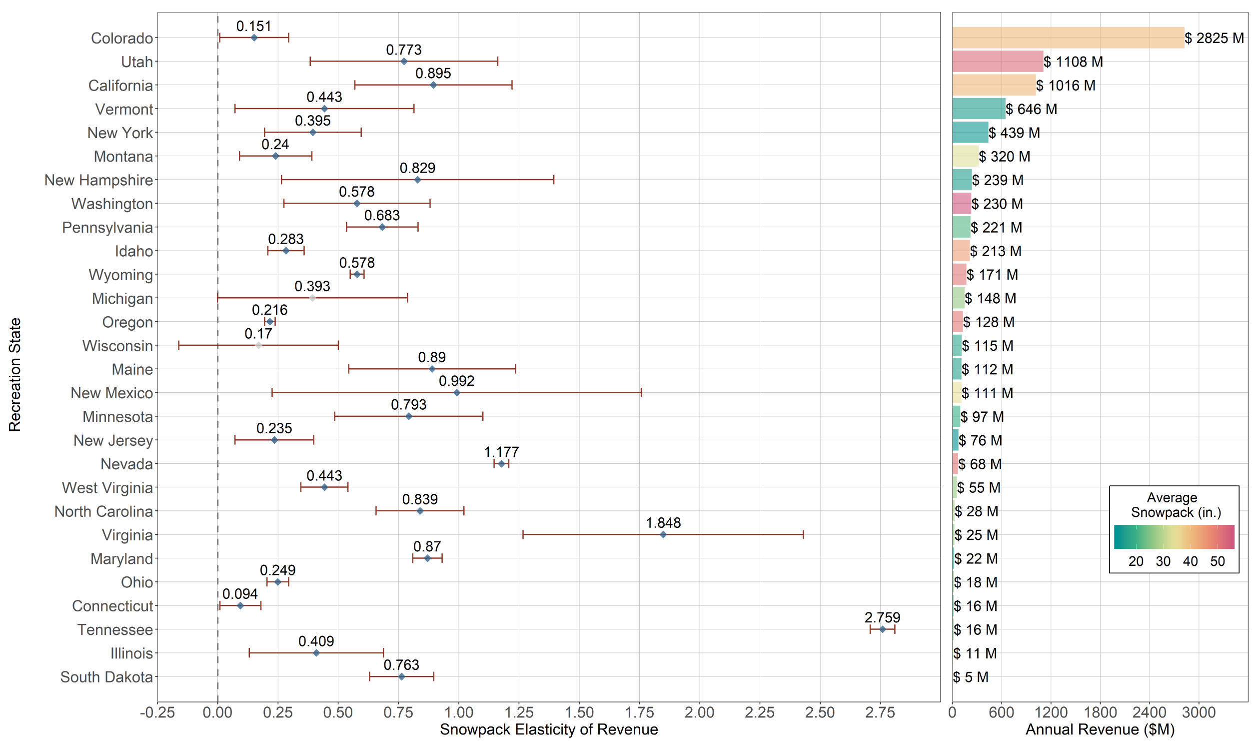
Our research design, which relies on plausibly random variation in snowpack within a season, provides several advantages in the literature on the recreational demand for snow. Previous approaches have been limited to cross-sectional data or course panels (spatially, temporally, or both), limiting their ability to control for unobservable characteristics underlying each market. The data we have collected 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 $\beta$ parameters in equation 2—that represent the slope of the revenue function in each state. We report these results in Figure 1 (left panel). These estimates reveal substantial heterogeneity between states, with the elasticity of snowpack ranging from 0.151 in Colorado to 2.759 in Tennessee. We find that some states like Colorado have large snow-related revenue streams ($2.82 billion annually, Figure 1 right panel), but are less responsive to marginal changes in mountain snowpack ($\beta = 0.151$). State-specific elasticities do not systematically vary with mean snowpack, suggesting each state and market has unique underlying characteristics that drive this variation.

Variation in elasticity estimates across states is important for generating expectations about revenue under future climate scenarios because baseline revenue, snowpack, and future climate conditions all vary significantly across states. These parameters allow for targeted revenue 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).

Figure 1: State-specific Elasticities



## 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 percentage deviation from average snowpack for each day in the sample.[7] 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 ($\beta_s$).

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

[7] 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.

daily revenue calculations to shorter ski seasons. By contrast, the method developed here relies on flexible estimates of the relationship between variation in revenues and variation in snowpack throughout the season. Modeling the behavioral response in this way accounts for both geographic and temporal substitution in the revenue function. We compare the current estimates 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. For example, if in a given year a resort received 70% of its average snowpack observed in the sample (2005-2017), the length of that resort's season was shortened by 30% (15% from the beginning of the season and 15% from the end of the season).[8]

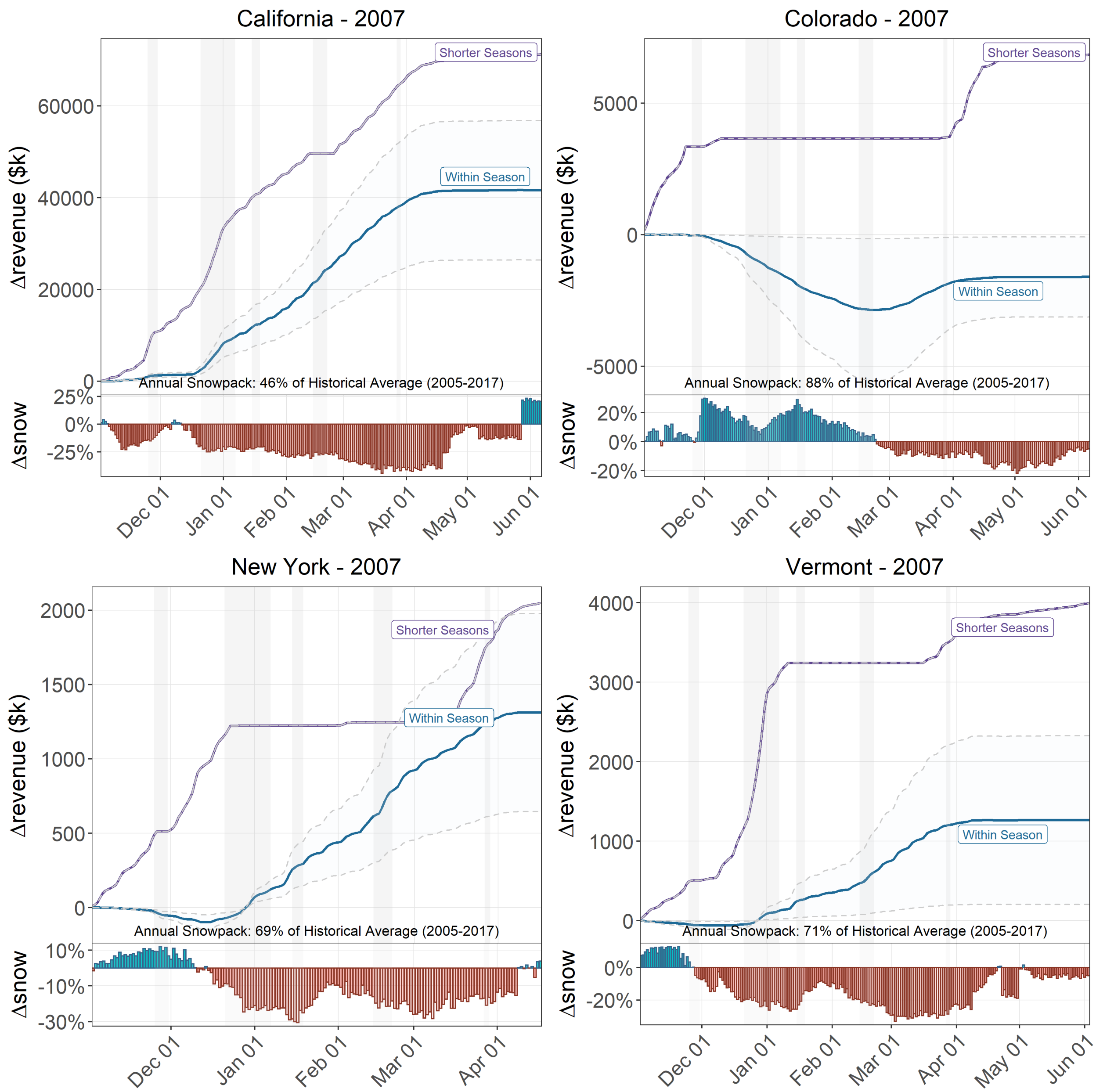
Figure 2 presents within-season revenue functions for four states in 2007—a lower than average year for snowpack across the US.[9] Our approach demonstrates that these within-season effects are critical. For example, when seasonal trends in visitation occur, such as around the Christmas or Spring Break 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. Substitution patterns in recreation decisions are also captured in this trend line.

In 2007, California, New York, and Vermont had much lower snowpack during key times of the season (holidays, shaded in gray) that accelerated the growth of the damages function; compared to Colorado that had better-than-average snowpack during those times

[8]These losses in season length can be partially addressed with artificial snowmaking, which typically only becomes cost-effective at low levels of snowpack. We focus on the mass of the snowpack distribution in this paper—at levels above where snowmaking would typically be applied—and leave the study of the potential impacts of artificial snowmaking for future work.

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

Figure 2: Within Sample Damages from Observed Snowpack - 2007




and ended the season with higher-than-average revenues, despite having a lower-than-average annual snowpack (88% of its long-run average). Our approach also captures substitution behavior observed within a resort season as well as across resorts and even regions within a season.

