Climate Change and the U.S. Market for Snow

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Abstract

Many mountain towns rely on climate amenities such as wintertime precipitation to generate local economic activity. However, climate models predict large reductions in annual snowfall that could greatly reduce the recreational value of these markets. Harnessing a unique panel of daily transactions from the short-term property rental market, we combine daily weather, daily resort snowpack, and daily resort snowfall to estimate the causal effect of changes in resort snowpack on visitation in 219 resort markets across the United States. We make three primary contributions to the study of climate change: 1) we develop a new method to estimate elasticities for climate amenities by matching the spatial and temporal variation in the level of the amenity with the frequency of related market transactions; 2) we derive state-specific snowpack elasticities for all major markets across the United States and find significant heterogeneity in the behavioral response across states; and 3) we estimate year-to-year variation in the recreation revenue from snowpack under current and future climate scenarios. We predict that resort markets could face reductions in local snow-related revenue of -40% to -80%, 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 $1.55 billion (RCP4.5) and $2.63 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).[2] Worldwide, there are 68 countries with operational ski resorts and established ski culture. Climate change threatens the viability of the snow sports industry by reducing the supply of precipitation, increasing average temperatures, and shortening the length of the snow season (Dawson and Scott, 2013; Wobus et al., 2017). Many rural mountain towns rely on snow to provide recreation opportunities that generate a significant portion of their local economic activity (White et al., 2016; Rosenberger et al., 2017). These communities may, therefore, be particularly vulnerable to the reductions in precipitation and increases in average temperatures that are predicted by climate models. However, existing research has been limited to spatially and temporally aggregated estimates, which the present study shows may substantially underestimate impacts.

Obtaining estimates of the demand for climate amenities, such as snowpack, is complicated by the fact that markets for snow do not explicitly exist (Champ et al., 2017). Instead, economists rely on nonmarket valuation methods that match variation in the level of the amenity with variation in related market transactions. However, the long-run mean of resort snowpack has exhibited very little variation from historical levels. This limits the applicability of established methods such as hedonic price analysis, which rely upon changes in housing prices to estimate the value of nearby amenities (Taylor, 2017). Short-

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

run changes in snowpack provide a key source of variation for identifying the relationship between recreation demand and snowpack since recreation decisions are often made in response to short-run fluctuations in snow conditions. But market transactions that match the frequency of short-run shocks in snowpack have been largely unavailable. Studies have instead relied upon market data that is aggregated geographically (county or larger), temporally (monthly or larger), or both. This paper addresses this mismatch by compiling daily market transactions (short-term property rentals) together with daily snowpack and weather, which we use to estimate the effect of changes in resort snowpack on recreational visits for every major resort market across the United States.

Due to the limited availability of high-frequency market transactions, existing work has characterized impacts using changes in snow tourism between high-snow versus low-snow years ("inter-season"). However, inter-season analyses are vulnerable to the confounding effects of other annual trends such as business cycles, fluctuations in macroeconomic growth, or local labor market conditions, all of which are correlated with weather patterns (Kahn et al., 2019). Existing estimates have also been limited to a single region (Dawson and Scott, 2013; Scott et al., 2007) or the national level (Rosenberger et al., 2017; Gilaberte-Búrdalo et al., 2014; Mendelsohn and Markowski, 1999), such that they cannot account for the geographic variation in predicted snowpack as illustrated by climate models. Researchers have emphasized the need for more precise elasticity estimates for quantifying the demand response to changes in snowpack (Loomis and Crespi, 1999).[3] Two decades later, however, no study has provided geographically targeted elasticity estimates

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

that quantify the relationship between recreation and snowpack. The second contribution of our paper responds to this key gap in the climate change literature by providing state-specific elasticities that can be applied to other measures of economic activity related to winter recreation. We show that significant heterogeneity in elasticities exists across markets, highlighting the importance of geographically targeted estimates for calculating damages under future climate.

