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Valuing Nonmarket Impacts of Climate Change on Recreation: From Reduced Form to Welfare

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Abstract
Nonmarket damages are largely missing from aggregate climate impact estimates, especially those related to outdoor recreation. One simple approach to measuring these missing impacts is to estimate dose-response functions to weather, and then to combine these functions with benefits transfer approaches to value the gained or lost recreational opportunities. In this paper, we analyze the potential and shortcomings of such an approach. Although seemingly simplistic, we show that this approach has attractive theoretical properties and can provide exact or conservative estimates of surplus changes under standard assumptions that are commonly used in the valuation literature. We assess the accuracy of this approximation in the context of several prior studies of environmental quality changes, and we also use this framework to generate illustrative climate impacts for outdoor recreation using nationally representative time-use data.

Keywords Nonmarket valuation · Climate change · Time allocation · Leisure demand

JEL Classifications J22 · Q51 · Q54

1 Introduction

Climate change will have far-reaching effects on many aspects of human activity, including agricultural and industrial productivity, real estate markets, human health, and even recreational opportunities. Crafting efficient climate policy requires a comprehensive understanding of these many consequences. A common approach for measuring climate damages is to identify the effects of short-term weather fluctuations on outcomes of interest (Dell et al. 2014). The resultant "dose-response" function can then be coupled with climate projections to infer responses to future climate change (Deryugina and Hsiang 2017).

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In terms of decision making, quantifying these responses is only a stepping stone. What ultimately matters for policy and management is the costs and benefits of these induced changes. In some cases, climate impacts translate naturally into welfare consequences using standard producer and consumer theory—particularly in research that focuses on market impacts such as agriculture (e.g., Deschênes and Greenstone 2007; Schlenker and Roberts 2009; Burke and Emerick 2016). Alternatively, macroeconomic approaches (e.g., Dell et al. 2012; Burke et al. 2015) measure the effects of temperature fluctuations on the growth of national GDP accounts, although by definition these are not measures of welfare nor do they account for nonmarket impacts. Our understanding of *nonmarket* implications of climate change—such as on human health and mortality, ecological function, and recreation—remains sparse, and additional links must be made before arriving at a final measurement of benefits or costs.

In this paper, we analyze a common framework for valuing climate change impacts on a large class of nonmarket activities, outdoor recreation, by tying together reduced-form climate estimates and classical environmental valuation techniques. In principle, valuing consumption changes is simple. Weather and climate can be conceptualized as shifters of the demand curve for outdoor recreation. The dose-response function will inform the magnitude of this shift, and the analyst can then integrate between original and shifted demand curves to capture the accompanying consumer surplus change. Thus, one only needs to estimate the dose-response function for the activity of interest and integrate accordingly.

Although theoretically straightforward, this approach is infeasible for empirical analysis. In order to map out the full demand shift, one would need to observe the quantity demanded under new and baseline weather *for every level* of opportunity cost (price). In practice, the shift (dose-response) is identified off of short-term weather fluctuations, revealing only a single point on the new demand curve. Thus, a problem arises: one can observe only the marginal effect of weather holding all else constant, but the full demand shift, including inframarginal changes, is necessary for welfare calculations.

We describe and analyze a straightforward framework for addressing this problem. This approach treats weather and climate as shifters of demand, approximating welfare changes as the product of average consumer surplus under baseline conditions and the estimated climate response. This approach has featured in several prominent past studies of climate and recreation demand (see, e.g., Mendelsohn and Markowski (1999) and Loomis and Crespi (1999)), and it holds promise for future applications because it is simple to apply. However, the underlying assumptions and potential shortcomings of this approach remain unexamined. Although the framework has been applied in prior work, it has primarily been used as a matter of convenience because of its modest data requirements; there has been no systematic analysis of its validity—a significant oversight. Thus, it is unclear how well it accords with welfare theory, raising questions about the reliability of resultant estimates.

This paper seeks to address this challenge. We look under the hood of this valuation method, elucidating its performance and potential pitfalls for several broad classes of empirical demand functions. Despite its simplicity, we find that it generates useful estimates under standard assumptions, and we analyze the potential error that may arise, showing that errors will tend to attenuate welfare estimates. We also provide several illustrations that highlight the usefulness of this approach. In one application, we show how this technique can generate reasonable estimates in the context of several existing studies. For all but one study, we successfully reproduce the consumer surplus changes reported in the papers exactly, consistent with the predictions of our theory. In the one case where our estimates diverge, we have only minimal (0.2%) error, and the direction of this error also accords with our theoretical predictions by (modestly) underestimating the true consumer surplus change. In a second application, we use the approximation to value climate impacts on a suite of outdoor recreation activities, ranging from swimming to hiking to skiing. Drawing on data from the American Time Use Survey (ATUS), we estimate dose-response functions that characterize the relationship between each activity and weather for the continental United States. By combining these estimates with climate predictions and recreational surplus values from prior work, we are able to project resultant welfare consequences, and we find positive net benefits by the end of the century. Although climate change will have differential impacts by locality (e.g., Mississippi versus Minnesota) and by activity (e.g., swimming versus skiing), we find that future warming will tend to stimulate outdoor recreation on net, consistent with complementary work using alternative data sources and richer identifying variation (Chan and Wichman 2020; Mendelsohn and Markowski 1999; Loomis and Crespi 1999).

This work is particularly important given practical constraints on data availability. Rigorous structural econometric techniques will offer more accurate and precise estimates than this reduced-form approximation, but they will be infeasible in many cases given steep data demands. The unfortunate reality, then, is that relevant nonmarket values, like recreation and leisure activity, will be ignored in policy contexts for want of detailed microdata. The approximation described herein offers an alternative pathway to plausible welfare estimates, even in the absence of such data. This approach empowers researchers and policymakers to leverage the vast body of existing work that generates reduced form estimates of climate impacts from *aggregate* data—thus making it possible to include vital, but often ignored, values in the cost-benefit ledger for climate change.

This paper brings together two primary lines of inquiry in environmental economics. First, our research relates closely with the quickly growing literature on estimating weather-response (or dose-response) functions to identify climate impacts. Prior work has investigated how climate will influence labor productivity (Graff Zivin and Neidell 2014), agriculture (Deschênes and Greenstone 2007; Schlenker and Roberts 2009; Burke and Emerick 2016), economic growth (Dell et al. 2012; Burke et al. 2015), and so forth. In all cases, these authors exploit short-term weather fluctuations to derive causal dose-response functions, which can in turn be used to infer future consequences of climate change for the activities in question. Rarely, however, do authors provide a welfare-theoretic framework for translating these impacts into welfare consequences.

Second, we draw from prior work on environmental valuation. There have been extensive efforts to understand the welfare implications of environmental changes, including water quality (e.g., Whitehead et al. 2000; Hanley et al. 2003), recreational amenities (e.g., Eiswerth et al. 2000; Morey et al. 2002), and cost of access to recreation sites (e.g., Englin and Cameron 1996). Our work follows in this tradition by valuing nonmarket impacts of climate through the effect of weather on recreational activity. Dundas and von Haefen (2020) likewise use weather anomalies to infer climate effects on recreational angling. Their structural econometric approach is supported by rich microdata on angling trips—something that is not always available to analysts. We therefore explore the validity of an approximation that is commonly used in the absence of such detailed data.

In addition, we build upon a large literature on benefits transfers, which explores how welfare measures from one context can be used to inform policy in a different context. While much of this literature examines applications across space, we effectively carry out a benefits transfer exercise across time to value impacts from future climate change, similar to Dundas and von Haefen (2020). In our empirical exercise, we use a simple value transfer. This approach is admittedly crude because it ignores heterogeneity in preferences across time and space, but we do so because our primary goal is to provide a parsimonious example of our approximation in action. Given appropriate data, more sophisticated benefits transfer approaches could be incorporated seamlessly into the broader valuation framework that we have outlined. Indeed, prior research has explored the welfare-theoretic basis for benefits transfers. In recent work, Newbold et al. (2018) discuss the importance of using benefits transfer functions that are theoretically sound, and they show how structure must be imposed on the benefits transfer function to ensure that a basic criterion for validity (the adding-up condition) is satisfied. Blow and Blundell (2018) take a nonparametric approach, showing how one can derive bounds on benefits measures for changing environmental quality. Our work is similar in spirit, as we do not specify a particular form for unobserved preferences, choosing instead to analyze a wide class of potential preference structures.

By tying together classic environmental valuation techniques and the more recent wave of reduced-form climate identification research, we provide a crucial link between reduced-form estimates and welfare. We cast in a new light the relationship between modern research on empirical identification and earlier work on preference restrictions, and the resultant estimates offer a useful complement to structural approaches to valuation.

In the next section, we model consumer behavior and construct the welfare measure to be scrutinized. Using a series of propositions and proofs, we show how the proposed welfare measure performs under common functional forms for demand. We find that it will typically offer conservative or exact estimates of true consumer surplus changes, and we verify this finding by showing consistency with prior results from the literature. In the subsequent section, we examine a nationally representative data set on individual time use decisions, focusing on outdoor recreation activities. Using the approach outlined in the theoretical section, we predict future impacts of climate change on recreational behavior. The final section summarizes and concludes.

2 Model

In what follows, we begin by constructing the approximate welfare measure to be analyzed. This common measure is calculated by combining a dose-response function, information about changes in environmental quality, and existing estimates of environmental amenity values. This measure can be applied to a wide range of contexts, although we highlight its usefulness for valuing climate change impacts given recent developments in reduced-form climate research.

2.1 Preliminaries

Before proceeding, it is worth clarifying several key insights underlying the approximation approach. First, this framework embeds a benefits transfer exercise. In essence, we seek to conduct a benefits transfer through time, as we use present-day estimates of environmental values to infer future welfare implications of climate change. As we will discuss, there are inherent challenges to benefits transfers, but we abstract away from these challenges; instead, our analysis focuses on how well this approximation matches true consumer surplus changes from a welfare-theoretic perspective, assuming that benefits are transferred without error. That said, the details of the benefits transfer element will matter greatly when implementing this framework in practice. We defer a more detailed discussion to the extant literature, referring interested readers to useful reviews by Boyle et al. (2010) and Johnston et al. (2015).

Second, this welfare measure seeks to approximate Marshallian consumer surplus. It is well known that consumer surplus is an imperfect indicator of welfare, as it does not in general reflect changes in underlying utility. Hicksian alternatives (i.e., compensating and equivalent variation), on the other hand, offer more theoretically grounded welfare estimates (Freeman et al. 2014; Phaneuf and Requate 2017) and will differ from the Marshallian measure by incorporating income effects (Bockstael and McConnell 1993). Even so, consumer surplus estimates are common in the environmental literature because they can be derived from directly observable behavior, and they are likely to align with Hicksian measures in many settings, particularly when income effects are small. As such, we focus on Marshallian consumer surplus, even though the conceptual basis for our analysis would be the same for Hicksian analogs.

Third, we measure the value of the nonmarket amenity (weather) through its effect on consumption of related goods and services (recreation demand). One can estimate a dose-response function that captures this relationship, and this dose-response will characterize an implicit marginal tradeoff between the good of interest and outside options, with the value of each mediated through weather. However, additional structure is required to derive welfare estimates. To this end, we conceptualize weather as an exogenous shifter of the demand curve for recreation, which implicitly imposes some structure on preferences. Alternatively, one can think about weather as an input into the household production of recreation. That is, a recreational outing y will be combined with weather W to produce recreation, and recreation in turn generates utility.

We now proceed to construct and analyze a model of climate-induced welfare changes. As we will describe, true consumer surplus changes will be unobservable, but we will seek to approximate such changes with available information. This approximation can be used for any specification of demand, and we will show how its performance will vary depending on the form of demand and the manner in which demand shifts in response to quality changes.