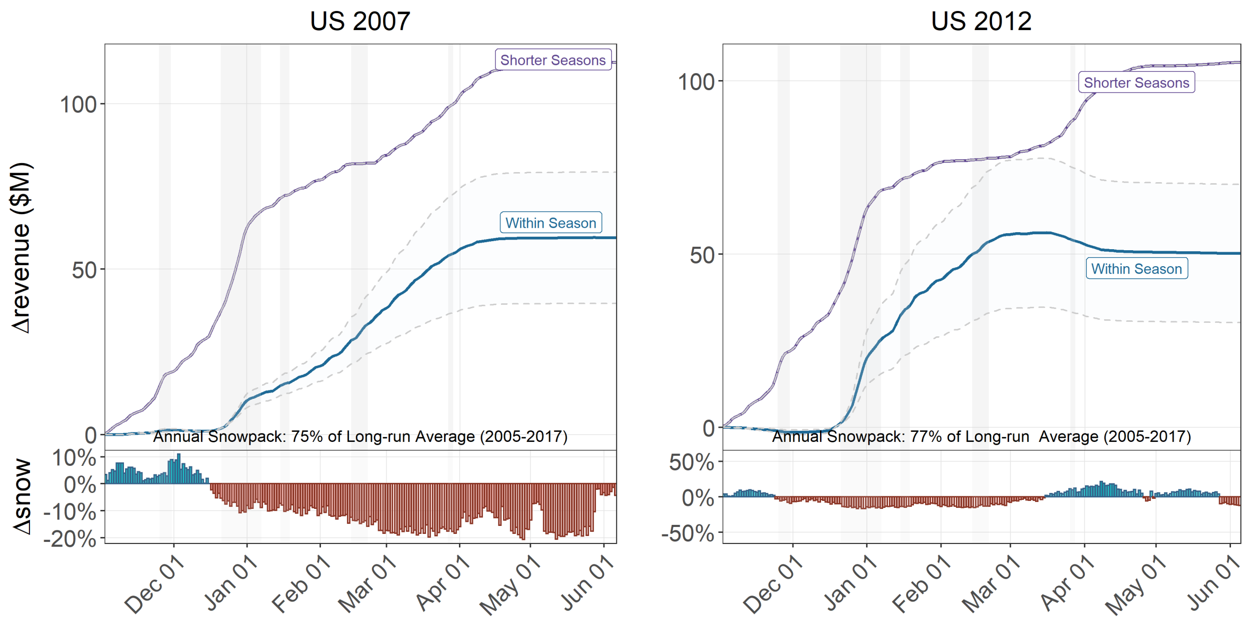
The comparison between the present (within-season) approach and currently established methods reveals two important differences: 1) our method provides consistently lower damage estimates due to its ability flexibly account for substitution and within-season variation in visitation using state-specific behavioral responses; 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). Using established season-length methods provides little information about when damages accrue throughout the season.[10]

The damages trendline that is estimated through a shortening of season length (shorter-season) is analogous to the conventional approach of estimating 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 extensive investment in artificial snowmaking. If the practice of artificial snowmaking expands dramatically, then the future costs associated with that technology may depart significantly from those observed today.

On the other hand, the *within-season* damages assume no change in season length and snowpack levels are maintained above the threshold that would push a resort into early

[10] 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, resulting in a state's *shorter-seasons* damages trendline 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-season* trend-line to be fixed at a given level (flat with a slope equal to zero).

Figure 3: Within Sample Damages from Observed Snowpack - US 2007 and 2012




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 that resorts at no point are forced to close. Figure 3 applies the method described above and aggregates daily revenue functions across the US for 2007 and 2012 winter seasons. While 2007 and 2012 received similar snowpack, the timing of snowpack accumulation results in a different shape of the damages function. Compared to the method of estimating shorter seasons, it is clear from Figure 3 that the timing of snowpack accumulation drives substitution throughout the season and dictates the slope of the resulting revenue 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 revenue response from deviations in snowpack under future climate is then:

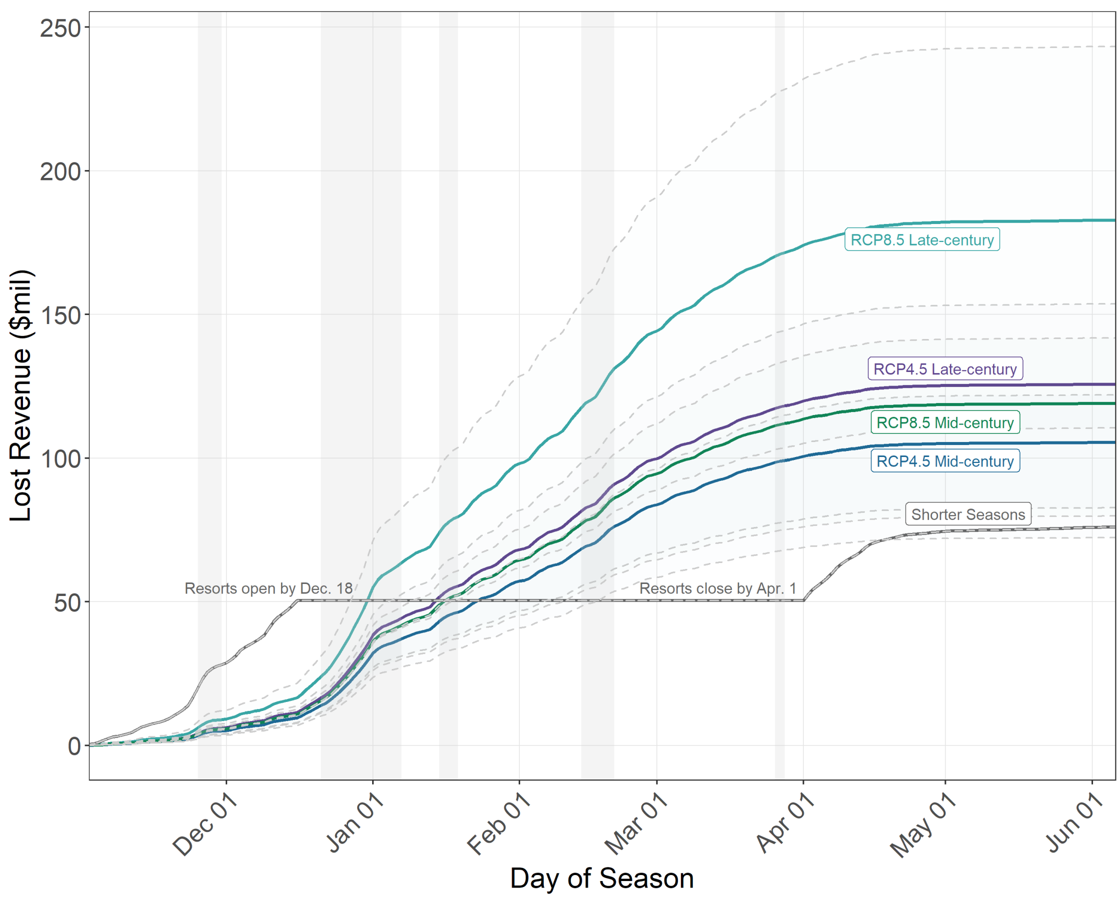
$$\Delta revenue'_{rd\overline{y}c} = \beta_s \times \overline{revenue_{ry}} \times \Delta snow'_{rd\overline{y}c}. \tag{6}$$

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 4 summarizes the results of the simulations and equation 7 under each RCP scenario and period. 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 18, and can remain open through the end of May. These estimates assume no other changes in revenues while the resorts are able to maintain feasible operating level of snowpack (Scott et al., 2007; Steiger, 2011; Dawson and Scott, 2013; Wobus et al., 2017; Steiger and Scott, 2020).

Figure 4: Within-season Damages Under Future Climate




An important take-away from Figure 4 is that damages resulting from the behavioral response to marginal changes in snowpack throughout the season quickly outpace damages from conventional estimation 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.

### 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).[11]

Figure 5 summarizes the results of the simulated decade under contemporaneous and late-century snowpack.[12] We report the average *total* revenues that are attributable to snowpack in each year $y$ of scenario $c$:

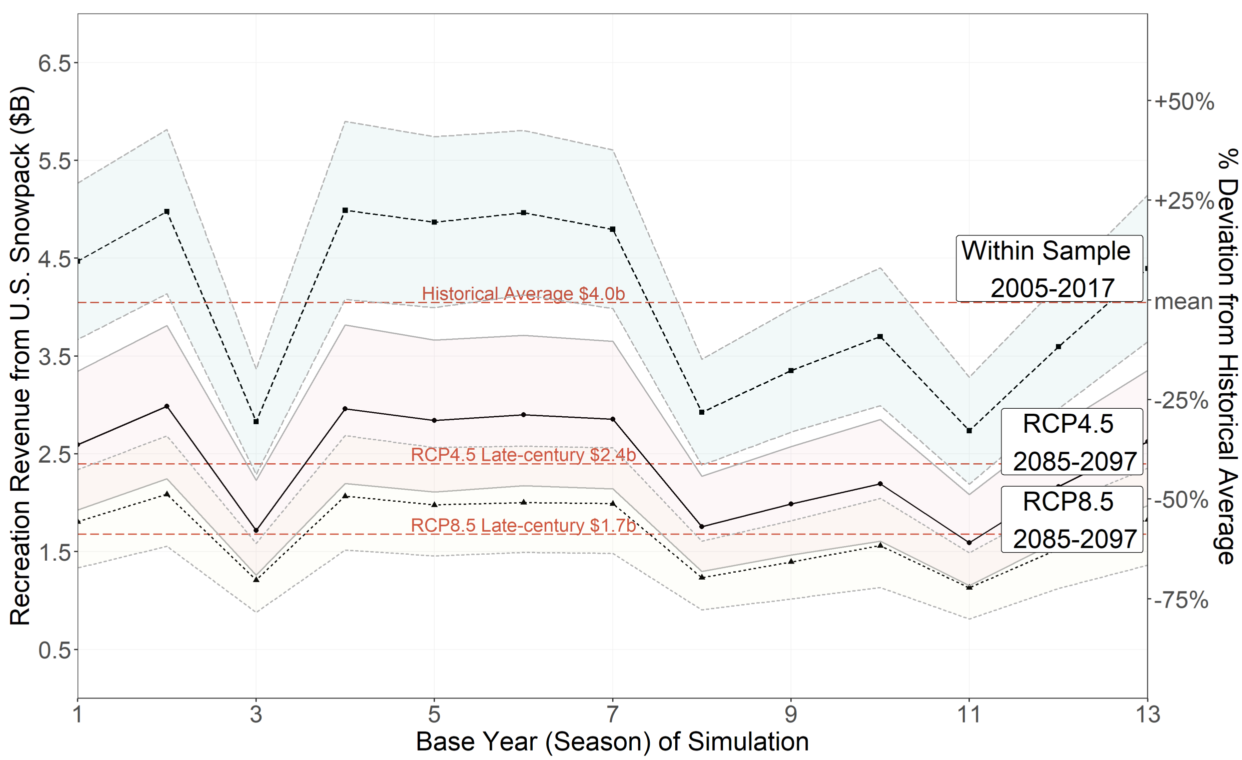
$$Revenue_{yc} = \sum_{rd}(\beta_s \times \overline{revenue_{rd}} \times snow_{rdyc}) \tag{8}$$

The three scenarios represented in Figure 5 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 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.