To estimate economic damages under future climate conditions, existing approaches have relied heavily on the assumption that demand is a linear function of season length (Rosenberger et al., 2017; Mendelsohn and Markowski, 1999).[4] Damages are identified in terms of changes on the extensive margin (fewer visits). While it is reasonable to assume that shorter seasons will result in fewer visits, this method fails to capture the demand response to reduced snowpack throughout the season. These existing studies estimate lost revenue (nationally) from a reduction in lift-ticket sales to be between $1 billion and $2 billion under future climate scenarios, equivalent to 20% to 40% of current lift-ticket sales. The climate modeling literature has provided similar estimates of economic losses using similar assumptions about the relationship between season length and visitation (Steiger et al., 2019; Wobus et al., 2017). The third contribution of our paper relaxes the restrictive assumption that recreational users only respond to season length. Instead, we develop a baseline metric of the value of snowpack that allows us to predict changes in visitation throughout the season. We find that losses could be nearly double the level of damage estimates provided in existing studies.

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

Prior studies using within-season variation have been limited to a single season and a few resorts (Englin and Moeltner, 2004; Morey, 1984).[5] We find evidence of substantial heterogeneity in snowpack elasticities across states, limiting the external validity of estimates from any particular resort. Other work has used monthly counts of overnight stays and monthly averages of snowpack to estimate the elasticity of overnight stays (Falk, 2010).[6] We test for differences between elasticities that are based on monthly aggregate measures and the daily measure that we use in this paper. Our results indicate that there is a substantial downward bias in the coefficient when elasticities are estimated at the monthly level.

This paper contributes to an emerging literature that uses short-run variation in climate amenities *and* the demand response to predict damages under future climate scenarios (Dundas and von Haefen, 2019; Chan and Wichman, 2018). We make three primary contributions to the study of climate change: 1) we develop a new method for estimating elasticities for climate amenities by matching the spatial and temporal variation in the level of the amenity (daily snowpack) with the spatial and temporal variation of market responses to the amenity (daily transactions in the short-term property rental market); 2) we derive state-specific elasticity estimates for all major resort markets across the United States and show that significant heterogeneity exists across states; and 3) we estimate the year-to-year variation in the contemporaneous value of snowpack in each state and use these estimates to simulate local economic damages under two future climate scenarios, RCP4.5 and RCP8.5. We find that resort markets could face reductions in local snow-

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

related revenues of -40% to -80% by the end of the century (2080). When this response is applied to expenditures on lift-tickets and overnight stays, the estimated annual damages in each state range from $2.5 million (South Dakota) to $637 million (California). Across the U.S., annual damages total to between $1.55 billion (RCP4.5) and $2.63 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, while still exploiting detailed variation in the level of the climate amenity (*snowpack*). We include controls for new snow observed within 24 hours (*snowfall*), a flexible polynomial of daily temperature (cubic), day of the week (Sunday through Saturday), and holiday weeks. Our estimating equation is:

$$ln(revenue)_{it} = \ \beta \ ln(snowpack)_{rt} + \delta_{rt} + \eta_{rt} + \psi_{im} + \epsilon_{it}. \tag{1}$$

This specification estimates the relationship between the natural logarithm of daily revenues for property i on each day t and the natural logarithm of *snowpack* in resort market r on each day t. The elasticity parameter, β, measures the effect of a change in resort snowpack on revenue. δ is a vector of new *snowfall* (<24 hours) indicator variables. 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). η includes an indicator for *holiday week*, *weekday*, and a cubic of daily *mean temperature.* The indicator for *holiday week* assumes a value of 1 for weekdays and weekends following a federal holiday.[7] ψ is a property-by-month-of-sample fixed effect that captures property-specific revenue trends across the study period. ϵ_{it} is the portion unexplained by the model.

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

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

$$ln(revenue)_{it} = \underbrace{\sum_{s=1}^{26} \beta_s \; ln(snowpack)_{rt}[State = s]}_{\substack{\text{State-specific} \\ \text{Elasticities}}} + \underbrace{\delta_{rt} + \eta_{rt} + \psi_{im}}_{\substack{\text{Panel Control} \\ \text{Variables}}} + \epsilon_{it}. \tag{2}$$

This allows us to examine heterogeneity in the revenue function by recovering an estimate

[7]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.

of state-specific responses to the climate amenity *snowpack*.[8] β has the following interpretation: a 1 percentage point increase in *snowpack* causes a β percentage point change in expected *revenue*. An important feature of our method is the direct relevance of the resulting coefficient, β, to current climate models. These models provide predictions of percent changes in expected precipitation and snow-water-equivalent measures relative to historical levels. When we combine these locally downscaled estimates from climate models with our localized elasticity estimates, we can use contemporaneous shocks in the weather to simulate responses in local recreation demand given predictions about future climate.