2.2 Basic Model

Consider a representative consumer who allocates her scarce budget I over a numeraire x and good y. Let p capture the price, implicit or explicit, of good y. y may denote a physical consumption good with a standard market price, or it may represent a nonmarket good like leisure activity that incurs a time cost or other opportunity cost. There is a vector W of environmental quality variables that influence the utility derived from y. That is, W does not confer utility in itself, but it affects the value of y, thus making it possible to value W through observed changes in y. We will focus primarily on W as a (vector of) weather variable(s), but it could stand in for any environmental quality dimension that shifts y, such as air quality, water quality, or availability of fish. We can write the consumer's problem as[1]

[1] We follow the framework of Phaneuf and Requate (2017), which maintains generality on the relationships between x, y, and W. Alternatively, one can conceptualize this problem in a household production framework where some index of recreation $z(y, W)$ is produced through a combination of recreational outings y and weather W. The latter makes explicit that weather only impacts utility through its impact on recreation.

$$\max_{x,y} U(x, y; W) \text{ subject to } \quad x + py = I,$$

which yields the demand function $y(p, I; W)$.

Consider two sets of climatic conditions, present and future, denoted by W_0 and W_1, respectively. Let us write the demand curve for each circumstance as $y_0(p)$ and $y_1(p)$, with accompanying choke prices $\bar{p}_0$ and $\bar{p}_1$.[2] Assume without loss of generality that $W_1 > W_0$ and that W_1 represents more favorable conditions, so that $\bar{p}_0 \leq \bar{p}_1$.[3] It is straightforward to reproduce the following analysis for a situation where W_1 represents less favorable conditions. We omit this derivation for the sake of brevity; however, the intuition and analysis are identical, with the approximation yielding a conservative estimate of the *cost* of lost activity.

For any prevailing price p^*, we can calculate consumer surplus as[4]

$$CS_0 = \int_{p^*}^{\bar{p}_0} y_0(p)dp$$

$$CS_1 = \int_{p^*}^{\bar{p}_1} y_1(p)dp,$$

and the climate-induced welfare effect from changing weather is simply

$$\Delta CS = CS_1 - CS_0.$$

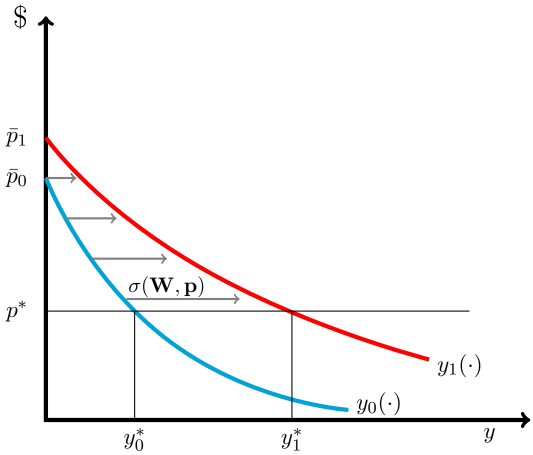
Figure 1 shows $y_0(p)$ and $y_1(p)$, which yield consumption levels y_0^* and y_1^*, respectively, with the area between these two curves representing ΔCS. Importantly, ΔCS reflects the value of additional consumption as well as the improved benefits from inframarginal units. For example, in a recreation demand model, this would include (1) the impact of additional trips (lost trips) at the margin as well as (2) enhanced (diminished) enjoyment from existing trips. These two elements can be seen in Fig. 1, respectively, as (1) the area enclosed by y_0^*, y_1^*, $y_1(\cdot)$, and p^*, and (2) the area between $y_0(\cdot)$ and $y_1(\cdot)$ from 0 to y_0^*. This is an important feature of our analysis—seeking to measure welfare changes for both marginal and inframarginal units—that is also shared by the structural approach of Dundas and von Haefen (2020). The overall welfare impact is simple to calculate in principle: one only needs to integrate between the demand curves over the appropriate range. Equivalently, if the "quality shift function" $\sigma(W, p)$ were known—i.e., the demand shifter defined implicitly by

[2] The choke price is defined as the (minimum) price at which demand for the good is zero, i.e., the y-intercept of the demand curve. While it is feasible for the choke price to be infinite or non-existent (e.g., if the demand curve asymptotes at the y-axis), we abstract away from such cases for now to simplify the theoretical exposition and to offer clearer graphical and mathematical intuition for the general framework.

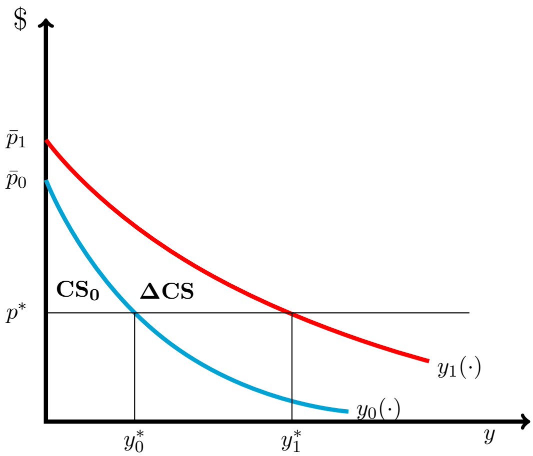
[3] This assumpton places an upper bound on the elasticity of the shifted demand curve. An alternative scenario where $\bar{p}_0 > \bar{p}_1$ would be rather unusual; it would require the original and shifted demand curves to cross, and it would imply that marginal willingness to pay decreases at low consumption levels but increases at high consumption levels. While this may be theoretically possible, we are not aware of any relevant empirical applications that allow crossing of this sort.

[4] Our framework assumes that weather (or climate) only influences the equilibrium consumption by shifting demand, so that p^*, the price or opportunity cost, remains fixed as climatic conditions change. Throughout, we focus on demand-side shifts while abstracting from potential changes in p^*. However, even if there were an accompanying change in p^*, its effects can be easily computed in parallel to the approximation that we describe below.

Fig. 1 Welfare measurement from environmental quality changes. When weather or environmental quality changes, the demand for y shifts, and the equilibrium quantity consumed increases from y_0^* to y_1^*. In turn, consumer surplus increases, as shown in the figures above



(a) Changing weather shifts demand from $y_0(\cdot)$ to $y_1(\cdot)$ according to the quality shift function $\sigma(W, p)$.



(b) The original consumer surplus is CS_0 while the new consumer surplus is $CS_1 = CS_0 + \Delta CS$, with the area between the two curves representing the change in welfare ΔCS.

$y_1(p) = y_0(p) + \sigma(W, p)$—one could simply integrate that quality shift function from p^* to $\bar{p}_1$ to measure the surplus change.

The crux of our analysis is that $y_0(p)$ may be observable to the analyst, but $y_1(p)$ generally is not, so we must propose an approximation that overcomes this information constraint. In practice, $y_0(p)$ will be revealed through consumer choice over some range of p. Purchasing decisions will reveal $y_0(p)$ for market goods, while demand can be inferred for nonmarket activities through valuation methods such as the travel-cost method or stated-preference elicitations. However, information on $y_1(p)$, and therefore the quality shift function, is more limited. One may observe $y_1(p^*)$ for the prevailing value of p^* through short-term weather variation. For example, one may observe a large rise in ice cream consumption on an unusually hot day while ice cream prices remain fixed, but it is much less likely that one can observe ice cream demand under extreme temperatures over a range of prices, as such climatic conditions are anomalous by definition. Thus, data constraints make identification of $y_1(p)$ over the full range of p infeasible. How, then, should one proceed?

The task is to approximate ΔCS using available information, namely the demand function $y_0(p)$ and a single point on $y_1(p^*)$ corresponding with current price p^*. The former can be estimated for nonmarket goods through standard environmental valuation techniques. The latter identifies the magnitude of the quality shift function at p^* and is the focus of the large and growing reduced-form climate literature. The question is how to combine these pieces of information and transform them into welfare estimates.

The approximation we investigate is as follows:

$$\begin{aligned}\Delta\widehat{CS} &= \Delta y \times \overline{CS}_0 \\ &= (y_1^* - y_0^*) \times \frac{CS_0}{y_0^*} \\ &= \frac{y_1^*}{y_0^*} CS_0 - CS_0,\end{aligned} \tag{1}$$

where $\overline{CS}_0$ is the average consumer surplus per unit of consumption under current conditions, and asterisks indicate the optimal quantity demanded at the given price p^*. Essentially, we multiply the predicted change in consumption by the average consumer surplus per unit of consumption. This seems like an intuitive way to estimate ΔCS, and indeed, this approximation has been used in the literature (Mendelsohn and Markowski 1999; Loomis and Crespi 1999). However, despite its intuitive appeal, it also seems rather ad hoc, and we are unaware of any prior work that explores the validity of this measure or the errors that may arise from it.[5]

Mathematically, this approach is equivalent to approximating the (unobserved) shifted demand function as $\hat{y}_1(p) = \frac{y_1^*}{y_0^*} y_0(p)$ and the associated consumer surplus as $\widehat{CS}_1 = \frac{y_1^*}{y_0^*} CS_0$. These various framings are useful for gaining intuition on subsequent propositions and proofs. Figure 2 offers a graphical depiction of $\hat{y}_1(p)$ and $\Delta\widehat{CS}$.

[5] In related work on valuing recreational sites, Morey (1994) describes the "consumer surplus per day of use," which is essentially the marginal surplus enjoyed by a consumer who experiences a price drop or a quality improvement. He notes that this value will be constant (and therefore scalable for welfare calculations) for *price* changes but not quality changes. For quality changes, scaling up consumer surplus per day of use by the usage amount will yield an accurate measure of welfare only under restrictive assumptions; namely, the utility per trip must be independent of the number of trips, such that the welfare effect can be calculated as a quality-equivalent price change. The approximation proposed in this paper may sound similar to the one proposed by Morey, so it is important to note that Morey's is based on a marginal measure, which may be difficult to estimate in practice, whereas ours is based on an average consumer surplus measure, which is readily available from prior work.

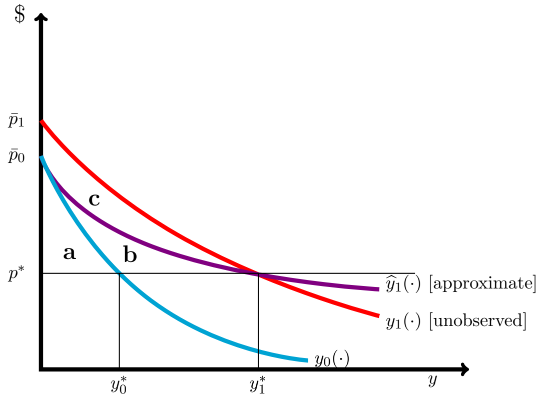


Fig. 2 Exact *CS* change compared with authors' approximation. Changing weather shifts demand from $y_0(\cdot)$ to $y_1(\cdot)$ The original consumer surplus is $CS_0 = a$ but the new consumer surplus is $CS_1 = a + b + c$, yielding $\Delta CS = b + c$. In the absence of the full demand curve, we approximate $\Delta\widehat{CS} = \frac{y_1^*}{y_0^*}CS_0 - CS_0$, which is captured by the area b

2.3 Assessing the Validity of this Approximation

We will now explore the conditions under which $\Delta\widehat{CS}$ is a reasonable estimate of the true (but unobserved) ΔCS, and we will outline the properties of the demand curve $y_1(p)$ that will lead to under- or overestimates of consumer surplus changes.