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

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 elasticity parameter (the standard error of $\beta$). Between 2005 and 2017, we observe the annual recreation revenue from snowpack shifting between -25% and +25% of historical averages. The within-sample deviations in 2007, 2012, and 2015 fall to around \$2.8 billion in annual revenue, which approaches the range predicted by mid-century climate models for RCP8.5. Under RCP4.5 and RCP8.5 (respectively), these estimates indicate that total recreation revenue could fall to between -35% and -40% 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

Figure 5: A Decade of Lost Revenues Future Climate



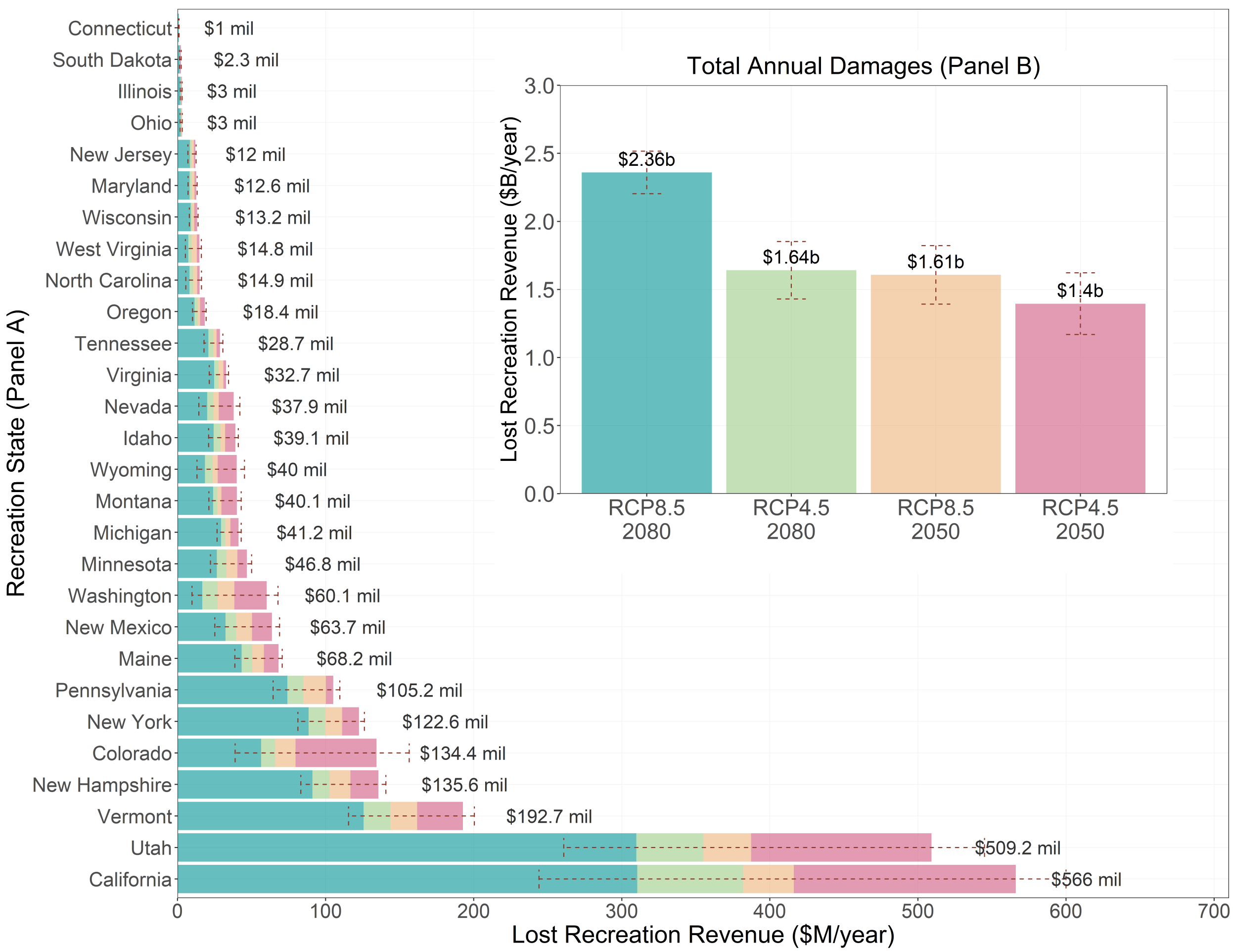
period. By the late-century period, the highest snowpack year in our simulation will generate merely half of the economic activity observed during the worst year in our contemporary sample.

The difference between each line in Figure 5 captures the annual economic damages across the US. We report the average difference over the 13 years in Figure 6. Panel A summarizes the expected annual losses in each state for each RCP scenario and period (mid- and late-century). The 90% confidence intervals represent the combined variation across the suite of CMIP5 models and the uncertainty in the elasticity parameter (the standard error of $\beta$). 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 US under both RCP scenarios and periods.

Average annual damages under RCP8.5 2080 range from $1 million in Connecticut (a 67% reduction in revenue from current levels) to $566 million in California (a 62% 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. It is reasonable to assume that there are other expenditures directly and indirectly linked to changes in snowpack in each resort 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 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 $\beta$);

Figure 6: Average Annual Losses Under Future Climate Scenarios




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 ($\beta = 0.895$) 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 ($\beta = 0.151$), 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.

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 estimating elasticities for climate amenities that vary at high spatial and temporal frequencies using high-resolution and high-frequency transaction data; 2) we derive state-specific snowpack elasticities in all major resort markets across the US and show that substantial heterogeneity exists across states; and 3) we simulate the contemporaneous value of snowpack in each state, along with economic damages under two future climate scenarios, RCP4.5 and RCP8.5. We predict damages (lost revenues) in percentage terms, which provide a lower-bound dollar estimate of lost economic activity in each state.

We find that resort markets could face annual reductions of -40% to -80% of snow-related revenue by the end of the century (2080). This is nearly double the magnitude of existing estimates 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 US between \$1.4 billion (RCP4.5) and \$2.36 billion (RCP8.5). The revenue impacts presented in this paper can be interpreted as a lower bound estimate of consumer surplus. The true welfare effects from reductions in snowpack could be substantially larger (Banzhaf, 2018).[13] Further 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.

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

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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 the underlying revenue functions for 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.

Also included:

Equations: A1-A13
Tables: A1 to A3
Figures: A1 to A10

## 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 (daily revenue) takes a zero when the property is vacant. We assume that it may not be optimal for profit maximizing owners to rent properties on all days as a result of variable costs (maintenance, wear and tear, cleaning, management, etc.). We allow for an equilibrium with vacancies. Any exogenous changes in the owner's profit function (such as a decrease in snowpack) will directly affect expected revenue.

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

$$ihs(revenue)_{it} = \underbrace{\sum_s \beta_s \; log(snowpack)_{rt}[State = s]}_{\substack{\text{State-specific}\\ \text{Elasticities}}} + \boldsymbol{Z'_{rt}\delta} + \boldsymbol{X'_{rt}\eta} + \psi_{im} + \varepsilon_{it}. \tag{A1}$$

The $\beta_s$ in our model can be explicitly defined as:

$$\beta_s = \frac{\partial ihs(revenue)_s}{\partial log(snowpack)_s}. \tag{A2}$$

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

$$Implicit\ Revenue_s = \beta_s \times \frac{\overline{Revenue_s}}{\overline{Snowpack_s}}. \tag{A3}$$

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 A3 is also the first part of equation A12:

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

The average annual revenue (the numerator in equation A12) is the average annual estimate of demand for lift tickets and overnight stays from equation A11:

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

The average annual revenue term in equation A11 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:

$$Rev_s^{snow} = \beta_s \times \frac{AR_s}{HS_s} \times HS_s = \beta_s \times AR_s. \tag{A4}$$

The historical recreation revenue from snowpack is defined as the expected annual revenue at the an average snowpack for any year in state $s$. This quantity reflects the proportion of annual revenue that can be directly attributed to snowpack at the resort. These are reported for each state alongside our main elasticity estimates in Figure 1 and in Panel B of Figure A5.

# 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 dataset includes more than 1.4 million properties and 410 million bookings spanning the contiguous United States.