3 Data

We estimate the behavioral response to changes in resort 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).[9] We observe daily transactions from August 2014 through May 2017, comprising three complete ski seasons. 67 resorts fall within 20km of at least one other resort. We study these as unified markets by computing the average level of the snowpack, snowfall, and temperature observed at each resort in the 20km buffer.

Daily snow conditions are recovered from historical records as reported by the resort (OnTheSnow.com, 2017). We recover two measures: 1) *snowpack*, the depth of the snow as reported by the resort each day; and 2) *snowfall*, the new snow that has fallen

[8] A full description of the estimating equation and alternative specifications can be found in the SI Appendix.

[9] We define a resort market using a 10km buffer around the resort. See SI Appendix for a full discussion.

within the last 24 hours at each resort. *Snowfall* is sparse with many zeros. As such, we classify it in bins of 3 inches and group every observation over 15 inches into the largest bin. The daily mean temperature is acquired from Oregon State's PRISM Climate Group (PRISM, 2018).[10]

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

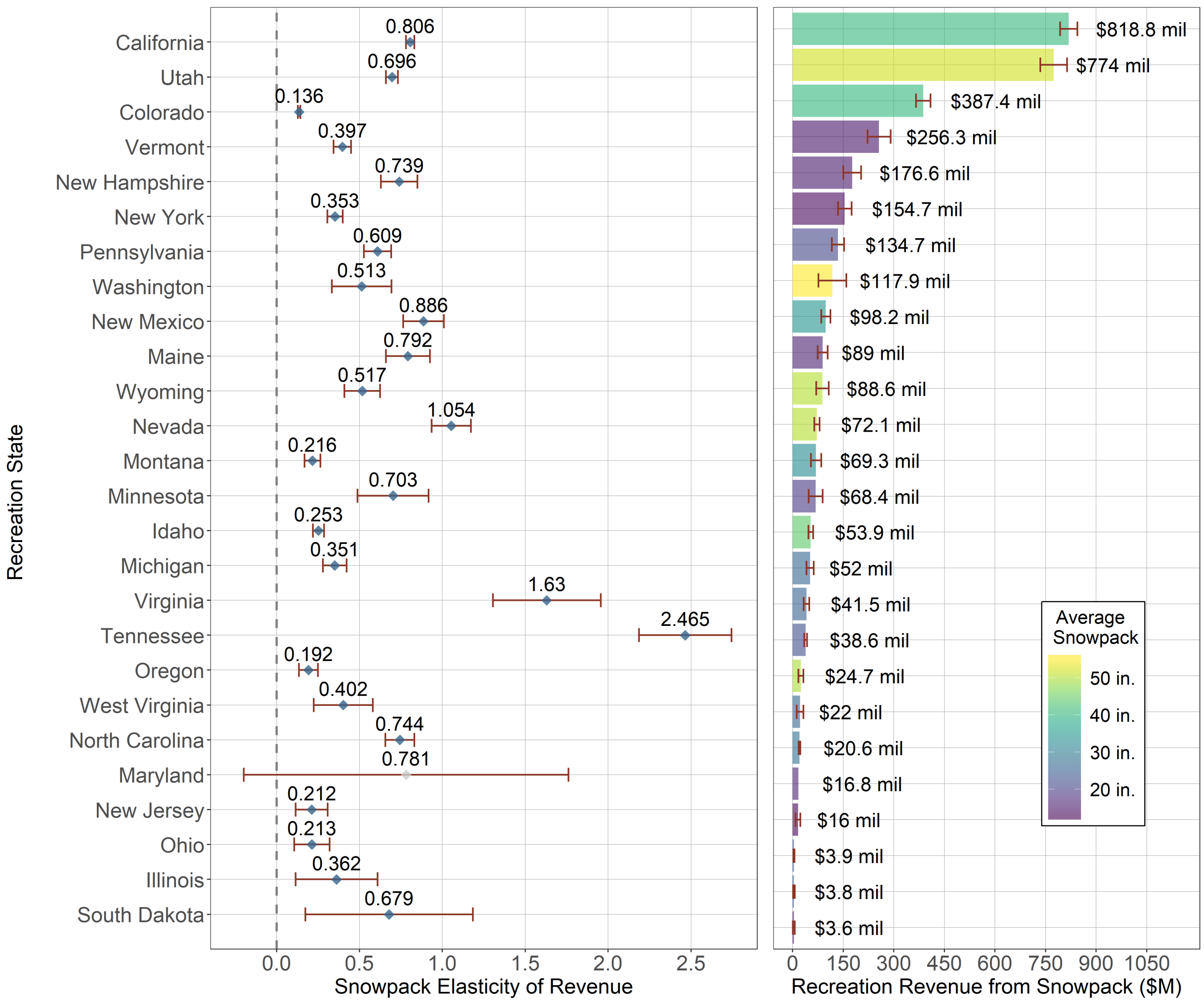
4 The Behavioral Response to Snowpack

We estimate the state-specific response to resort snowpack in the form of elasticities (β parameters in equation 2) that represent the slope of the revenue function in each state.

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

We report these results in Figure 1 (left panel). These estimates reveal substantial heterogeneity between states, with the elasticity of snowpack ranging from 0.136 in Colorado to 2.465 in Tennessee. We find that some states like Colorado have large snow-related revenue streams ($2.84 billion annually, Figure S1), but are less responsive to changes in

Figure 1: State-specific Elasticities



Note: The left panel presents the β's described in equation 2 and represent the slope of the revenue function in each state market. Coefficients are ranked in order of states with the highest recreation revenue from snowpack (equation 4, right panel). These parameters allow for more accurate models of changes in expenditures related to changes in snowpack under future climate scenarios. This is important given the considerable heterogeneity expressed in regional projections of snowpack.