The error from Eq. 1 is

$$\begin{aligned}\Delta\widehat{CS} - \Delta CS &= \frac{y_1^*}{y_0^*}CS_0 - CS_0 - (CS_1 - CS_0) \\ &= \frac{y_1^*}{y_0^*}CS_0 - CS_1.\end{aligned} \tag{2}$$

We will have an exact measure of the Marshallian consumer surplus change if $CS_1 = \frac{y_1^*}{y_0^*}CS_0$, which will hold with certainty in the special case where the unobserved demand curve is a simple scaling of $y_0(p)$ as follows:

$$y_1(p) = \frac{y_1^*}{y_0^*}y_0(p) = \hat{y}_1(p). \tag{3}$$

Meanwhile, $\Delta\widehat{CS}$ will yield a conservative estimate when

$$\begin{aligned}CS_1 &\geq \frac{y_1^*}{y_0^*}CS_0 \\ \int_{p^*}^{\bar{p}_1} y_1(p)dp &\geq \frac{y_1^*}{y_0^*}\int_{p^*}^{\bar{p}_0} y_0(p)dp.\end{aligned}$$

To show that $\int_{p^*}^{\bar{p}_1} y_1(p)dp \geq \frac{y_1}{y_0}\int_{p^*}^{\bar{p}_0} y_0(p)dp$, it is sufficient to verify that, for all $p^* \leq p \leq \bar{p}_0$,

$$\begin{aligned}y_1(p) &\geq \frac{y_1^*}{y_0^*}y_0(p) \\ \frac{y_1(p)}{y_0(p)} &\geq \frac{y_1^*}{y_0^*},\end{aligned} \tag{4}$$

By definition, this expression holds with equality at p^*. Thus, to ensure that $\Delta\widehat{CS}$ is conservative, we need only prove that this expression holds for other values of p in the specified range.

Lemma 1 *If $\frac{y_1(p)}{y_0(p)}$ is increasing in p over the range $p^* \leq p \leq \bar{p}_0$, then Condition 4 will be satisfied, and $\Delta\widehat{CS}$ will underestimate ΔCS.*

We will characterize the error under two broad classes of empirical demand models:

$$y = f(p) + \sigma(W, p) \tag{5}$$

$$\log(y) = f(p) + \sigma(W, p), \tag{6}$$

where $f(p)$ captures the basic demand (price-quantity) relationship and $\sigma(W, p)$ is a flexible "quality shift function" that denotes how the demand curve shifts in response to changes in W.

Conveniently, $f(p)$ is the demand curve studied in much of the environmental valuation literature, whereas $\sigma(W, p)$ is the primary object of interest in the reduced-form climate literature.[6] In our exposition, we allow both $f(p)$ and $\sigma(W, p)$ to be fully general and to take on any functional forms, although we will highlight several special cases below because of their empirical relevance and the intuition they provide. We will refer to Eq. 5 as demand "in levels" and Eq. 6 as demand "in logs" or a "semilog" specification.

The performance of the approximation in Eq. 1 will depend on the demand specification and the manner in which demand shifts. We will show that Eq. 1 *underestimates* true consumer surplus changes for many standard demand models. This is a desirable property, consistent with the principle of favoring a null conclusion over a false positive. We also show that this approximation will correspond exactly with the true, unobserved surplus change when the demand function and quality shift function adhere to certain properties. Indeed, such is the case for several popular demand specifications, such as Poisson and negative binomial models, for which our approach will yield exact consumer surplus changes under common assumptions.

2.3.1 Demand in Levels

Consider the demand function

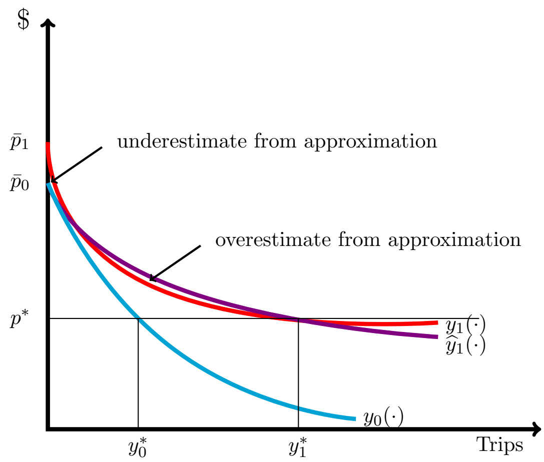
$$y(\cdot) = f(p) + \sigma(W, p), \tag{7}$$

where the demand shift is some flexible function $\sigma(W, p)$.

Proposition 1 *For a demand in levels: if the quality shift function increases in p (i.e., $\frac{\partial\sigma}{\partial p} > 0$), then $\Delta\widehat{CS}$ will underestimate the consumer surplus change. If the quality shift function decreases in p (i.e., $\frac{\partial\sigma}{\partial p} < 0$), then the error will be ambiguous, and the sign of error will depend on the relative magnitudes of the price elasticity of demand and the price elasticity of the quality shift function.*

[6] Recall, however, that $\sigma(W, p)$ can only be estimated at $p = p^*$ given typical data constraints.

Fig. 3 Welfare change from weather changes. Changing weather shifts demand from $y_0(\cdot)$ to $y_1(\cdot)$. Approximating the change in consumer surplus as $\Delta CS \approx \frac{y_1^*}{y_0^*} CS_0 - CS_0$ may have countervailing errors when there is an interaction between the demand shift and price. Note that the approximation will underestimate CS changes at low y (high p) and overestimate change for high y (low p). The net error will depend on the relative magnitudes of each



Proof Normalize $\sigma(W_0, p) = 0$ such that we have

$$\begin{aligned} y_1(\cdot) &= f(p) + \sigma(W_1, p) \\ y_0(\cdot) &= f(p), \end{aligned}$$

giving

$$h(p) \equiv \frac{y_1(\cdot)}{y_0(\cdot)} = \frac{f(p) + \sigma(W_1, p)}{f(p)}.$$

We can calculate $h'(p) = \frac{\frac{\partial \sigma}{\partial p} f(p) - \sigma(W_1, p) f'(p)}{f(p)^2}$, which is positive if and only if

$$\begin{aligned} \frac{\partial \sigma}{\partial p} f(p) &> \sigma(W_1, p) f'(p) \\ \frac{p}{\sigma} \frac{\partial \sigma}{\partial p} &> \frac{p}{f(p)} f'(p) \\ \varepsilon_{\sigma,p} &> \varepsilon_{f,p} \end{aligned} \tag{8}$$

where $\varepsilon_{f,p}$ is the price elasticity of demand and $\varepsilon_{\sigma,p}$ is the price elasticity of the quality shift function $\sigma(\cdot)$. When $\frac{\partial \sigma}{\partial p} \geq 0$, this expression holds trivially because $\varepsilon_{f,p} < 0$ by the law of demand. However, when $\frac{\partial \sigma}{\partial p} < 0$, we can rewrite this condition as

$$|\varepsilon_{\sigma,p}| < |\varepsilon_{f,p}|.$$

That is, Lemma 1 will hold as long as the price elasticity of the quality shift function is smaller in magnitude than the price elasticity of demand. Intuitively, this implies that the graph of $y_1(\cdot)$ should be steeper than that of $y_0(\cdot)$ for any given p. This is a reasonable condition that we might expect to hold in standard cases (i.e., ruling out "crossing" of demand curves). However, even if it does fail to hold in certain unusual cases, $\Delta\widehat{CS}$ may *still* underestimate true CS changes, and the result will depend on the quantitative tradeoff presented in Fig. 3. □

Proposition 1 applies to any demand function of the form described in Eq. 7. Although it does not provide clear-cut prescriptions, it is fully general. Several special cases offer more unambiguous results.

Corollary 1 *If the quality shift function is linear in W, then $\Delta\widehat{CS}$ will underestimate the magnitude of consumer surplus changes.*

Proof Consider demand of the form

$$y = f(p) + \gamma W,$$

which captures the underlying demand curve *f*(*p*) along with a constant linear quality shifter $\sigma(W, p) = \gamma W$. We maintain the assumption (without loss of generality) that W_1 is more favorable than W_0, so it must be the case that $\gamma > 0$. Define

$$\begin{aligned} h(p) \equiv \frac{y_1(\cdot)}{y_0(\cdot)} &= \frac{f(p) + \gamma W_1}{f(p)} \\ &= 1 + \frac{\gamma W_1}{f(p)}, \end{aligned}$$

Then we can compute $h'(p) = -\frac{f'(p)\gamma W_1}{f(p)^2} > 0$, satisfying Lemma 1. □

Thus, if the demand shift is linear in *W*, $\Delta\widehat{CS}$ gives a conservative estimate of consumer surplus changes.

Corollary 2 *If the quality shift function is linear in an interaction of W and p, then $\Delta\widehat{CS}$ will understimate ΔCS if (i) the interaction coefficient is positive, or (ii) the interaction coefficient is negative and demand is sufficiently elastic.*

Proof Consider a quality shift function that allows for interactions between weather and price, $\sigma(W, p) = \gamma W + \theta W \times p$. For W_1 to be more favorable than W_0, it must be the case that $(\gamma + \theta p) > 0$. We have

$$\begin{aligned} y_1(\cdot) &= f(p) + \gamma W_1 + \theta W_1 \times p \\ y_0(\cdot) &= f(p), \end{aligned}$$

giving

$$h(p) \equiv \frac{y_1(\cdot)}{y_0(\cdot)} = \frac{f(p) + W_1(\gamma + \theta p)}{f(p)}.$$

We have $h'(p) = \frac{((\theta f(p) - f'(p)(\gamma + \theta p))W_1}{f(p)^2}$, which is positive if and only if

$$\begin{aligned} \theta f(p) - f'(p)(\gamma + \theta p) &> 0 \\ \theta f(p) &> f'(p)(\gamma + \theta p) \\ \frac{\theta p}{\gamma + \theta p} &> \frac{p}{f(p)} f'(p) \equiv \varepsilon_{f,p} \end{aligned} \tag{9}$$

where $\varepsilon_{f,p}$ is the price elasticity of demand. This inequality holds trivially if $\theta \geq 0$. If instead $\theta < 0$, then the condition can be rewritten as follows:

$$|\varepsilon_{f,p}| > \left|\frac{\theta p}{\gamma + \theta p}\right|.$$

This relationship holds if demand is sufficiently elastic or if θ is sufficiently small. □

Notice that as $\theta \to 0$, we approach the case treated in Corollary 1. Even if this condition fails, consumer surplus may still be underestimated, but this will depend on the quantitative tradeoff presented in Fig. 3.

2.3.2 Demand in Logs

Consider the general class of semilog demand specifications of the form

$$\log(y) = f(p) + \sigma(W, p), \tag{10}$$

which includes the oft-implemented Poisson and negative binomial models as special cases.

Proposition 2 *For semilog demand: if the quality shift function increases (decreases) in p, then* $\Delta\widehat{CS}$ *will underestimate (overestimate)* ΔCS. *If the quality shift function is constant in p, then* $\Delta\widehat{CS}$ *will be an exact measure of* ΔCS.