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

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

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

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

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

# C Alternative Specifications and Discussion

A more general form of our primary estimating equation (equation 1) consists of a national average revenue function using all markets in the sample. This specification omits the interaction between *snowpack* and an indicator for each state. Table A1 summarizes these results. Column 1 estimates the average revenue function for all resort markets and provides a baseline estimate for the parameter of interest $\beta$. We estimate the average snowpack elasticity of revenue to be 0.262. This implies that for every 1% reduction in mountain snowpack, revenues will decline by 0.262% on average across the Unites States. To estimate regional heterogeneity in the revenue function, we introduce regional interaction terms with *snowpack* to recover the snowpack elasticity specific for each region $k$:

$$\begin{aligned} ihs(revenue)_{it} = &\sum_k \beta_s \ log(snowpack)_{rt}[Region = k] \\ &+ \boldsymbol{Z'_{rt}}\boldsymbol{\delta} + \boldsymbol{X'_{rt}}\boldsymbol{\eta} + \psi_{im} + \varepsilon_{it}. \end{aligned} \tag{A5}$$

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 A8.

Columns 2 and 3 in Table A1 summarize the underlying heterogeneity in the revenue function identified using equation A5. Column 2 introduces an interaction between *snowpack* and two general regions, Central-East and Mountain-West. Column 3 introduces an interaction between *snowpack* the six regions as determined by the NSAA. Coefficients reported in this table have the same interpretation as our state-specific elasticities. On average, we observed greater responsiveness to marginal changes in snowpack in the eastern regions of the U.S., while the western regions who receive much higher average annual snowfall and more favorable snowpack are less responsive (as measured in percentage point reductions in revenue). All models control for binned *snowfall*, property-by-month-of-sample fixed effects, a cubic of *mean temperature*, and an indicator for *holiday week*.

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

$$\begin{aligned} ihs(revenue)_{it} = &\sum_{c} \beta_s \ log(snowpack)_{rt}[C = c] \\ &+ \boldsymbol{Z'_{rt}}\boldsymbol{\delta} + \boldsymbol{X'_{rt}}\boldsymbol{\eta} + \psi_{im} + \varepsilon_{it}. \end{aligned} \tag{A6}$$

Here, $C$ represents variables defining property characteristics. Table A2 summarizes the results of equation A6. In column 1 we include the results of the main specification, equation

1. Column 2 of table A2 introduces an interaction between *snowpack* and full-time rentals (properties that are always available for the public to rent — no "blackout days" scheduled by the owner). This sample addresses potential simultaneity resulting from property owners that list their property for rent only when demand is high (Farronato and Fradkin, 2018). This larger coefficient on the rental properties suggests that renters can sort into full-time rentals more quickly, or that owners maintain a personal schedule (blackout days) that is unaffected by demand shocks. Columns 3 and 4 introduce an interaction between *snowpack* and other property characteristics to examine substitution behavior when snowpack is low versus when snowpack is high. We find that revenues increase for nearby properties when snowpack is higher.

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

$$\begin{aligned} ihs(revenue)_{it} = &\sum_{d} \beta_s \ log(snowpack)_{rt}[Snowpack = d] \\ &+ \boldsymbol{Z'_{rt}\delta} + \boldsymbol{X'_{rt}\eta} + \psi_{im} + \varepsilon_{it}. \end{aligned} \tag{A7}$$

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

$$\begin{aligned} ihs(revenue)_{it} = &\sum_{d}\sum_{k} \beta_{dk} \ log(snowpack)_{rt}[Snowpack = d][Region = k] \\ &+ \boldsymbol{Z'_{rt}\delta} + \boldsymbol{X'_{rt}\eta} + \psi_{im} + \varepsilon_{it}. \end{aligned} \tag{A8}$$

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 A3 where the $\beta$'s are relative daily revenues for each snowpack bin (the reference level of revenue is 0). For example, a coefficient estimate of 1.239 (the 50-60 inch bin) indicates that an additional day with snowpack between 50-60 inches results 123.9% higher revenues relative to no snowpack on the same day. Panel A summarizes the national revenue function using binned *snowpack* (equation A7, and panel B summarizes the regional binned *snowpack* (equation A8). In both cases, the revenue functions exhibit diminishing returns to scale. The regional model, however, suggests that losses in the Mountain-West states could be much larger than we estimate if snowpack falls to below 30-40 inches of average snowpack. This poses a particularly large threat to these states and local economies if changes in snowpack falls above the mean predicted by climate models.

As discussed in the introduction of the main text, we demonstrate the implications of using a more coarse level of analysis (monthly) to derive elasticity estimates. This model uses total revenue and the average levels of weather and snowpack in each calendar month. This is comparable to the estimation strategy used in Falk (2010). We do this for both the national average revenue function (the monthly version of equation 1) and the state-specific revenue functions (the monthly version of equation 2). For month $m$ of season $y$ in resort market $r$ this is:

$$ihs(revenue)_{rm} = \beta \log(snowpack)_{rm} + \boldsymbol{X'}_{rm}\boldsymbol{\delta} + \boldsymbol{\eta}_{rm} + \psi_y + \varepsilon_{rm}. \tag{A9}$$

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

$$\begin{aligned} ihs(revenue)_{rm} = &\sum_s \beta_s \; log(snowpack)_{rm}[State = s] \\ &+ \boldsymbol{X'_{rm}}\boldsymbol{\delta} + \boldsymbol{\eta}_{rm} + \psi_y + \varepsilon_{rm}. \end{aligned} \tag{A10}$$

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 $\delta$ summarizes their relationship with revenue. The parameter $\eta$ is a resort market by calendar-month fixed effects (i.e. January through December indicator variables). The parameter $\psi$ is a operating season (year) fixed effect. Results from our monthly estimation can be found in Figure A2. We present state-specific elasticities estimated using monthly data (left), daily data (middle), and the bootstrapped difference between the two (right). We find that the average magnitude of the error ($\beta^{monthly} - \beta^{daily}$) is large. Most states suggest attenuation in the coefficient when we aggregate from daily estimates up to monthly. This can be seen when the difference between the two is less than zero (right panel). The monthly aggregates even yield negative elasticities in some cases, suggesting additional bias in specifications that do not match the temporal variation in amenity levels with the temporal variation in market transactions. The differences were obtained by bootstrapping the estimation of both daily and monthly models 200 times and taking the difference between the coefficients in each iteration. Statistically insignificant coefficients are indicated by a lighter (greyed) shade of marker.

# 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.[14] 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:

$$AR_s = \underbrace{V_s \times P_s^{pass}}_{\substack{\text{Daily}\\ \text{Visits}}} + \underbrace{OS_s \times P_s^{bed}}_{\substack{\text{Overnight}\\ \text{Stays}}} \tag{A11}$$

To calculate the annual recreation revenue from snowpack, $Rev^{snow}$, we combine our derived response parameter $\beta_s$ 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:

$$Rev_{st}^{snow} = \underbrace{\beta_s \times \frac{AR_s}{HS_s}}_{\substack{\text{Implicit}\\ \text{Revenue}}} \times CS_{st}. \tag{A12}$$

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

The first term in equation A12, 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 A12, 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 $1.5 million in Connecticut to $909 million in California (Figure 1, right panel). This is the proportion of local economic activity that is directly related to mountain snowpack. It is reasonable to assume there are indirect (spillover) effects of snowpack on local revenues, making these estimates a lower bound (Loomis and Crespi, 1999). A strength of the state-specific elasticity estimates (the $\beta_s$'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:

$$\sum_{s} Rev_{st}^{snow} \tag{A13}$$

and report these Figure A7. In the next section, we demonstrate an application to estimate economic damages under current (seasonal variation) and future climate scenarios. We present the direct effects of changes in snowpack on two primary expenditures directly related to outdoor recreation.

## E Additional Tables

Table A1: Regional Heterogeneity

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

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

**Note:** Column 1 presents the most general specification used in this study, estimating the average revenue function across all 219 resort markets in our data (equation 1). Columns 2 and 3 begin to dissect the underlying spatial heterogeneity in the average revenue function (equation A5). Column 2 introduces an interaction between *snowpack* and two general regions, Central-East and Mountain-West. Column 3 introduces an interaction between *snowpack* the six regions as determined by the NSAA. The coefficients presented in this table are interpreted in the same way as our state-specific elasticities of demand.

Table A2: Property Characteristics

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

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

**Note:** Column 1 again presents the most general specification used in this study, estimating the average revenue functions for all reservations and all resorts (equation 1). Columns 2 through 4 examine sensitivity of this general specification to certain characteristics of the property (equation A6). Column 2 introduces an interaction between full-time rental properties (i.e. no "blackout" days) and *snowpack*. The average elasticity is larger for rental properties. We hypothesize that this difference is largely due to the fact that owners who occasionally occupy their property likely do so when the snow conditions are most desirable. Column 3 introduces an interaction between *snowpack* and a variable indicating whether or not a property is within 2km of the resort. This result suggests that when snowpack is larger, people prefer to be closer to the resort. The final specification, column 4, further desegregates the characteristics of the property and their relationship with *snowpack*. When snowpack is larger, people prefer to be closer to the resort and exhibit some trade-offs between the number of bedrooms, bathrooms, and maximum number of guests. This suggests that people are substituting for smaller properties that are closer to the resort but allow for more guests (e.g. bunk beds).