resort snowpack ($\beta = 0.136$). State-specific elasticities do not systematically vary with mean snowpack, suggesting each state and market has unique underlying characteristics that drive this variation.

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

5 The Contemporaneous Value of Snowpack

To operationalize the estimation of damages under future climate scenarios, we first develop a baseline metric of the recreation revenue from snowpack. This is done using 13 years of within-sample variation in snowpack and two primary expenditures directly related to snow recreation in each local market.[11] 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

[11] 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*.

stays each year (NSAA, 2018). Average annual revenue AR in each state s is then:

$$AR_s = \underbrace{V_s \times P_s^{pass}}_{\substack{\text{Daily}\\\text{Visits}}} + \underbrace{OS_s \times P_s^{bed}}_{\substack{\text{Overnight}\\\text{Stays}}} \tag{3}$$

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

$$Rev_{st}^{snow} = \underbrace{\beta_s \times \frac{AR_s}{HS_s}}_{\substack{\text{Implicit}\\\text{Revenue}}} \times CS_{st}. \tag{4}$$

The first term in equation 4, implicit revenue, is analogous to a conventional implicit price in the nonmarket hedonic price literature. It describes the additional amount of annual revenue generated by an additional inch of snowpack, or the marginal annual recreation revenue from an inch of snowpack. When multiplied by the contemporaneous snow, the second term in equation 4, we recover the annual recreation revenue from snowpack for each year of our sample. This provides us with year-to-year variation in the revenue impacts of snowpack that are independent of annual business cycles and macroeconomic trends.[12]

The average recreation revenue from snowpack in each state varies significantly across states, ranging from \$3.6 million in South Dakota to \$818 million in California

[12]See SI Appendix for further discussion of equation 3 and 4

(Figure 1, right panel). This is the proportion of local economic activity that is directly related to resort snowpack. It is reasonable to assume there are indirect (spillover) effects of snowpack on local revenues, making these estimates a lower bound (Loomis and Crespi, 1999). A strength of the state-specific elasticity estimates (the β_s's) is that they can be applied to other measures of economic activity that are directly related to snow-related recreation to construct more comprehensive estimates in states where additional data is available.