Proof Using the form $\log(y) = f(p) + \sigma(W, p)$ and normalizing $\sigma(W_0, p) = 0$, we have:

$$\begin{aligned}\log(y_1) &= f(p) + \sigma(W, p)\\ \log(y_0) &= f(p)\end{aligned}$$

or

$$\begin{aligned}y_1 &= e^{f(p)+\sigma(W,p)}\\ y_0 &= e^{f(p)}.\end{aligned}$$

At p^*, we have $\frac{y_1^*}{y_0^*} = e^{\sigma(W,p^*)}$. Define $\hat{y}_1(\cdot) \equiv \frac{y_1^*}{y_0^*} y_0(\cdot)$, where $\hat{y}_1$ is the approximation of $y_1(\cdot)$ that yields $\Delta\widehat{CS}$. If $\sigma(W, p)$ is invariant in p (i.e., $\frac{\partial\sigma}{\partial p} = 0$), then $\hat{y}_1(\cdot) = y_1(\cdot)$ If instead $\frac{\partial\sigma}{\partial p} > 0$, then $\hat{y}_1 < y_1$, and $\Delta\widehat{CS}$ will underestimate ΔCS. Lastly, if $\frac{\partial\sigma}{\partial p} < 0$, then $\hat{y}_1 > y_1$, and $\Delta\widehat{CS}$ will overestimate ΔCS. □

In the case of semilog specifications, the function $\sigma(W, p)$ becomes a simple scaling factor that stretches the demand function horizontally (i.e., $y_1 = y_0 e^{\sigma(W_1,p)}$). If this scaling factor is constant in p, then demand will be stretched by the same amount at p^* as at all other values of p, yielding $\Delta\widehat{CS} = \Delta CS$. If the scaling factor varies in p, then $\Delta\widehat{CS}$ will systematically under- or overestimate ΔCS.[7]

[7] An alternative way to frame this result is to begin with the assumptions that (i) demand *f*(*p*) is truly semi-log and (ii) the quality shift function is invariant in price—both of which are commonly assumed in the valuation literature. In this light, our analysis describes how departures from these assumptions could lead to over- or under-estimates of impacts. We thank an anonymous reviewer for noting this alternative framing.

The semilog specification is very common in the valuation literature, especially the Poisson and negative binomial forms. As Kling (1989) observes, most practitioners prefer the semilog form because of its goodness-of-fit properties. Examples abound, including Eiswerth et al. (2000), Whitehead et al. (2000), Hanley et al. (2003), and Eom and Larson (2006). Most such studies assume $\frac{\partial\sigma}{\partial p} = 0$, and we are aware of only one study (discussed below) that explicitly models and estimates $\frac{\partial\sigma}{\partial p}$, and it reports $\frac{\partial\sigma}{\partial p} > 0$. Therefore, we are not aware of any existing applications for which Eq. 1 would overestimate consumer surplus changes in practice, per Proposition 2. Therefore, the assumptions that lead to conservative estimates of consumer surplus changes are not at all unusual, and indeed, they are rather standard in the broader literature on nonmarket valuation.

2.4 Testing this Approximation Using Prior Work

Here, we assess the accuracy of $\Delta\widehat{CS}$ by applying it to prior work on valuation of environmental quality changes. First, we should note that most authors implictly assume that $\frac{\partial\sigma}{\partial p} = 0$, which ensures a parallel shift when demand is specified in levels and a constant scaling factor when demand is specified in logs. Thus, $\Delta\widehat{CS}$ will be an exact measure of ΔCS if true demand is semilog; meanwhile, it will yield a conservative estimate of ΔCS if demand is specified in levels.

Indeed, for prior work that employs a semilog specification, we can reproduce authors' original estimates of CS_1 and ΔCS exactly using our parsimonious measure $\Delta\widehat{CS} = \Delta y \times \overline{CS}_0$. We should stress that we do *not* intend to discount the value of prior work; the estimations undertaken in the following studies are crucial for generating the initial CS_0 measure, something that our analysis cannot generate on its own and instead takes as given from other sources. Rather, the replications that we undertake below demonstrate that the welfare impacts of quality changes can be reasonably estimated and predicted with our approximation, *assuming* some initial baseline CS_0 is already available to the analyst. One way to obtain a baseline estimate for CS_0 is through benefits transfer (as we do), which enables researchers to generate welfare estimates for a wide range of activities. However, one can also generate original estimates of one's own (as the studies below do).

Eiswerth et al. (2000) combine revealed preference and contingent behavior survey data to investigate how water levels in Nevada's Walker Lake influence recreation behavior in the area. They report average per trip consumer surplus values of \$88 for one of their empirical specifications. They also estimate that individuals will make an additional 0.132 trips per year for each one-foot increase in water levels. Calculating $\Delta\widehat{CS} = \Delta y \times \overline{CS}_0$ gives a consumer surplus change of \$11.62 per foot of water level increase, which matches their results (within a small rounding error). Hanley et al. (2003) conduct a similar study to value coastal water quality improvements at beaches in Scotland. In a sample of 331 respondents, they predict an increase from 3,954 to 4,006 beach trips per year due to improvements in water quality. This implies an increase in visitation of 52 trips overall or $\Delta y = 0.157$ trips per respondent. Multiplying this change by their calculated consumer surplus per trip ($\overline{CS}_0 = -\frac{1}{\alpha} = £37.037$) gives an increase in surplus of £5.81 per person per year, which matches with their estimates. In both cases, we find an exact match between

$\Delta\widehat{CS}$ and the authors' reported values because of the semilog demand function and the implicit assumption that $\frac{\partial\sigma}{\partial p} = 0$.[8]

The more interesting case is when $\frac{\partial\sigma}{\partial p}$ is not assumed to be zero. To our knowledge, Whitehead et al. (2000) are the only authors to estimate full demand curves before and after a quality change while allowing the demand shift to depend on p (i.e., $\frac{\partial\sigma}{\partial p} \neq 0$).[9] They combine revealed- and stated-preference techniques to estimate a semilog recreation demand function for trips to Pamlico Sound in North Carolina, allowing for quality-price interaction on the right-hand side. Their estimates suggest that $\frac{\partial\sigma}{\partial p} > 0$, because their estimated quality-price interaction (which they call "D_3 TCP") coefficient is positive.

They report a baseline consumer surplus value of $CS_0 = \$64.14$ per trip under current site quality, and they predict that the number of trips per person will rise from 1.88 to 2.49 with the environmental quality change. Using the estimates from their empirical model, they predict $CS_1 = \$84.99$ per trip under improved quality, which amounts to a change in consumer surplus of $\Delta CS = \$20.85$ per trip.

We can now assess how well Eq. 1 approximates the consumer surplus change. Given their estimates of the quality-price interaction ($\frac{\partial\sigma}{\partial p} > 0$), we should expect Eq. 1 to underestimate the true effect according to Proposition 2. Using Eq. 1, we calculate $\Delta\widehat{CS} = \frac{2.49}{1.88}64.14 - 64.14 = \$20.81$. Thus, in spite of the fact that our approximation lacks the richness of their full empirical model, we underestimate their calculated surplus change by only \$0.04, an error of less than 0.2 percent. Not only does this exercise confirm the theoretical results regarding underestimation of true surplus changes, it also demonstrates that this error can be exceedingly small, at least for this particular application.

In summary, the assumptions that are necessary for $\Delta\widehat{CS}$ to perform (semilog demand and zero shift elasticity) are the same assumptions that are commonly used in the valuation literature. Our theoretical framework assures us that the error will be minimal in many cases, as it is for the Pamlico Sound application. In the two studies that empirically estimate the shift elasticity, $\frac{\partial\sigma}{\partial p}$ is found to be small and will therefore introduce minimal error, per Eq. 2.

3 Empirical Application

In the previous section, we tested the accuracy of $\Delta\widehat{CS}$ by cross-validating it with prior work on demand for recreational sites and environmental quality changes. We verified that it performed as predicted by our theory, and we also showed that the error, at least for that application, was small.

In the remainder of this paper, we look forward and consider the problem of climate change. Although there has been extensive work documenting a wide array of climate change impacts, measures of nonmarket outcomes remain sparse. For one, it is difficult to identify the *causal* impacts of climate on human activity, and this problem is

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[8] Of course, the analyst's assumption of a semilog function does not guarantee that this function actually reflects the underlying data-generating process. This highlights an additional advantage of our theoretical exposition: it provides a means for characterizing the error that may arise from such misspecification.

[9] Hilger and Englin (2009) also do so in a semilog framework, but they find an insignificant coefficient on $\frac{\partial\sigma}{\partial p}$. Their finding further supports our suspicion that errors of this sort are unlikely to affect the performance of the approximation we describe.

Table 1 Primary activity categories used for aggregate measures of outdoor recreation

Outdoor recreation (all)	Outdoor recreation (limited)
Playing baseball[S]	
Playing basketball[S]	
Biking	Biking
Boating	Boating
Climbing, spelunking, caving	
Participating in equestrian sports[S]	
Fishing	Fishing
Playing football[S]	
Golfing[S]	
Hiking	Hiking
Hunting	Hunting
Playing racquet sports[S]	
Participating in rodeo competitions[S]	
Rollerblading	
Playing rugby[S]	
Running	Running
Skiing, ice skating, snowboarding	Skiing, ice skating, snowboarding
Playing soccer[S]	
Softball[S]	
Walking	
Participating in water sports	Participating in water sports

Activities are adopted from the 2003–2016 American Time Use Survey. Each is a subcategory of the Sports, Exercise, and Recreation time use primary category. Activities marked with a superscript S are designated as sports

compounded by the challenge of estimating welfare changes for nonmarket goods and services. We now show how to tackle these dual challenges by applying our theory in a novel context.

Our analysis proceeds in three distinct parts: we empirically estimate a quality shift function $\sigma(W, p^*)$ using an extensive data set on individual time use and recreation behavior; we obtain estimates of W_1 and W_0 from climate projections and observed weather; and we combine these values with estimates of CS_0 using a database of recreation values from the environmental valuation literature. Through this application, we highlight an important and powerful feature of our proposed approximation technique: it offers a theoretically founded means for combining reduced-form climate impacts estimates with existing nonmarket valuation calculations to generate plausible predictions of climate damages (or benefits) in welfare terms.

Before proceeding, we should emphasize that this empirical exercise is intended to illustrate our framework using a new empirical application. There are necessarily caveats and shortcomings to the empirical analysis, which we will discuss, but we do not believe these issues detract from the underlying conceptual contribution.

Table 2 Summary statistics for participation in recreational activities

	Mean	SD	Average number of participants per day (in 1000s)	Average minutes per activity per day (conditional on participating)	Consumer surplus value per day (US$2016)
Outdoor recreation (all)	0.115	0.320	27,877	101.22	69.05
Outdoor recreation (nonsport)	0.098	0.298	23,712	88.52	69.05
Outdoor recreation (limited)	0.043	0.204	10,461	121.55	69.05
Boating	0.002	0.042	426	178.36	83.34
Cycling	0.006	0.075	1,352	83.64	47.52
Fishing	0.005	0.067	1,091	251.82	77.37
Hiking	0.002	0.040	389	146.00	78.27
Hunting	0.002	0.048	569	289.72	71.84
Running	0.014	0.119	3464	52.61	60.37
Skiing, ice skating, snowboarding	0.001	0.031	234	190.22	66.30
Participating in water sports	0.014	0.117	3340	107.49	27.79

All statistics are weighted to account for nationally representative stratified sampling design. Consumer surplus estimates are taken from the OSU Recreation Use Value Database (RUVD) as a simple average across all primary consumer surplus (CS) values for each activity. Aggregate CS values are approximated as the simple average across all CS estimates in the RUVD

3.1 Data

We use data from the American Time Use Survey (ATUS) from 2003 through 2016. The ATUS is a nationally representative survey intended to capture how Americans allocate their time. The survey format instructs respondents to document how each minute was spent for a given 24-hour period. The recreational activities that we study are shown in Table 1, and we present summary statistics for participation rates and time allocated to each activity in Table 2. We construct three aggregate outdoor recreation variables that capture all outdoor recreation (including team sports), all outdoor recreation (excluding team sports), and a "limited" outdoor recreation variable comprising bicycling, boating, fishing, hiking, hunting, running, skiing, ice skating, snowboarding, and water sports. We omit recreation activities that take place primarily indoors (e.g., bowling).

ATUS responses are also linked with responses to the Current Population Survey. From these data, we gather household and respondent characteristics as controls for preferences toward recreation participation decisions. Specifically, we construct indicator variables for educational attainment of the respondent, race, age, income groups, and employment and retirement status.