Table A3: Monthly vs. Daily Specifications

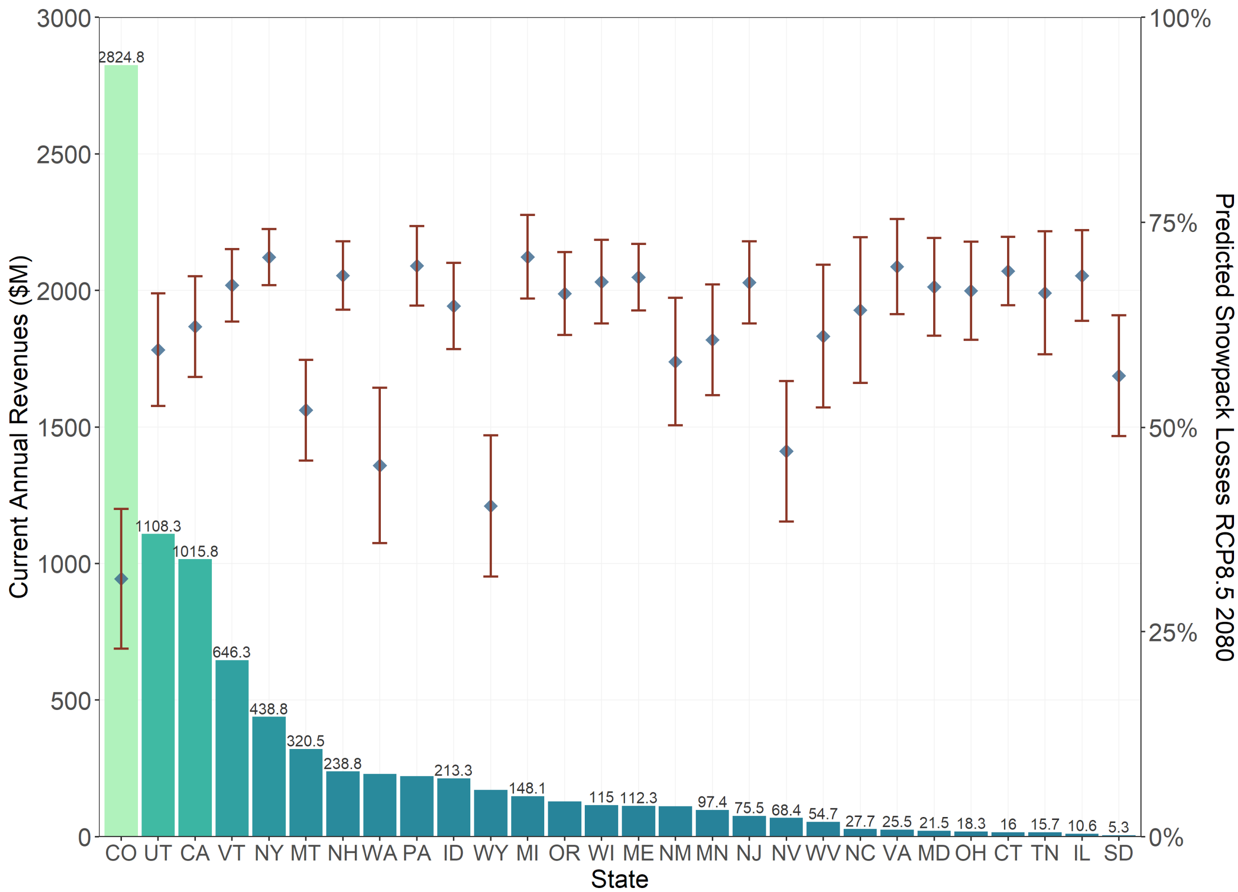
| | (1) Monthly | (2) Daily |
|---|---|---|
| log(Snowpack) | 0.125** | 0.291** |
| | (0.054) | (0.137) |
| Market × Month FE | Y | N |
| Season FE | Y | N |
| Clu. SE | Market | Market |
| Property × Month of Sample FE | N | Y |
| Weekday FE | N | Y |
| Observations | 2,201 | 12,903,718 |
| Adjusted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

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

**Note:** Here we compare average revenue functions when estimated at different temporal scales (equations A9 and 1). Column 1 represent the results of the monthly-level of observations (equation A9). Monthly-level analyses are the finest (most granular) temporal scale offered in the existing literature. Column 2 estimates using the full set of daily observations (equation 1), which is the method we develop in this paper. The average snowpack elasticity of revenue is 45% smaller than the estimate derived from the daily specification. The attenuation could be due to various forms of bias that are introduced when aggregating to the monthly level. First, measurement error (classical) can be exacerbated during aggregation. Second, monthly observations must relax the vector of fixed effects from a *property* × *month-of-sample* controls to a more vulnerable set of two additive controls: (1) *market* × *month*; and (2) *season* fixed effects. Relaxing these can introduce unobservable variation across months (time varying) as well as unobservable variation in the market structure of the rented properties (time invariant). Figure A2 summarizes the difference between monthly and daily estimates at the state level, along with bootstrapped differences between the point estimates.

# F Additional Figures

Figure A1: Current Annual Revenue and Predicted Snowpack Loss

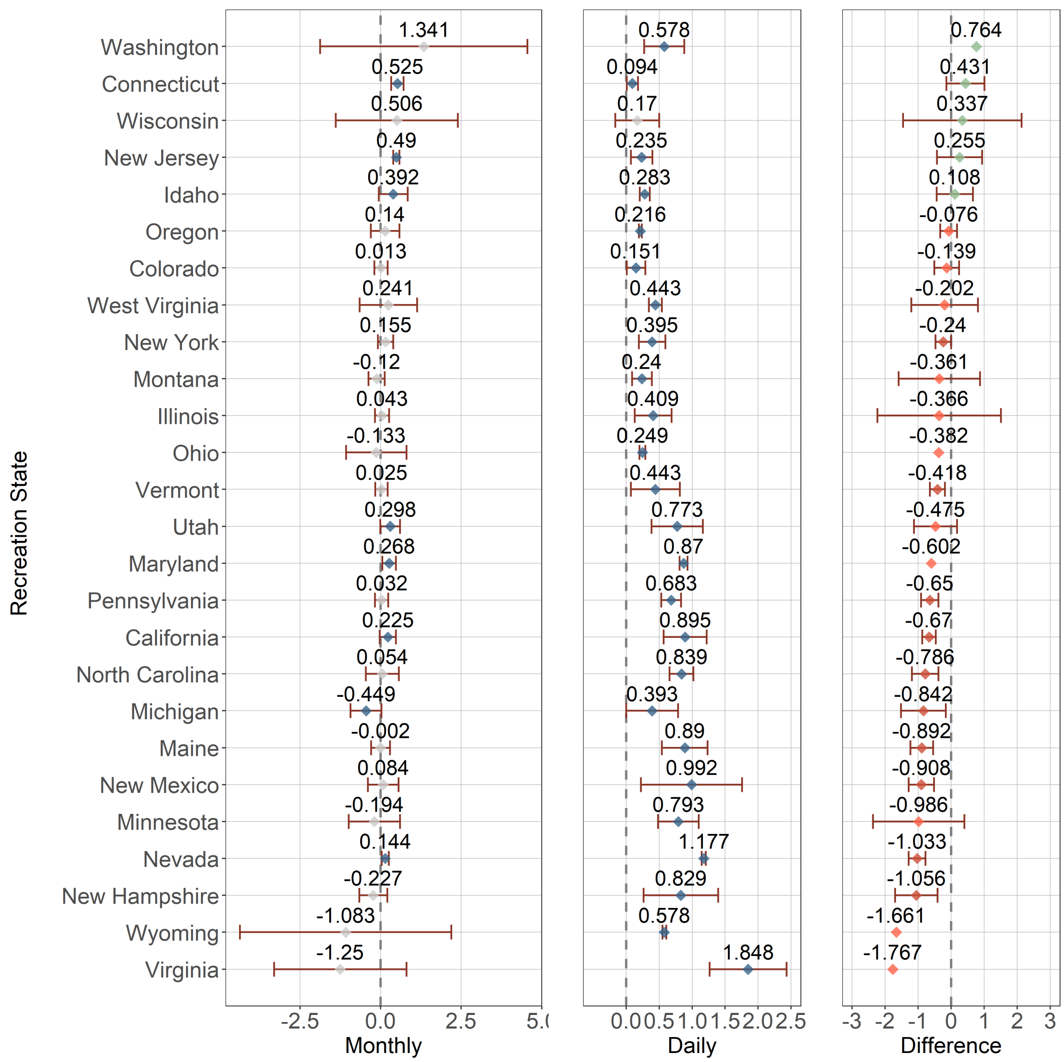



**Note:** Figure A1 provides a summary of current (average) annual revenues and the predicted loss in average snowpack under RCP8.5 according to the suite of CMIP5 climate models. Current (average) annual revenues (in millions) in each state $s$ consist of 2 cost components and are calculated as:

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

This is also equation A11 from the main text. Visitation statistics are drawn from NSAA (2018). Total average annual revenue across all 26 states is estimated at $8.82 billion per year.

Figure A2: Monthly vs. Daily Estimates




**Note:** Figure A2 presents state-specific elasticities estimated using monthly data (left), daily data (middle), and the bootstrapped difference between the two (right). The daily estimates are the primary estimates used throughout our analysis. The average magnitude of the error ($\beta^{monthly} - \beta^{daily}$) is large. Most states suggest attenuation in the coefficient when we aggregate daily observations up to the monthly level. This can be seen when the difference between the two is less than zero (right panel). In many cases, the monthly aggregates even yield negative (although statistically insignificant) elasticities, suggesting additional bias is introduced in the estimation of a model that does not match the temporal variation in the level of the amenity with the frequency at which the market transactions are taking place. The differences were obtained by bootstrapping the estimation of both daily and monthly models using 200 iterations and taking the difference between the coefficients in each iteration. In the right panel, if the confidence interval bounds zero (almost all do) then monthly and daily are not statistically different from each other. If there is no confidence interval, it was too large to show and also bounds zero. South Dakota and Tennessee are omitted from the monthly analysis as we do not have enough monthly observations to estimate these states. Statistically insignificant coefficients from the monthly and daily models are indicated by a lighter (greyed) shade of marker.