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

$$\sum_{s=1}^{26} Rev_{st}^{snow} \tag{4.1}$$

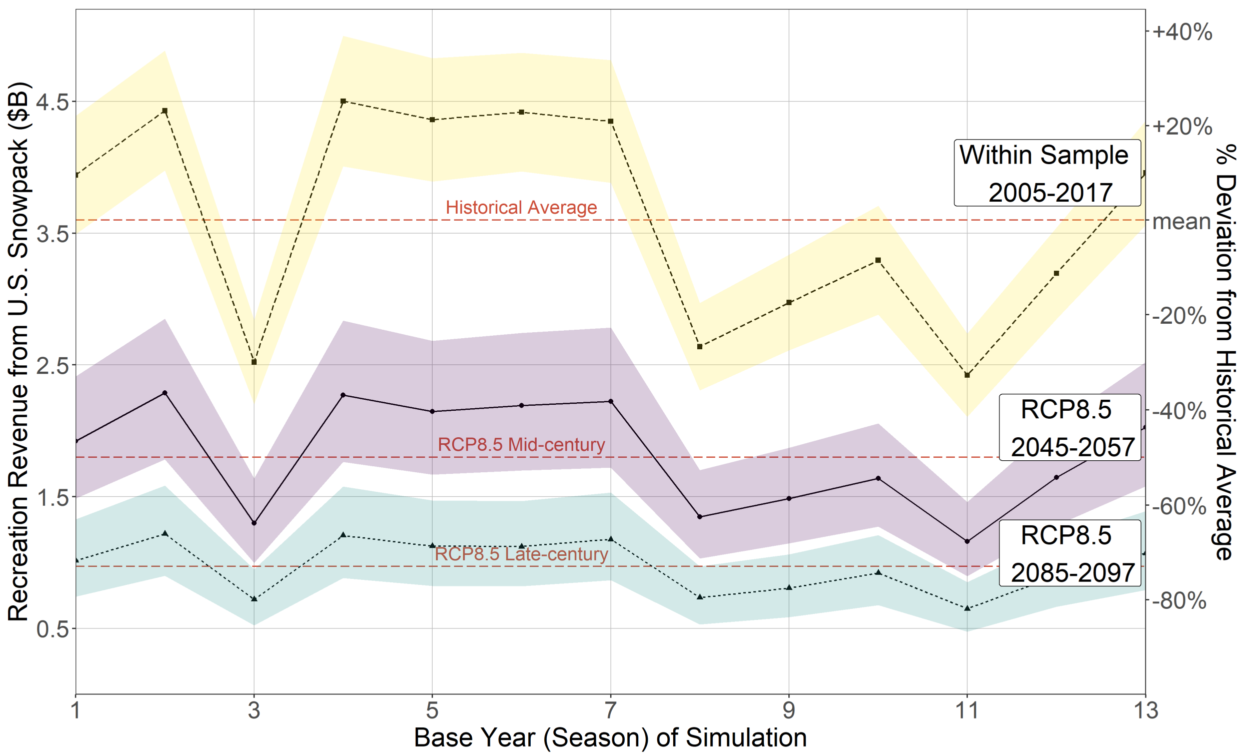
and report these Figure 2. In the next section, we demonstrate an application to estimate economic damages under future climate scenarios. We present the direct effects of changes in snowpack on two primary expenditures directly related to outdoor recreation.

6 Economic Damages

We use the within-sample trends for the period 2005-2017 to construct the baseline seasonal variation in each state and then estimate changes in expected snowpack under future climate scenarios. We estimate the effects of resort-specific predicted changes in snowpack from the suite of CMIP5 climate models (Reclamation, 2013), which yields estimates for 13 years of snowpack trends in each state under RCP4.5 and RCP8.5 scenarios. Using these simulations of year-to-year trends in snowpack, we estimate the annual recreation revenue by modifying equation 4 to replace the contemporaneous snowpack CS with the predicted snowpack PS in simulation year t':

$$Rev_{st'}^{snow'} = \beta_s \times \frac{AR_s}{HS_s} \times PS_{st'}. \tag{5}$$

Figure 2: Recreation Revenue from Snowpack



Note: Figure 2 presents the results of equations 4.1 and 5.1. These use within-sample snowpack and predicted snowpack for RCP8.5 to simulate year-to-year variation in the annual recreation revenue from snowpack. The three scenarios represent: 1) an average decade currently (within-sample); 2) an average decade under RCP8.5 by mid-century (2045-2067); and 3) an average decade under RCP8.5 by late-century (2085-2097). Values represent the total (aggregated) recreation value of snowpack across the 26 states (left axis) and its deviation from historical averages (right axis). The x-axis represents each year (season) in the simulation. For example, year 1 in the within-sample simulation would be 2005. Similarly, year 1 in the RCP8.5 mid-century simulation would be 2045.