Additionally, we require geographic information for respondents to match with weather and climate variables. In the publicly available 2003–2016 ATUS data, county of residence is provided for respondents in 2016 only. We append this information for the previous years with a request from the IPUMS American Time Use Survey Data Extract Builder (Hofferth et al. 2017).

We link the diaries of ATUS respondents with contemporaneous daily weather conditions. For each day between 2003 and 2016, we assemble daily summary statistics for temperature, precipitation, snowfall, and snow depth for weather stations within the respondents' county of residence. Weather data is assigned to the diary day for the ATUS respondent. For respondents who lack county information, we merge state-level summary statistics of weather. Our weather variables are derived from weather station data in the Global Historical Climate Network Daily summary file (GHCN-Daily). We spatially match each weather station to county (state) boundaries and collapse our variables of interest using simple averages, ignoring missing values.

3.2 Empirical Strategy

In our empirical framework, we seek to illustrate the value of our conceptual contribution. To do so, we focus on identifying the value of changes in outdoor recreation attributable to changes in weather. We implement a simple and commonly used framework to estimate a reduced-form dose-response function of weather fluctuations on economic outcomes. We model the extensive margin for participation in outdoor recreational activities. Let R^j_{icrst} represent individual i's binary choice to participate in recreational activity j in year t. Subscripts c, r, and s represent, respectively, the respondent's county, climate-region, and the season in which the activity took place. We define our outcome variable as equal to one if time use survey respondents report allocating any amount of time on activity j during their diary day, and zero otherwise. Although we observe the choice of an individual to participate in a given activity on a given day, we use this information to capture how nationally representative rates of participation change in response to local weather changes. Conceptually, scaling to total participation in a given activity aligns closely with the direct demand function in our theoretical framework.

We specify the following estimating equation

$$R^{j}_{icrst} = \alpha + f(W_{crst}|\Theta) + \beta X_i + \zeta_{rs} + \tau_t + \varepsilon_{icrst} \tag{11}$$

where $f(W_{crst}|\Theta)$ is a flexible function of prevailing weather conditions at the county or state level parameterized by Θ, X_i is a vector of individual-specific attributes, ζ_{rs} are climate-region-by-season fixed effects, and τ_t are year dummies.[10] The error term ε_{icrst} is clustered to account for correlation within counties. We estimate Eq. 11 using logistic regression weighted to account for the nationally representative survey sampling design.

In line with other reduced-form climate impact studies, we seek to estimate the coefficient vector Θ. In our application, $f(\cdot)$ defines the relationship between a suite of weather variables and the likelihood of choosing to participate in a given recreation activity, conditional on household characteristics and common climate-region, seasonal, and year fixed effects. We choose a flexible functional form for the weather-response function. Note that this weather-response function corresponds to the "quality shift function" $\sigma(W, p^*)$ described in the theory section above. We specify

$$\begin{aligned} f(W_{crst}|\Theta) = \sum_{a}^{A} \gamma_a 1[T_{crst} \in a] + \sum_{b}^{B} \gamma_b 1[P_{crst} \in b] \\ + \sum_{d}^{D} \gamma_d 1[\text{ Snowfall}_{crst} \in d] + \sum_{e}^{E} \gamma_e 1[\text{ Snow Depth}_{crst} \in e] \end{aligned} \tag{12}$$

where the first summation over a indicates a set of A 5° Celsius temperature bins that equal one if observed daily average temperature at the county level falls in bin a and zero otherwise. In our primary models, we use average daily temperatures, defined as the simple average of maximum and minimum temperatures. An observation with a daily maximum of 35°C and a daily minimum of 20°C would fall in the 25-30°C bin, so a daily average temperature exceeding 30°C is quite extreme. That said, we also include a set of results using maximum daily temperature bins in the online appendix; this analysis produces similar results. Likewise, the second summation over b indicates a set of B 10-millimeter precipitation bins that equal one if observed daily precipitation falls in bin b and zero otherwise. The third summation captures daily snowfall in three 5-millimeter bins, and the fourth summation captures snow depth in four 50 millimeter bins.

Upon estimating the model in Eq. 11, we use the estimated parameters to project changes in recreation due to changes in weather, providing us with measures of y_0^* and y_1^* from our theoretical model. For this exercise, we specify mean monthly temperature changes and percentage changes in precipitation for the period 2050–2100, relative to base years of 1950-2000 at the county level for each of the RCP scenarios. For our projections, we take an average of projected temperature and precipitation for each month of the year, which summarizes monthly changes in weather for the 2050-2100 period within each county. We assume that temperature changes are additively constant and that precipitation changes are

[10] In the ATUS data, we are able to link approximately 45% of survey respondents to counties; for the remaining 55% of respondents, the finest geographic identifier we have is the state. We use county-level average weather for the respondents that have county identifiers and state-level average weather for everyone else.

Table 3 Temperature and precipitation change projections by climate region for 2050–2100 relative to 1950–2000

	RCP 2.6		RCP 4.5		RCP 6.0		RCP 8.5	
	Temp (deg C)	Prcp. (%)	Temp (deg C)	Prcp. (%)	Temp (deg C)	Prcp. (%)	Temp (deg C)	Prcp. (%)
Northwest	1.2	1.3	1.7	− 0.0	1.8	0.5	2.8	− 0.2
West	1.1	− 0.8	1.6	− 3.4	1.7	− 5.6	2.6	− 5.8
Southwest	1.3	0.9	1.9	− 0.3	2.1	0.8	3.2	− 3.6
Northern Rockies and Plains	1.4	3.2	2.1	3.6	2.3	5.0	3.3	5.5
South	1.2	− 0.0	1.8	− 2.0	1.9	− 1.1	2.9	− 4.7
Southeast	1.0	2.7	1.5	1.9	1.7	2.8	2.5	1.7
Ohio Valley	1.3	2.4	1.9	2.9	2.1	4.4	3.1	3.5
Upper Midwest	1.5	3.5	2.2	4.3	2.5	5.5	3.4	6.1
Northeast	1.4	3.9	1.9	4.5	2.2	6.6	3.1	6.0

Average monthly temperature changes (in degrees C) and precipitation changes (in percentage changes) for 2050–2100 are averages for each climate region in our sample relative to 1950–2000. Climate-region averages are the multimodel monthly mean change from CMIP5 models running the given scenario. All statistics are weighted to account for ATUS' nationally representative stratified sampling design.

proportionally constant. Equation 11 is based on daily observations, so we assign the same projected weather changes to all days within a given month. Because our climate data use 1950-2000 as a baseline period but our recreation sample spans 2003–2016, we assume that changes scale linearly, and we remove the changes that occurred prior to our sample.[11] We assume no change in snowfall or snow depth; if snowfall decreases monotonically with climate change, this would bias our results toward zero for positive responses to snowfall and away from zero for negative responses. Mean temperature and precipitation changes used for our projection exercise are presented in Table 3. We summarize these changes by climate region, weighted using ATUS survey sampling weights, although our projections are applied at the county level.

3.3 Results

We now present findings from our dose-response analysis followed by climate impact and valuation results.

3.3.1 Responsiveness to Weather

We present coefficients from our primary estimation results in Table 4. As shown, temperatures below the omitted temperature bin (16–20°C) generally have negative coefficients

[11] This strategy effectively pins our baseline year midway between 1950 and 2000 (i.e., 1975) and our projection year midway between 2050 and 2100 (i.e., 2075). We pin our sample at 2010 and so we assume that 0.35 of the model-projected change in temperature and preciptation occurs prior to 2010. So, we rescale our weather predictions by 0.65.

Table 4 Estimation results from logit regression

	Outdoor Recreation			Cycling	Boating	Fishing	Hiking	Hunting	Running	Skiing	Watersports
	(all)	(nonsport)	(limited)								
Temp. Bin: < 0°C	−0.53	−0.47	−0.37	−1.09	−2.65	−1.73	−1.39	0.48	−0.47	2.84	−0.28
	(0.07)	(0.07)	(0.10)	(0.26)	(0.86)	(0.29)	(0.46)	(0.33)	(0.17)	(0.48)	(0.22)
Temp. Bin: 1–5°C	−0.36	−0.35	−0.43	−0.78	−3.75	−1.53	−0.82	0.95	−0.39	1.75	−0.53
	(0.05)	(0.06)	(0.09)	(0.20)	(1.06)	(0.30)	(0.41)	(0.27)	(0.16)	(0.47)	(0.20)
Temp. Bin: 6–10°C	−0.21	−0.18	−0.24	−0.50	−1.06	−0.79	−0.51	0.89	−0.22	1.22	−0.55
	(0.04)	(0.04)	(0.07)	(0.16)	(0.61)	(0.24)	(0.28)	(0.25)	(0.13)	(0.45)	(0.16)
Temp. Bin: 11–15°C	−0.09	−0.06	−0.17	−0.33	−0.60	−0.28	0.09	0.49	−0.16	0.21	−0.42
	(0.03)	(0.03)	(0.06)	(0.15)	(0.29)	(0.15)	(0.25)	(0.25)	(0.12)	(0.61)	(0.14)
Temp. Bin: 21-25°C	0.08	0.11	0.25	0.02	0.28	−0.07	0.26	−0.16	0.14	−0.51	0.63
	(0.03)	(0.03)	(0.05)	(0.11)	(0.17)	(0.16)	(0.22)	(0.38)	(0.10)	(0.79)	(0.10)
Temp. Bin: 25- 30 °C	0.04	0.07	0.24	0.08	0.23	−0.75	−0.71	−0.53	0.03	−1.41	0.83
	(0.05)	(0.05)	(0.07)	(0.14)	(0.22)	(0.20)	(0.40)	(0.35)	(0.13)	(1.69)	(0.12)
Temp. Bin: > 30°C	−0.09	−0.05	0.19	0.17	−0.66	−0.71	−0.70	−0.98	0.21	−0.32	0.72
	(0.06)	(0.08)	(0.11)	(0.24)	(0.36)	(0.31)	(0.32)	(0.68)	(0.16)	(1.16)	(0.17)
Prcp. Bin: 1–10 mm	−0.02	−0.00	0.01	0.03	−0.14	0.34	0.05	0.46	−0.00	−0.05	−0.13
	(0.03)	(0.03)	(0.04)	(0.11)	(0.15)	(0.14)	(0.20)	(0.23)	(0.09)	(0.29)	(0.07)
Prcp. Bin: 11–20 mm	−0.19	−0.21	−0.19	0.09	−0.90	−0.26	−0.85	0.09	−0.01	0.45	−0.49
	(0.05)	(0.06)	(0.08)	(0.23)	(0.38)	(0.25)	(0.42)	(0.37)	(0.13)	(0.47)	(0.13)
Prcp. Bin: 21–30 mm	−0.40	−0.42	−0.59	−0.59	−0.68	−0.73	−1.78	−0.27	−0.38	1.27	−0.94
	(0.10)	(0.11)	(0.14)	(0.35)	(0.53)	(0.38)	(1.02)	(0.54)	(0.25)	(0.52)	(0.28)
Prcp. Bin: > 30 mm	−0.17	−0.17	−0.51	−0.81	0.45	−0.48	0.30	−0.02	−0.63	1.52	−0.47
	(0.08)	(0.08)	(0.13)	(0.28)	(0.37)	(0.39)	(0.34)	(0.55)	(0.25)	(1.12)	(0.20)
Snowfall Bin: 1–5 mm	−0.02	−0.01	−0.05	−0.24	−0.10	−0.06	0.70	0.23	−0.05	−0.05	−0.30
	(0.05)	(0.05)	(0.07)	(0.18)	(0.47)	(0.17)	(0.25)	(0.20)	(0.13)	(0.30)	(0.12)

Table 4 (continued)