Figure A3: Estimates of Relative Revenue by Snowpack Bins

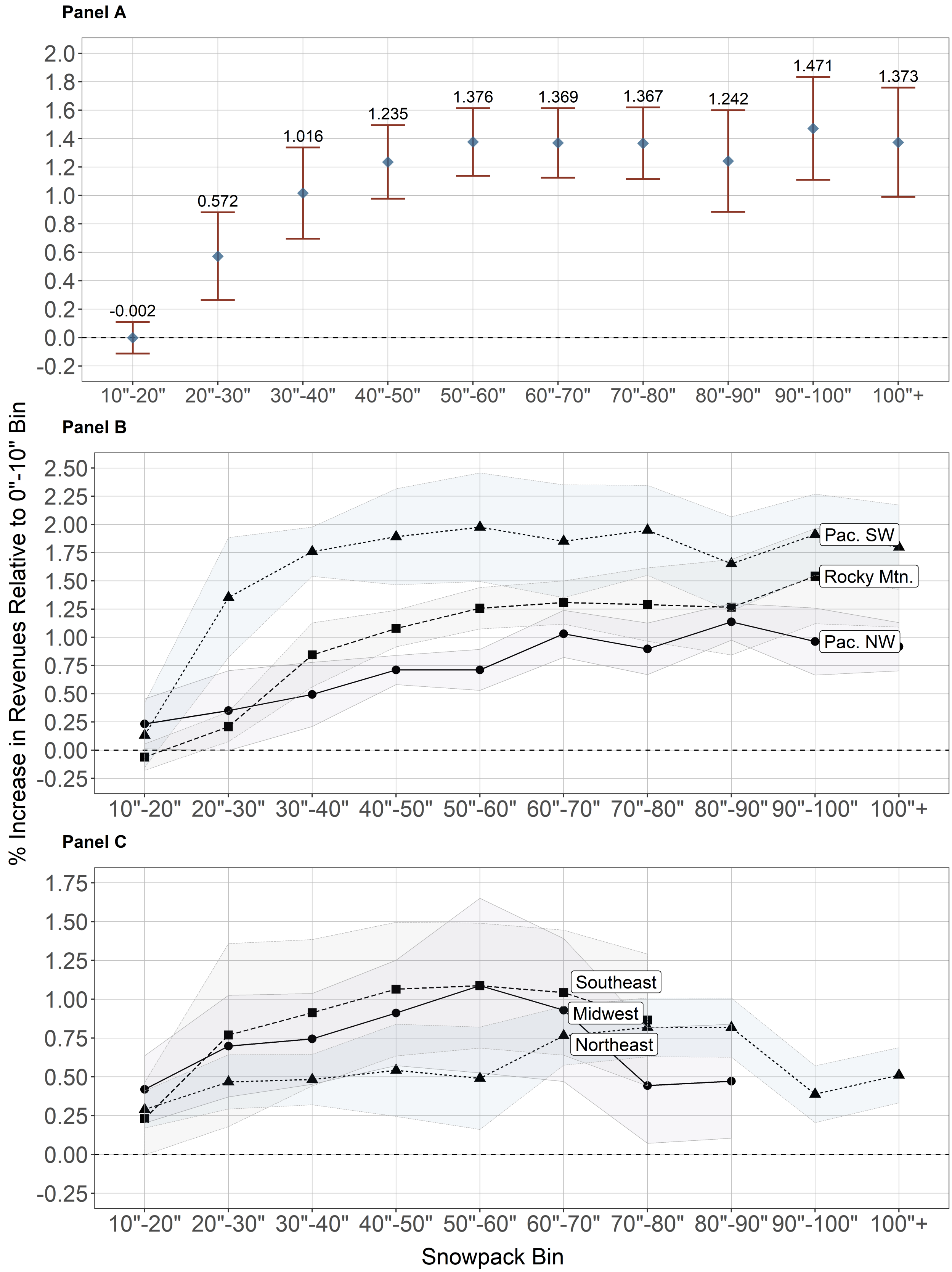


Figure A4: Within Sample Damages from Observed Snowpack - 2012

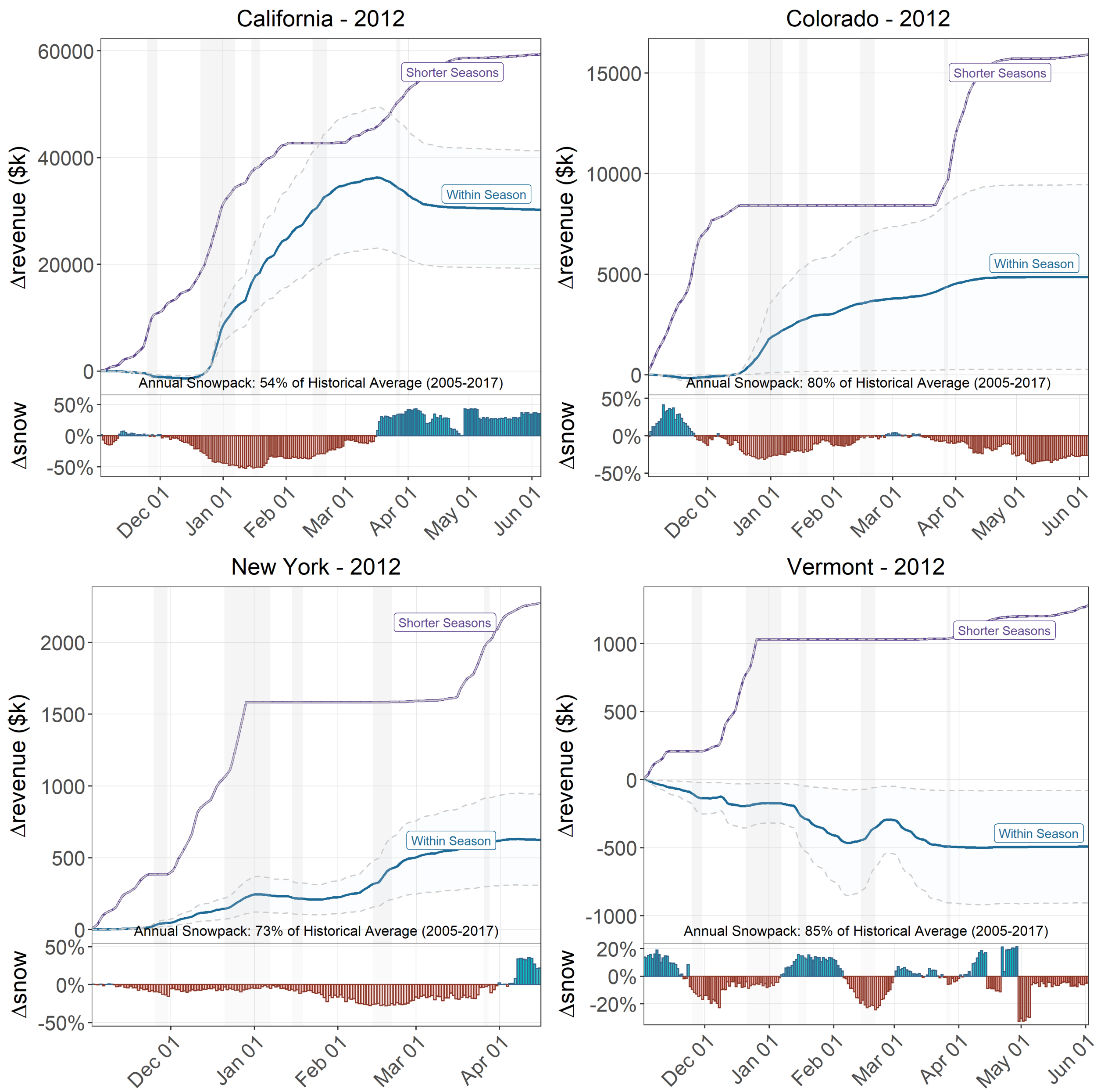
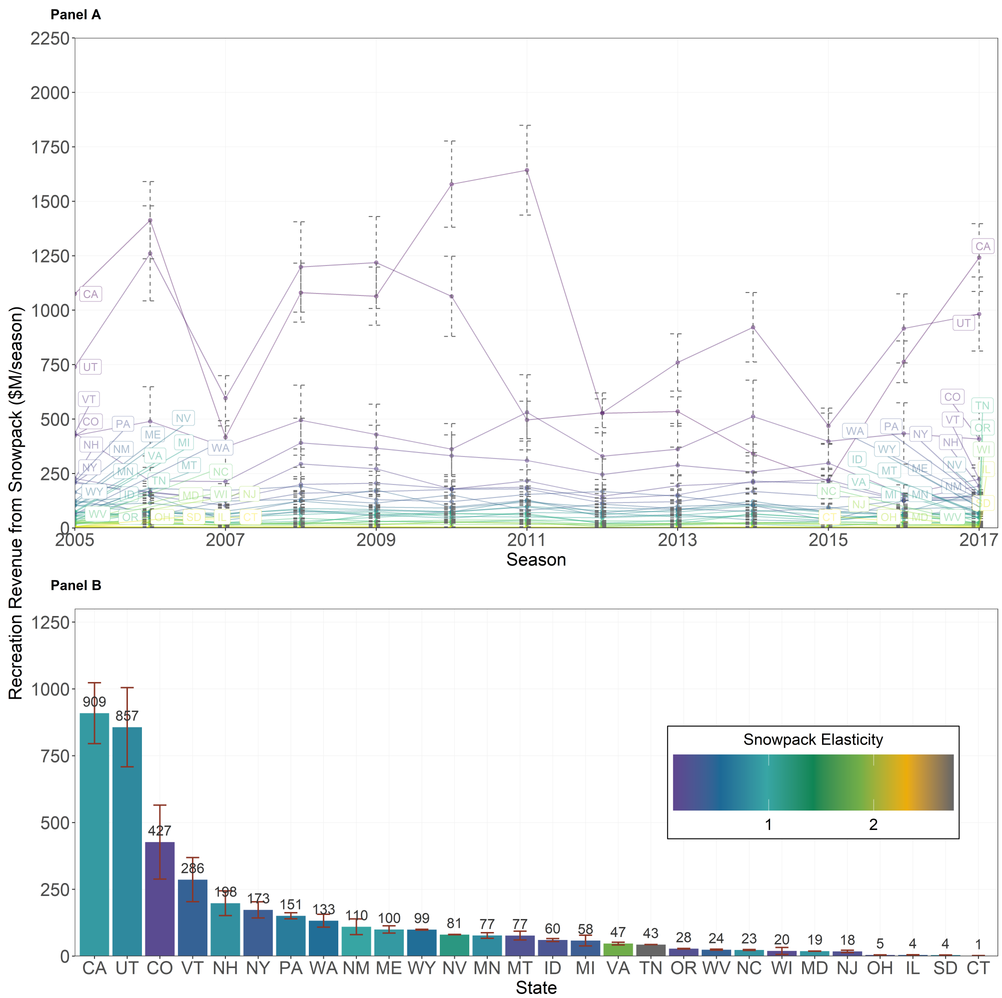