We report the total recreation revenue in each simulation year t' from equation 5:

$$\sum_{s=1}^{26} Rev_{st'}^{snow'} \tag{5.1}$$

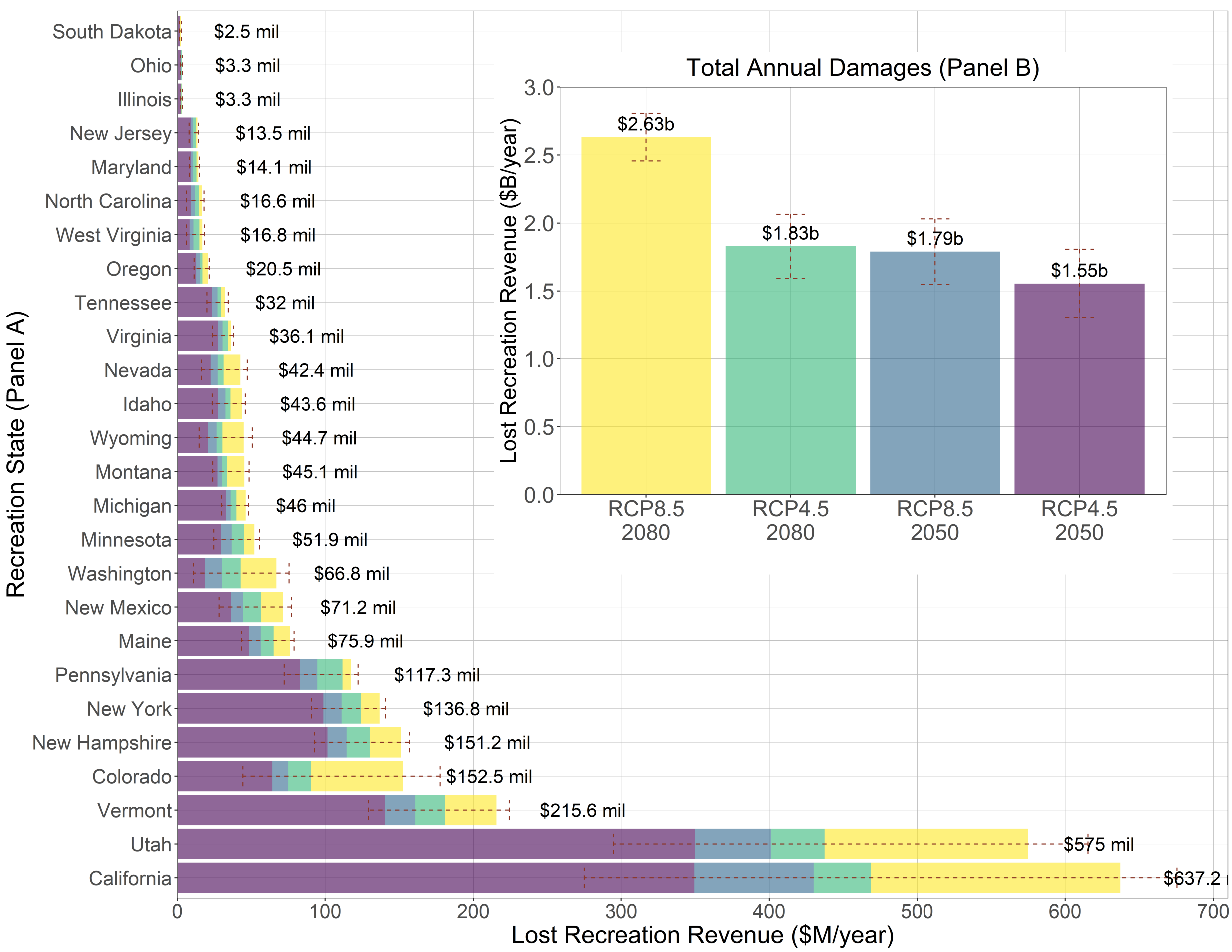
also in Figure 2. The year-to-year variation and deviation from the historical mean can be seen using the axis on the right side of the figure. 95% confidence intervals are also reported for each simulation.Between 2005 and 2017, we observe the annual recreation revenue from snowpack shifting between -25% and +25% of historical averages. The within-sample deviations in 2007, 2012, and 2015 fall to around $2.5 billion in annual revenue, which approaches the range predicted by mid-century climate models for RCP8.5. Under RCP8.5 simulations, these estimates indicate that total recreation revenue could fall to between -40% and -60% by mid-century and -60% to -80% by late-century. Revenue in the year with the highest snowpack during the mid-century period is approximately equivalent to the lowest snowpack year in the contemporaneous period. By the late-century period, the highest snowpack year in our simulation will generate half of the economic activity observed during the worst year in our contemporary sample.