	Outdoor Recreation			Cycling	Boating	Fishing	Hiking	Hunting	Running	Skiing	Watersports
	(all)	(nonsport)	(limited)								
Snowfall Bin: > 5 mm	0.06	0.07	0.18	0.16	0.72	−0.28	−0.08	0.28	0.26	0.43	−0.03
	(0.06)	(0.07)	(0.09)	(0.18)	(0.30)	(0.26)	(0.26)	(0.24)	(0.19)	(0.30)	(0.14)
Snow Depth Bin: 0–50 mm	−0.08	−0.06	0.03	0.02	−0.01	−0.20	0.11	0.01	0.02	−0.13	0.16
	(0.04)	(0.05)	(0.06)	(0.18)	(0.43)	(0.25)	(0.26)	(0.19)	(0.10)	(0.28)	(0.13)
Snow Depth Bin: 50–100 mm	−0.07	0.01	0.06	0.07	0.31	0.36	−0.07	0.02	−0.12	0.19	0.20
	(0.06)	(0.07)	(0.10)	(0.25)	(0.57)	(0.36)	(0.47)	(0.29)	(0.21)	(0.28)	(0.28)
Snow Depth Bin: > 100 mm	−0.01	−0.05	0.06	0.17	0.91	0.36	0.59	−0.56	−0.20	0.16	0.29
	(0.08)	(0.09)	(0.14)	(0.41)	(0.83)	(0.33)	(0.36)	(0.71)	(0.27)	(0.28)	(0.30)
Edu $\geq$ college (=1)	0.31	0.41	0.35	0.72	0.10	−0.81	0.99	−1.27	0.62	0.70	0.30
	(0.02)	(0.02)	(0.04)	(0.09)	(0.13)	(0.14)	(0.19)	(0.17)	(0.07)	(0.22)	(0.07)
Race nonwhite (= 1)	−0.17	−0.24	−0.57	−0.41	−1.39	−0.36	−1.15	−1.30	−0.31	−1.39	−0.80
	(0.03)	(0.04)	(0.07)	(0.12)	(0.32)	(0.12)	(0.25)	(0.34)	(0.08)	(0.34)	(0.14)
Age $\geq$ 70 (= 1)	−0.08	−0.04	−0.56	−0.21	−1.41	−0.70	−0.89	−1.10	−1.27	−0.33	−0.34
	(0.04)	(0.04)	(0.08)	(0.20)	(0.31)	(0.20)	(0.32)	(0.33)	(0.27)	(1.05)	(0.13)
Income < 25k (= 1)	−0.25	−0.18	−0.37	−0.55	−0.57	−0.38	−0.67	0.80	−0.33	−0.34	−0.38
	(0.05)	(0.05)	(0.08)	(0.18)	(0.33)	(0.20)	(0.36)	(0.34)	(0.14)	(0.63)	(0.12)
Income 25–50k (= 1)	−0.13	−0.12	−0.10	−0.32	0.11	−0.28	0.15	1.30	−0.16	0.51	−0.11
	(0.05)	(0.05)	(0.08)	(0.18)	(0.26)	(0.16)	(0.28)	(0.31)	(0.14)	(0.53)	(0.12)
Income 50–75k (= 1)	0.01	−0.02	0.13	−0.16	0.07	−0.09	0.10	1.09	0.17	0.49	0.27
	(0.05)	(0.05)	(0.07)	(0.17)	(0.27)	(0.18)	(0.28)	(0.33)	(0.13)	(0.54)	(0.12)
Income 75–100k (= 1)	0.12	0.10	0.25	0.01	0.54	0.00	−0.46	1.37	0.33	0.69	0.33
	(0.05)	(0.05)	(0.08)	(0.20)	(0.25)	(0.23)	(0.28)	(0.35)	(0.13)	(0.49)	(0.13)
Income > 100k (= 1)	0.28	0.22	0.40	0.13	0.63	−0.29	0.18	0.97	0.60	0.51	0.41
	(0.05)	(0.05)	(0.08)	(0.18)	(0.27)	(0.24)	(0.36)	(0.36)	(0.14)	(0.46)	(0.11)

Table 4 (continued)

	Outdoor Recreation			Cycling	Boating	Fishing	Hiking	Hunting	Running	Skiing	Watersports
	(all)	(nonsport)	(limited)								
Employed (= 1)	−0.55	−0.34	−0.35	−0.45	0.21	−0.07	−0.35	1.03	−0.35	−0.44	−0.61
	(0.03)	(0.03)	(0.04)	(0.10)	(0.17)	(0.10)	(0.23)	(0.19)	(0.07)	(0.24)	(0.08)
Retired (= 1)	−0.03	0.18	−0.45	−0.13	0.50	0.30	0.03	0.94	−1.69	−2.14	−0.43
	(0.04)	(0.04)	(0.07)	(0.17)	(0.25)	(0.18)	(0.34)	(0.38)	(0.21)	(0.78)	(0.11)
Observations	181,335	181,335	181,335	180,437	158,565	180,620	181,335	179,964	181,335	125,338	181,335
Pseudo-R sq.	0.0329	0.0325	0.0509	0.0506	0.114	0.0617	0.107	0.139	0.0619	0.190	0.111
Log pseudolikelihood	−4.27e+11	−3.83e+11	−2.09e+11	−4.05e+10	−1.39e+10	−3.35e+10	−1.32e+10	−1.76e+10	−8.70e+10	−7.32e+09	-8.00e+10

Dependent variable is whether a household participated in a given activity. All models include climate-region-by-season and yearly fixed effects. Standard errors are clustered at the state level. All models are adjusted for sampling weights to account for the nationally representative survey design. Asterisks indicating statistical significance are suppressed for clarity

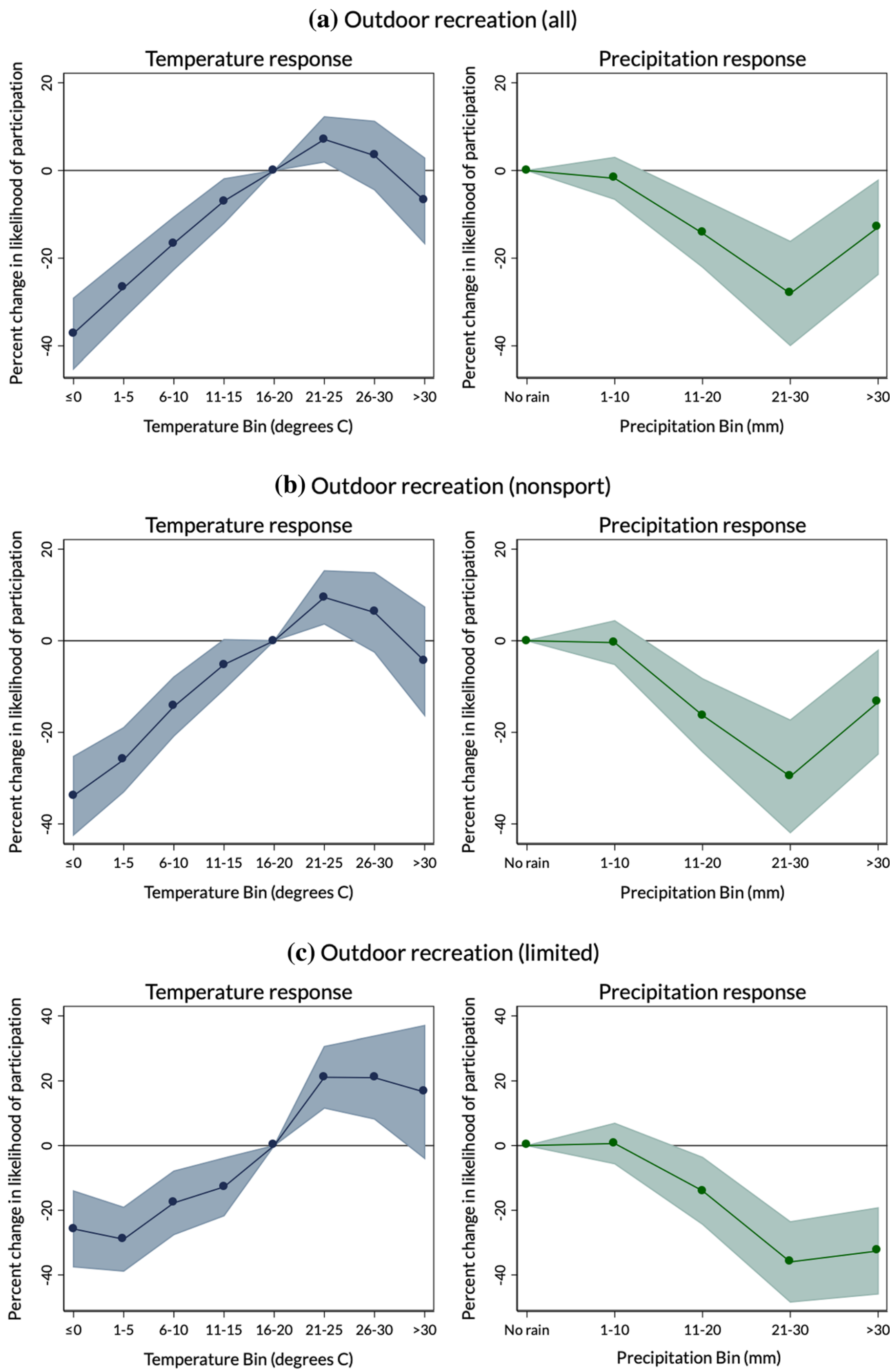


Fig. 4 Relationship between aggregate recreation and daily weather. Percentage changes (and 95% CI) are calculated as the marginal effect from logistic regression, centered at the sample mean of each covariate, divided by the weighted sample mean of the dependent variable

for each of our activity categories. Notably this statistic is positive for hunting and skiing, which typically take place during colder seasons. Precipitation is generally negatively correlated with participation in our activities, with the exception of skiing.[12]

To put these coefficients into context, we graphically illustrate the weather-response relationship for each of our activity categories. We calculate marginal effects from our previously estimated logit model at the weighted sample mean of each covariate. Then, we calculate percentage changes for each activity by dividing the marginal effects (and their 95 percent confidence intervals) by the weighted sample mean of the dependent variable. We present these results graphically for our temperature and precipitation bins for each of our activity categories in Figs. 4 and 5.

For our three aggregate measures of outdoor recreation (all, nonsport, and limited), the relationship between recreating and contemporaneous weather is similar. Individuals participate in recreation less during colder temperatures relative to the omitted 16–20°C bin. Recreation generally peaks in the 21–25°C bin, before diminishing again in the warmest bins, where confidence intervals overlap with zero. For our limited set of aggregate recreation activities (defined in Table 1), we continue to see positive responses of about 15–20 percent increases in recreation participation for days above 30°C relative to more moderate temperatures, although our confidence intervals overlap with zero. For precipitation, recreators appear willing to tolerate a small amount of rain (fewer than 10 mm per day) but generally reduce their participation rates as the daily amount of rain increases.

Our aggregate measures of recreation, however, mask activity-specific responses to weather. For example, the response of cycling to temperature may be quite different than that of skiing. In Fig. 5, we show weather-response functions for eight of our major recreational activities (which jointly constitute our "limited" recreation variable). Boating and fishing display similar responses, with a noticeable reduction on very hot days relative to our aggregate results. Cycling participation increases monotonically with each temperature bin, although participation on hot days is statistically similar to that of more moderate temperatures. Only precipitation greater than 20 mm has a noticeable impact on cycling. The results for hiking suggest that hikers dislike extremely hot and cold temperatures. Precipitation reduces participation in hiking, although the largest preciptation bin is statistically similar to zero.