Figure A5: Annual Recreation Revenue from Snowpack in each State




**Note:** Figure A5 presents estimates of the recreation revenue from snowpack in each state $s$ and within-sample year $t$:

$$Revenue\ from\ Snowpack_{st} = \beta_s \times \frac{Annual\ Revenue_s}{Historical\ Snowpack_s} \times Contemporaneous\ Snowpack_{st} \qquad \text{(A12)}$$

Panel A present the year-to-year recreation revenue from snowpack in each of the 26 states from 2005 to 2017 operating seasons. Panel B presents the average annual recreation revenue from snowpack over this period. These state-level simulations are an intermediate step for aggregate estimates presented in figures A7, A6, and 5.

Figure A6: Within Sample and RCP4.5 Simulations

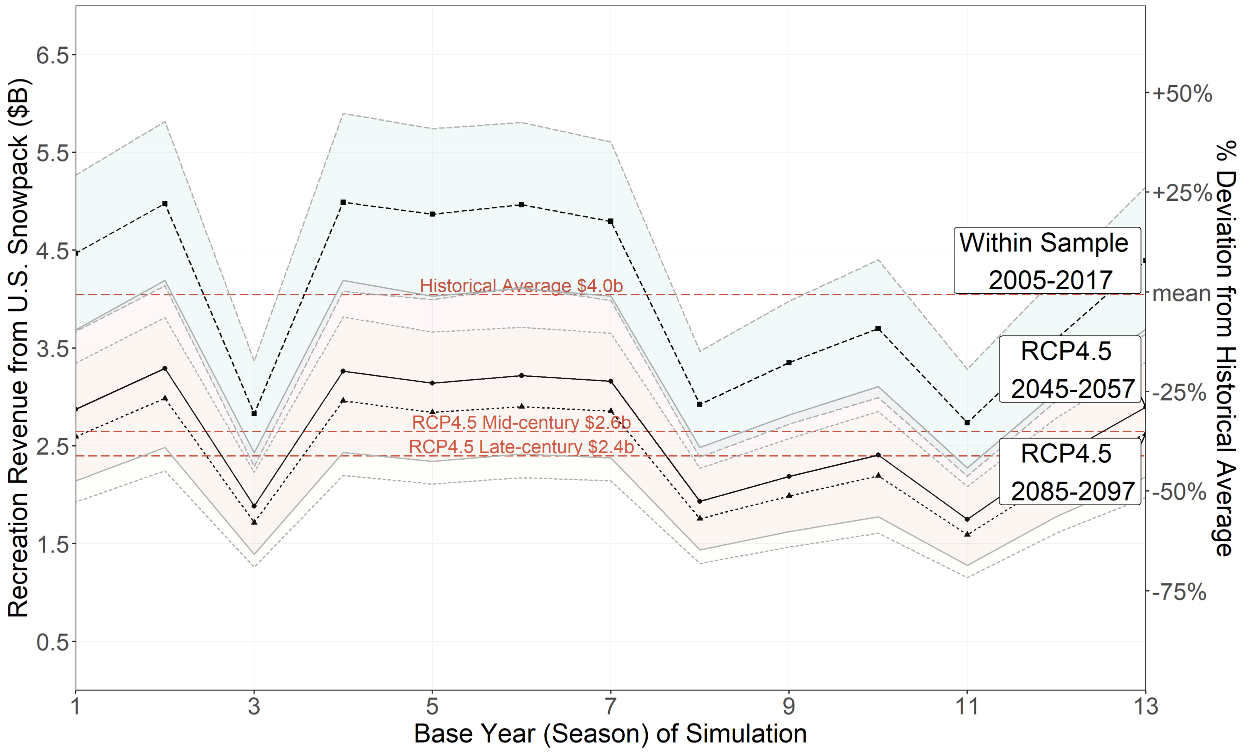