The difference between equations 4 and 5 ($Rev_{st}^{snow} - Rev_{st'}^{snow'}$) captures the annual economic damages in each state. We compute total annual damages across the United States using the sum of the 26 states in our sample:

$$\sum_{s=1}^{26} (Rev_{st}^{snow} - Rev_{st'}^{snow'}). \tag{6}$$

We report the average difference over the 13 years in Figure 3. Panel A summarizes the expected annual losses in each state for each RCP scenario and period (mid- and late-century). The 95% confidence intervals represent the variation across the suite of CMIP5 models. The confidence intervals range from the lower-bound of the least damaging scenario (RCP4.5 2050) to the upper-bound of the most damaging scenario (RCP8.5 2080). Panel B presents the aggregate damages across the United States under both RCP scenarios and periods.

Figure 3: Lost Recreation Revenue



Note: Annual state-level damages are stacked by RCP scenario (Panel A). Total damages (Panel B) are aggregate annual damages across all 26 states by RCP scenario (equation 6). The 95% confidence intervals represent the variation across the suite of CMIP5 climate models, and range from the lower-bound of the best-case scenario (RCP4.5 2050) to the upper-bound of the worst-case scenario (RCP8.5 2080).

Average annual damages under RCP8.5 2080 range from \$2.5 million in South Dakota (a 69% reduction in revenue from current levels) to \$637.2 million in California (a 78% reduction in revenue). These estimates reflect the lost recreation revenue from snowpack using only the two expenditures stated in equations 3 and 4 (lift ticket sales and overnight stays). It is reasonable to assume that there are other expenditures directly and indirectly linked to changes in snowpack in each resort market. Our estimates of lost revenues provide a lower bound on consumer surplus. The demand for snow among recreational visitors may greatly exceed the value that is captured in revenue impacts. Other work in progress focuses on estimating these values (Parthum and Christensen, 2019).

Variation in damages is the composite of three underlying factors: 1) each state's unique relationship between snowpack and local economic activity (the state-specific β); 2) the state's baseline level of snow-based revenue (Figure S1); and 3) the state's predicted change in snowpack under future climate scenarios (also depicted in Figure S1). California, for example, has large existing levels of snow recreation (over \$1 billion each year) in addition to a large elasticity of snowpack ($\beta = 0.806$) and is also predicted to lose a substantial percentage of the average annual snowpack (-60% to -80%). Other states, such as Colorado, might have much higher annual revenue streams (over \$2.84 billion), but are less responsive to changes in the snowpack ($\beta = 0.136$), and are also predicted to have smaller shocks in average annual snowpack given future climate conditions (-30% to -50%).

7 Discussion and Conclusions

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

We find that resort markets could face reductions of -40% to -80% of snow-related revenue by the end of the century (2080). This is nearly double the magnitude of existing estimates. When this is applied to existing expenditures on lift-tickets and overnight stays, we estimate damages across the U.S. to be between \$1.55 billion (RCP4.5) and \$2.63 billion (RCP8.5). The revenue impacts presented in this paper can be interpreted as a lower bound estimate of consumer surplus. The true welfare effects from reductions in snowpack could be substantially larger (Banzhaf, 2018).[13] Further refinement is necessary to better understand how consumers choose to substitute between markets and the implications of climate change on their welfare. Other recent work highlights the uncertainty and potential for much larger variability in climate outcomes than is represented in the avail-

[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).

able CMIP5 models (Christensen et al., 2018). Industries that depend on snow recreation face the threat of substantial losses if climate continues to warm at faster rates than those reflected by the CMIP5 scenarios.

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