For hunting, we see increases in participation on the cold end of the distribution, with little reaction to hot temperatures or precipitation. This result could be driven by rigid constraining factors associated with typical hunting seasons in the fall and winter. Running appears similarly unresponsive to wet or very hot temperatures, but we observe participation decreases on very cold days. Sensibly, participation in skiing, ice skating, and snowboarding increases with colder temperatures and precipitation. Although we do not present figures for snowfall and snow depth, these factors are also positively associated with winter recreation. Finally, participation in water sports (e.g., swimming) increases when it is very hot out, and decreases when it is very cold or wet.

In sum, we find that outdoor recreation is most responsive to extremes on either end of the temperature distribution, but the direction of the effect is activity-specific. Further, more precipitation tends to discourage outdoor recreation, an almost universal response

[12] Coefficients on socioeconomic characteristic correspond generally with expectations. Higher-income and higher-educated households participate more frequently in outdoor recreation, while nonwhite households and older populations participate less frequently in recreation. Results for employed and retired households are mixed and activity-specific.

Fig. 5 Activity-specific relationship between recreation and daily weather. Percentage changes (and 95% ▶ CI) are calculated as the marginal effect from logistic regression, centered at the sample mean of each covariate, divided by the weighted sample mean of the dependent variable

across activities that we study. These results are intuitive: for some activities (e.g., swimming), hot temperatures complement the desirability of participation; for other activities (e.g., skiing), cold temperatures are complementary. These weather responses form the foundation for our climate projections. If recreators dislike cold temperatures, but tolerate hot temperatures fairly well, then any climate-induced rightward shift in the temperature distribution may induce a net increase in outdoor recreation.

3.3.2 Climate Impact Results

For each of our activities and our three aggregate recreation groups, we project the expected change in participation under a set of climate scenarios for 2050–2100. The four RCP climate scenarios characterize four possible climate futures, with RCP 2.6 predicting relatively little warming and RCP 8.5 predicting extreme warming. For our purposes, we are interested in the spatially explicit multimodel mean monthly change in temperature and precipitation within each scenario.

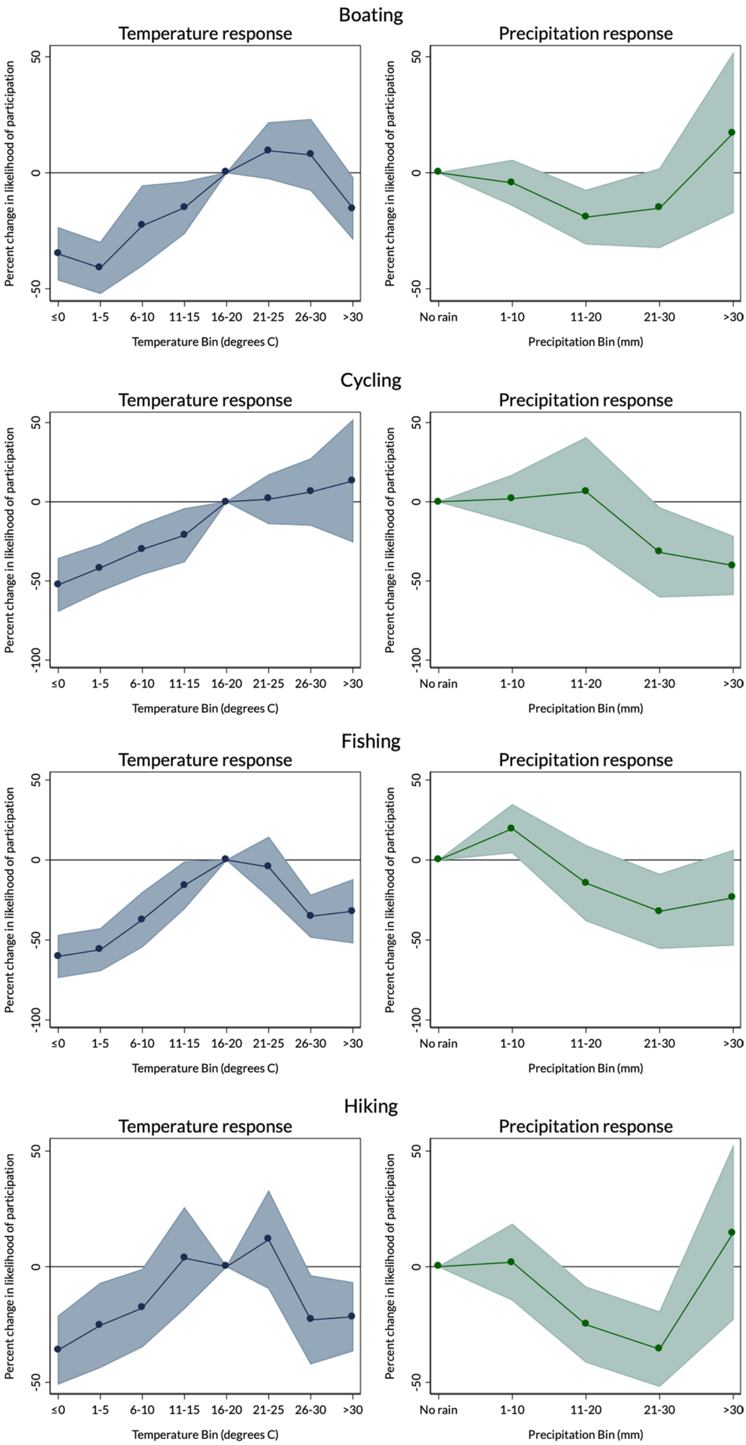
By scaling observed temperature and precipitation by anticipated changes in 2050–2100, we can predict likely changes in recreation participation using the estimated relationships in Table 4. First, we predict participation under current observed weather conditions, then we predict participation under weather conditions perturbed by each of our climate scenarios. We take the difference of these two predictions to be our measure of climate impacts on recreation activity, which corresponds with Δy from our welfare framework. We present these statistics as percentage changes (from the weighted sample mean) for each activity and each climate scenario in Table 5.

For each climate scenario and each of our aggregate recreation categories, we see strictly positive impacts. That is, our nationally representative results predict that climate change will induce increases in participation in outdoor recreation activities by 2050–2100 on the order of 1.1–4.7 percent. This result is largely consistent with the central estimate of a 5.5 percent increase in outdoor recreation that Chan and Wichman (2020) find using micro data from bicycle sharing programs. This result is also consistent with the central range of the aggregate impacts estimated in Mendelsohn and Markowski (1999).

Climate impacts for specific activities are mixed. For running, boating, cycling, and water sports, we estimate large positive impacts of climate change on participation across all climate scenarios. For hunting and skiing, we see increasingly negative and large impacts on participation. The effects for hiking and fishing are relatively small, suggesting that the benefit from a reduction in cold days is almost completely offset by the negative effects from more hot days.

3.3.3 Valuing Climate Impacts

We can produce a plausible lower-bound of welfare changes using the reduced-form relationship in Eq. 11 and anticipated changes in weather due to climate. To do so, we calculate the expected change in recreation participation in person days per year and multiply this value by average consumer surplus estimates from the literature. In the previous subsections, we obtained measures of W_0, W_1, and $\sigma(W, p^*)$, which can be compiled into a single



Boating
Temperature response
Precipitation response
Cycling
Temperature response
Precipitation response
Fishing
Temperature response
Precipitation response
Hiking
Temperature response
Precipitation response
Percent change in likelihood of participation
50
0
-50
-100
≤0
1-5
6-10
11-15
16-20
21-25
26-30
>30
Temperature Bin (degrees C)
No rain
1-10
11-20
21-30
>30
Precipitation Bin (mm)

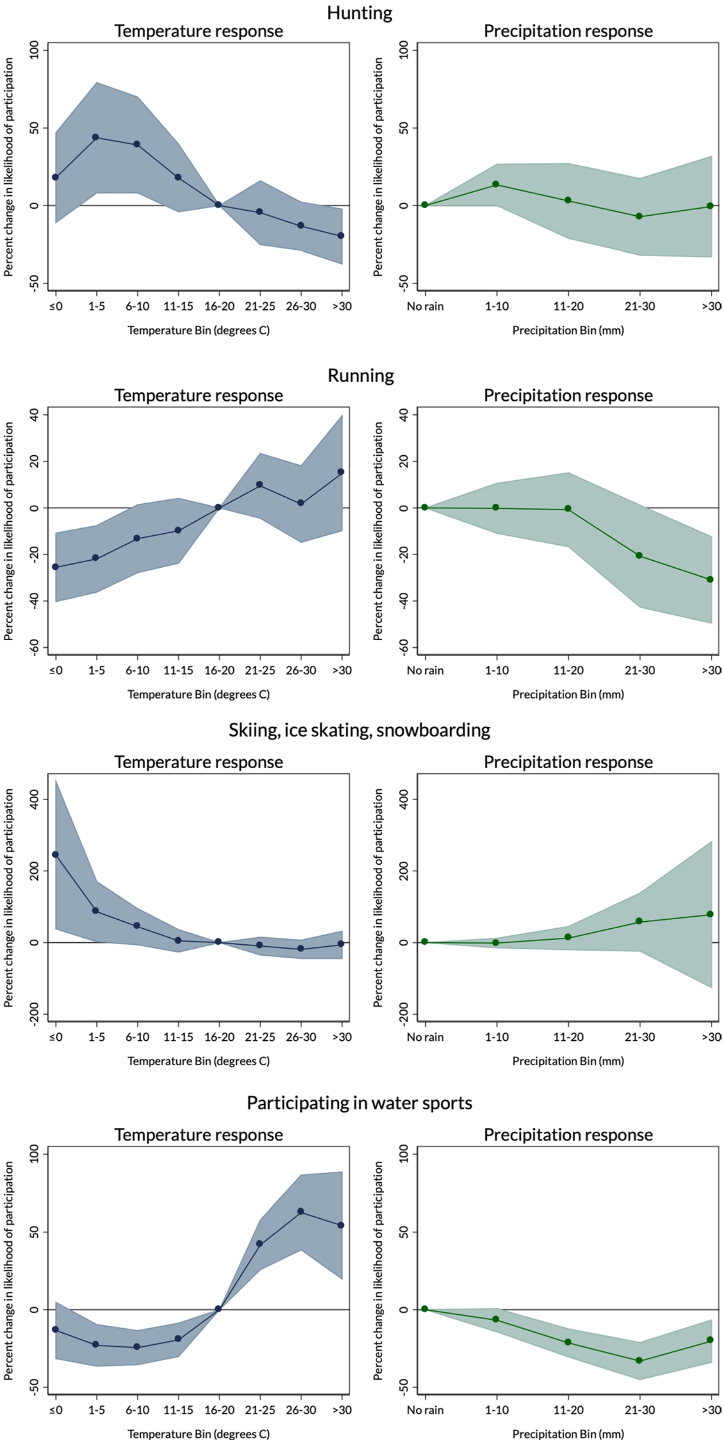


Fig. 5 (continued)

Table 5 Climate impacts on activity-specific participation rates by RCP scenario, 2050–2100

	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
Outdoor recreation (all)	1.1	1.5	1.7	2.2
Outdoor recreation (nonsport)	1.1	1.6	1.7	2.2
Outdoor recreation (limited)	2.1	3.0	3.3	4.7
Boating	3.3	4.8	5.3	7.7
Cycling	2.6	3.0	3.2	2.4
Fishing	0.0	0.0	0.3	– 0.6
Hiking	0.9	1.0	1.4	0.8
Hunting	– 4.5	– 6.4	– 6.8	– 10.9
Running	1.7	2.5	2.8	4.1
Skiing, ice skating, snowboarding	– 16.1	– 23.6	– 26.3	– 35.5
Participating in water sports	5.7	8.2	8.9	12.7

All statistics are percentage changes in participation rates from their weighted sample means

Table 6 Annual welfare impacts of climate change on recreation activities by RCP scenario (consumer surplus estimates in billions of 2016 USD), 2050-2100

	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
Outdoor recreation (all)	7.71	10.68	11.73	15.05
Outdoor recreation (nonsport)	6.66	9.27	10.16	13.19
Outdoor recreation (limited)	5.50	7.97	8.68	12.33
Boating	0.34	0.39	0.41	0.31
Cycling	0.78	1.13	1.25	1.81
Fishing	– 0.01	0.00	0.08	– 0.19
Hiking	0.10	0.11	0.15	0.09
Hunting	– 0.67	– 0.96	– 1.01	– 1.63
Running	1.29	1.91	2.14	3.15
Skiing, ice skating, snowboarding	– 0.91	– 1.34	– 1.49	– 2.00
Participating in water sports	1.93	2.77	2.98	4.24

Notes: All values are consumer surplus changes in billions of US$2016. Positive values indicate welfare gains and negative values indicate welfare losses. Statistics for Outdoor Recreation (all) and Outdoor Recreation (nonsport) are calculated using the mean consumer surplus value for all recreation in the OSU RUVD. Outdoor recreation (limited) is calculated as the sum total of the 8 activity-specific welfare impacts within each climate scenario. Representative Concentration Pathways (RCP) scenarios are reported in Sun et al. (2015)

measure of Δy. We now draw on prior estimates of $\overline{CS}_0$ from the Recreational Use Values Database to complete our calculation of $\Delta\widehat{CS} = \Delta y \times \overline{CS}_0$ (Oregon State University 2016).