Figure A7: Within Sample and RCP8.5 Simulations

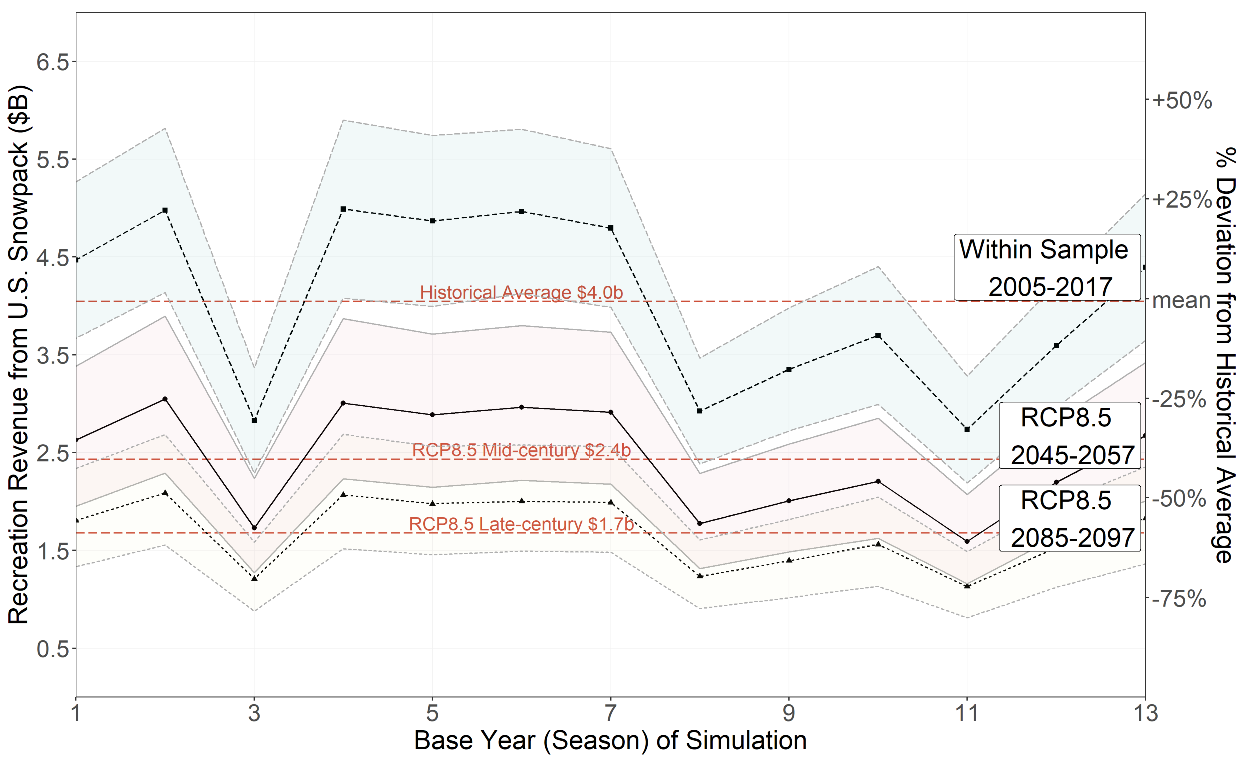
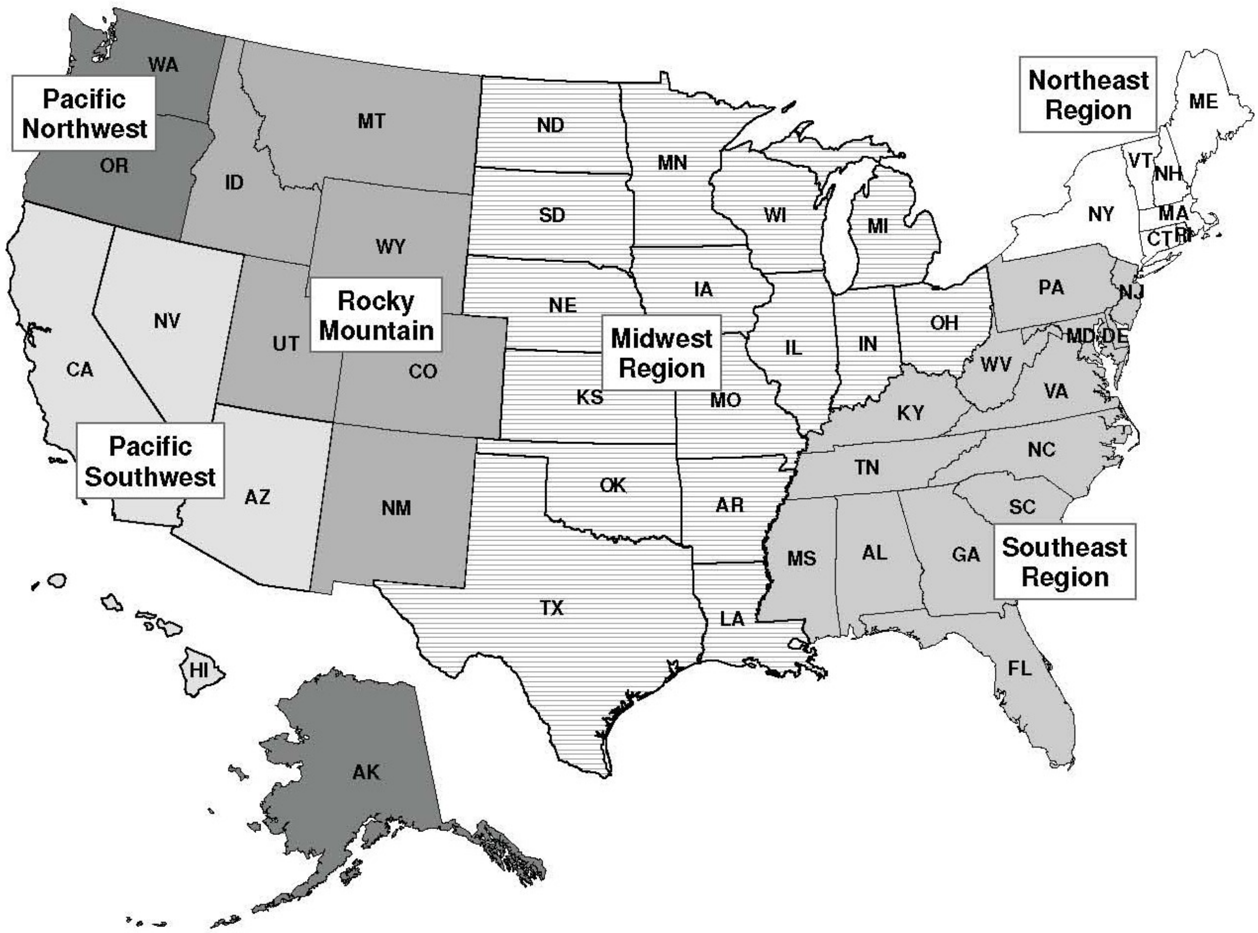
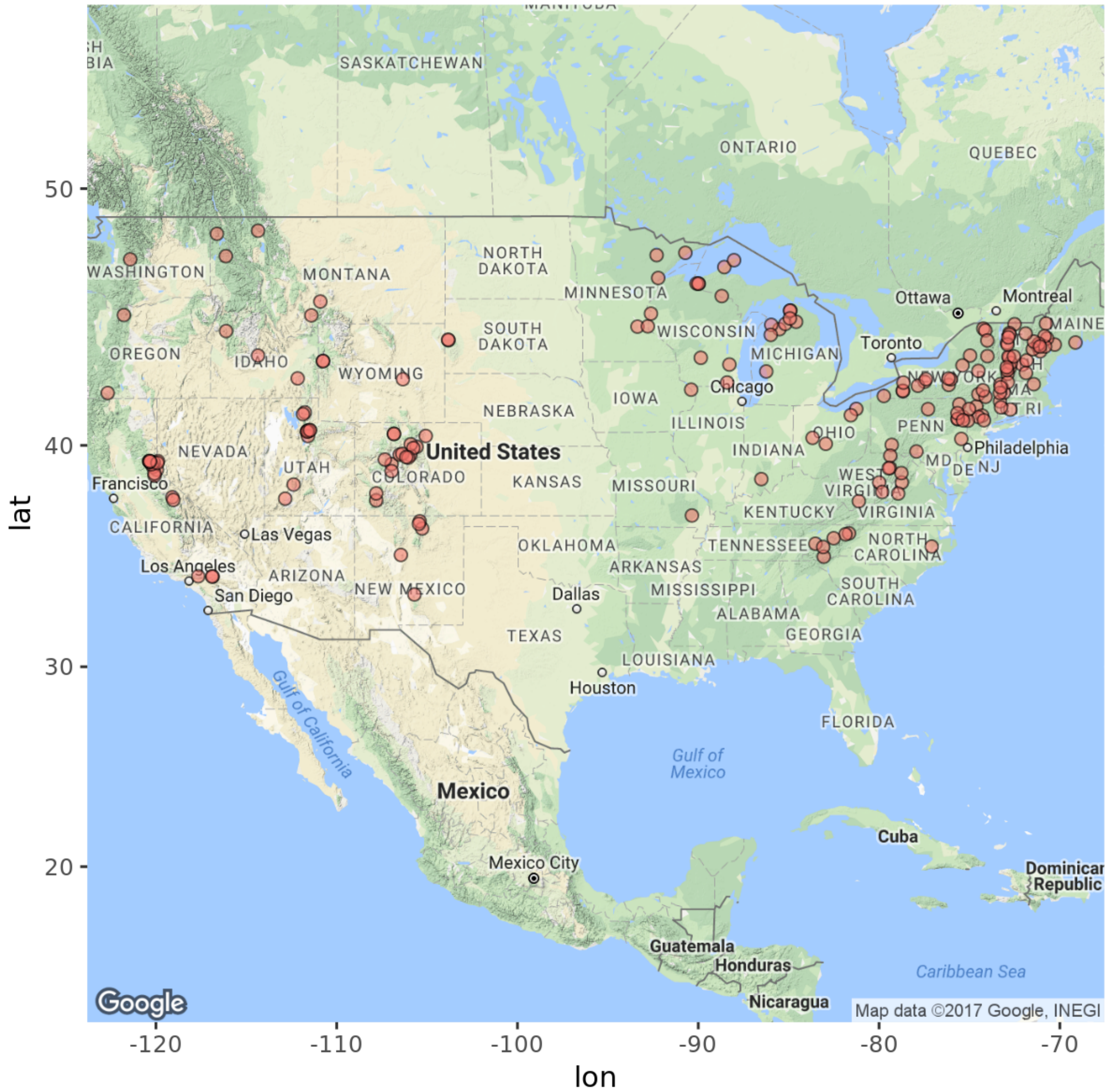


Figure A8: NSAA Resort Regions



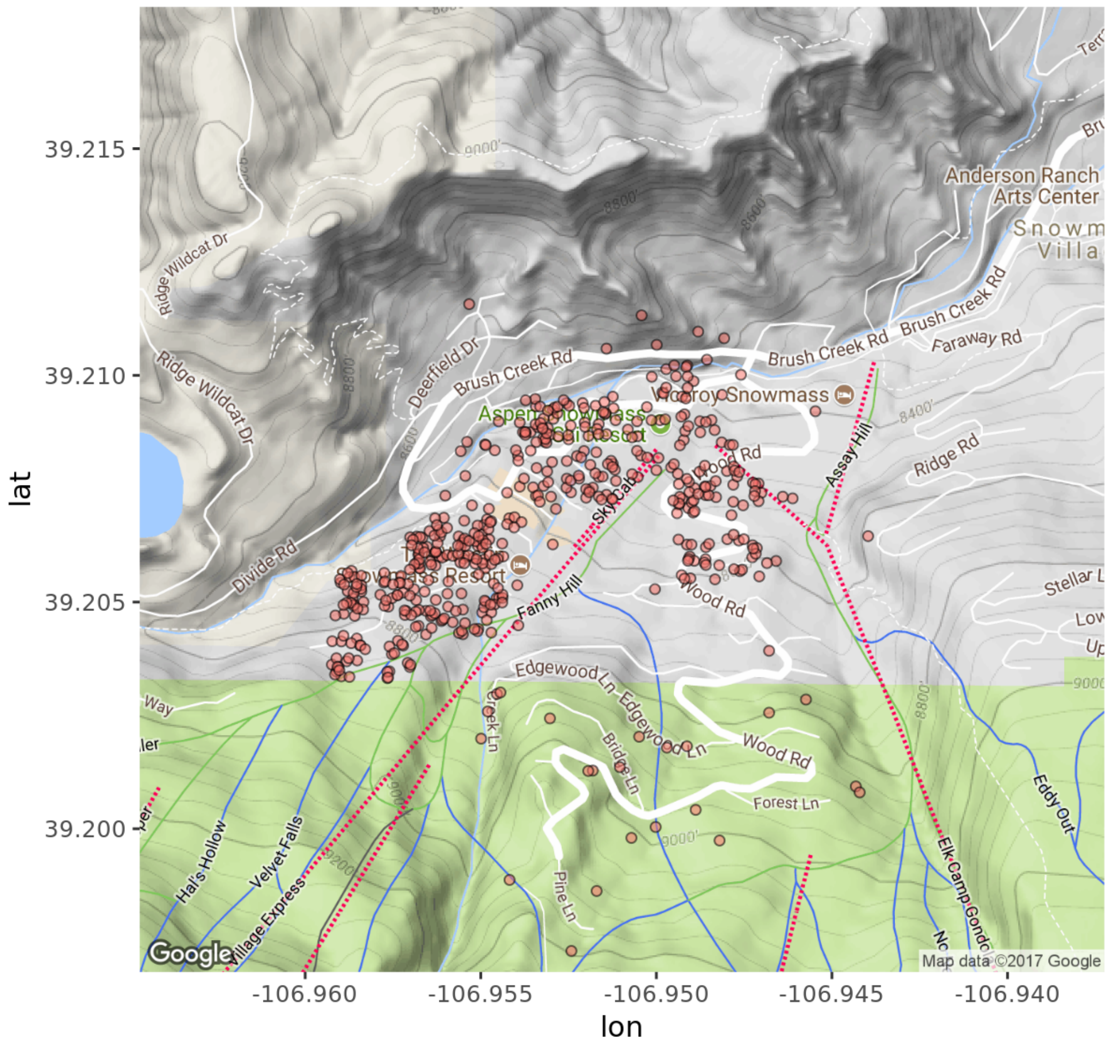

**Note:** Figure A8 presents the regions across the U.S. as defined by the NSAA (NSAA, 2018). These are the regions specified in equation A5.

Figure A9: Spatial Distribution of Resorts Throughout the United States




**Note:** Figure A9 presents the spatial distribution of the 219 resort markets considered in this study.

Figure A10: Spatial Distribution of Airbnb Properties in Aspen, CO




**Note:** Figure A10 presents the spatial distribution of short term rental properties within a 10km buffer near Aspen, Colorado.