Our results are presented in Table 6. Taking an average consumer surplus value for all outdoor recreation, we can approximate a net effect for our three aggregate recreation measures. This value ranges from $5.5 billion to $15.1 billion per year depending on the aggregate variable and climate scenario. Although rough, our estimates for overall outdoor recreation in our most extreme scenario is on the lower end of the estimates of Mendelsohn and Markowski (1999) for 2060 under a 5°C scenario ($14.4 billion to $26.5 billion per year). We use different data and different variation in our data to estimate our weather-response function, a different climate projection and time horizon, and different consumer surplus values, but the agreement in the order of magnitude of these estimates is notable.

For activity-specific results, we find the largest welfare gains for cycling, running, and water sports, totaling (respectively) \$1.3 billion, \$2.1 billion, and \$3.0 billion annually under the RCP 6.0 scenario. Within the same climate scenario, we estimate annual welfare losses for hunting and skiing on the order of \$1.0 billion and \$1.5 billion, respectively. Although we do see welfare losses for these relatively high value winter activities, these losses are offset by gains in other sectors. This is due, in part, to low levels of participation in skiing and hunting compared with more commonplace activities such as cycling, running, and swimming. Adding up our eight activity-specific welfare estimates within each scenario provides an estimate of net aggregate climate welfare impacts on recreation demand (our limited outdoor recreation variable) ranging from \$5.5 to \$12.3 billion.

4 Caveats and Considerations

There are a number of caveats to our analysis, both in terms of the specific empirical exercise on recreation demand as well as the broader framework for valuation.

4.1 Empirical Exercise

While the data exercise from the previous section could be extended on various dimensions, we keep the empirical content compact for the sake of brevity and for clarity in illustrating the overarching conceptual framework. Hence, we view our results as rough estimates rather than precise valuations. The precision of these estimates could be improved along several dimensions with a more refined analysis.

First, we have estimated a relatively simple model to capture the responsiveness of outdoor recreation to changes in weather.[13] Our justification is that our welfare framework is intended to leverage the vast quantity of reduced-form models in the empirical climate damage literature, the majority of which mirror the general specifications of our model in Eqs. 11 and 12. Structural models of recreation participation decisions can be implemented (e.g., Dundas and von Haefen 2020), although the data requirements are steep and the modeling assumptions are relatively strict. By contrast, our approach is based on nationally representative recreation participation decisions across a variety of activities.

Second, we note that our estimates embed a benefits transfer exercise. When drawing on prior estimates of recreation values, we are conducting a (mean) value transfer from the study sites to a much broader policy context: nationwide outdoor recreation activity. Basic value transfers of this sort are prone to bias, and researchers advise using more sophisticated function transfer methods (Boyle et al. 2010; Johnston et al. 2015).[14] We

[13] Along these lines, our empirical exercise uses short-term weather fluctuations to infer responses to climate—in line with the extant literature—but doing so abstracts from the issue of adaptation and may thus differ from future climate impacts (Dell et al. 2014; Massetti and Mendelsohn 2018). A more sophisticated approach, such as long-difference estimates (Burke and Emerick 2016), could capture likely effects of adaptation and may better approximate future climate impacts.

[14] Alternatively, one may consider our empirical exercise to be a function transfer that assumes a semilog form for demand and a quality shift function that does not vary with price. In this light, errors will arise if

acknowledge that our use of more parsimonious value transfers may introduce bias, but we do so to maintain clarity and to focus on the broader conceptual contribution. That said, our average values come from the Recreational Use Values Database (Oregon State University 2016), which catalogs many studies for each activity. Notably, the between-region variation within each activity is relatively low while the overall nationwide averages have small standard errors.[15,16] Thus, we suspect that the bias from basic value transfers will be relatively small compared to some of the broader issues we document below. A second related concern is that we implicitly assume that the underlying consumer surplus values are stable across time, when in fact values may change. This will be of particular concern if preferences or the quality of the amenity itself evolve over time (Englin et al. 2006; Hilger and Englin 2009).

However, this last set of issues stemming from the benefits transfer portion could, in principle, be corrected or improved upon without fundamentally altering the other elements of the analysis. While deeper investigation along these dimensions is beyond the scope of this paper, we see this as a ripe opportunity for future research. In order to generate more precise estimates using this framework, it will be important to improve implementation of the benefits transfer section along multiple dimensions—time, space, and subpopulations—that are relevant for climate change. Incorporating these insights alongside our overarching framework will generate more reliable estimates that are better aligned with the current state-of-the-art in environmental valuation.

4.2 Broader Considerations

In addition to the specific concerns surrounding our empirical recreation analysis, we should also note a number of broader considerations regarding our overarching valuation framework.

For one, in our theoretical analysis, we describe the qualitative conditions under which our approximation yields exact or biased estimates. However, without knowing the true form of the shifted demand function $y_1(\cdot)$, it is difficult to say *quantitatively* how large potential biases may be. Recent work by Dundas and von Haefen (2020) provides evidence on this front. They use detailed data and a two-level nested logit model to estimate how climate change affects fishing participation. Using this information, they generate welfare estimates and compare them to a simple approximation akin to the one described in this paper. They find that the simple approximation will undervalue losses by 15–49%.[17] This is consistent with our finding—that our approximation will tend to underestimate welfare changes—and provides some insight on the potential size of this bias.

Footnote 14 (continued)

actual demand departs from the assumed semilog form or if the quality shift function varies with price. We thank an anonymous reviewer for this suggestion.

[15] See, for example, the summary table in the RUVD summary document.

[16] However, a salient concern would arise if inclusion in the RUVD or initial selection of study site is correlated with the value of the corresponding activity.

[17] The more complicated two-level modeling approach makes it difficult to frame their estimation equation in terms of our modeling approach, unlike the studies using semilog specifications described above. Even so, this study offers interesting insight into the potential size of bias using a wholly different demand specification.

Further, like all long-run projections, we cannot anticipate all changes in the US economy that may affect preferences for recreation or the supply of environmental resources conducive to recreation, especially given the far-reaching effects of climate change. In essence, standard dose-response analyses quantify short-run partial equilibrium changes rather than longer-term general equilibrium ones. We have a limited understanding of how demand for recreation and opportunity costs would change with climate-induced changes in ecosystems or environmental services that complement recreation.[18]

Finally, we should reemphasize that our theoretical analysis focuses on two broad classes of demand functions. Focusing on these cases allows us to generate crisp predictions regarding the error from our welfare framework. Within these two classes of demand, we remain very general in our exposition, both in terms of the specific functional form of the price-quantity relationship and the nature of the quality shift function. However, in principle, one could construct demand curves that shift or deform in any number of ways, including in ways that generate overestimates. Therefore, our predictions are valid *under standard demand assumptions made in the extant literature*, but do not necessarily generalize to more unusual specifications. That being said, we think our analysis examines the specifications that have the greatest practical relevance, i.e., those that are commonly used in empirical demand estimation.

We believe these specifications and underlying assumptions to be plausible. We highlight the linear and semilog demand specifications because of their prevalence and applicability, but conclusions will differ if the true functional form underlying recreation demand differs from the ones we analyze. However, we stress that such concerns are not unique to the present analysis. Any attempt to measure welfare changes—including a vast body of empirical environmental valuation work—will be sensitive to functional form assumptions. The approach we describe is no different than other work in this regard, but it does offer a useful framework for analyzing potential errors that could arise in such cases.

Lastly, we have emphasized throughout that our approximation will tend to yield conservative estimates. But why would a conservative approximation be preferred to an overestimate? In theory, both can beget policies with similar deadweight loss. Consider a benefit-cost analysis for climate policy. Under common practice, nonmarket values for many recreation activities may be omitted entirely for lack of credible studies. Relative to this baseline, including conservative estimates for these missing benefits/damages can push the policy closer to the optimum while continuing to err in the same direction as the status quo. Thus, such a practice will unambiguously improve upon the status quo. In this light, an approximation that overestimates missing benefits/damages might be less desirable. It may pull the policy far from (and in a different direction from) the status quo, which may be less politically viable and attract greater scrutiny and doubt from detractors of the policy. Doing so can also lead to greater error than the status quo.

5 Conclusion

Optimal climate policy requires a comprehensive understanding of climate impacts. In this paper, we have proposed a transparent, simple measure for valuing nonmarket consequences of climate change. This approach draws from and unites two separate literatures on

[18] Dundas and von Haefen (2020) also describe this as a challenge for their analysis.

environmental valuation and reduced-form climate damage estimation. It provides a framework for combining techniques from each to develop much-needed welfare estimates of nonmarket climate damages.

In deriving this approximate welfare measure, we investigate its theoretical properties with an eye toward empirical application. Overall, the accuracy of this measure will depend on the functional form of the demand function that underlies consumer behavior. We show that it provides reliable estimates of consumer surplus changes with predictable errors. For many commonly used functional forms, this approach will yield an exact measure of surplus changes.

We use this approach in two distinct settings to demonstrate its empirical relevance. First, we use the framework to reproduce estimates of environmental value changes from prior research. We find that it matches reported values exactly in many circumstances, and in cases where it does not, the error is predictable in sign and negligible in magnitude. Then, we use it to estimate climate impacts on outdoor recreation. By amalgamating weather and time-use data, climate model projections, and recreational use values, we find that climate change will beget recreation benefits on the order of \$5.5 billion to \$15.1 billion annually. We could obtain even more precise estimates by using more refined benefits transfer techniques and models of consumer choice. However, for this paper, we seek primarily to demonstrate $\Delta\widehat{CS}$ as a conceptual contribution, and we view these refinements and extensions as promising avenues for future research.

Overall, our work fills an important niche in the literature. Reduced-form approaches, using weather fluctuations for econometric identification, are becoming increasingly prevalent as a means for predicting climate impacts. Although such studies are useful for generating precise, causal responses to weather, it is not immediately clear how to translate these behavior changes into welfare implications, a gap that we attempt to fill here for recreation impacts. In this way, our approach bears similarities to the sufficient statistics literature, which seeks to reduce the analytical burden of welfare calculations (see Chetty (2009) for a review). Our analysis has a similar flavor. Although we cannot observe the full, quality-shifted demand curve under climate change, we can still credibly estimate welfare changes using a point estimate of the weather dose-response function. By bridging the gap between reduced-form climate impact research and the extensive literature on environmental valuation, we provide a missing link between nonmarket climate impacts and welfare.

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