

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

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Abstract

Nonmarket damages are largely missing from aggregate climate impacts, although reduced-form research is beginning to quantify these effects. We propose a general, theoretically consistent method for calculating welfare changes for nonmarket climate damages. This approach has minimal data requirements and provides a bridge between standard valuation techniques and reduced-form climate impact research. We elucidate the theoretical properties of our welfare measure, showing that it tends to produce exact or conservative estimates of surplus changes. We illustrate our approach by estimating impacts of climate change on outdoor recreation using nationally representative time-use survey data, which reveals substantial net welfare gains by the end of the century.

Key Words: Nonmarket valuation, climate change, time allocation, leisure demand

JEL codes: J22, Q51, Q54

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1 Introduction

Climate change will have far-reaching effects on 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 to 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).

In terms of decisionmaking, 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 outline a framework for valuing nonmarket impacts of climate change 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 a nonmarket good or service. The dose-response function will inform the magnitude of this shift, and the analyst can then integrate between old and new 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 turns out to be 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 (the one corresponding to the current price). 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. Such an approach is difficult even for market

value estimation because the data requirements are prohibitive, and the challenge is further compounded for nonmarket estimation.

To meet this challenge, we describe and analyze a straightforward measure for the value of climate change impacts on nonmarket consumption. In particular, we propose that welfare changes can be approximated as the product of average consumer surplus under baseline conditions and the estimated climate response. Only two simple pieces of information are necessary: (1) baseline consumer surplus or demand estimates, which can be calculated using benefits transfer techniques or extracted from prior work, and (2) a dose-response function that quantifies induced changes from short-term weather shocks. In this way, we view our approach as a bridge between reduced-form climate damage estimation and theoretically consistent valuation techniques, similar in spirit to a sufficient statistics approach to estimating welfare changes (Chetty, 2009).

This approach is particularly attractive because it is simple to apply and modular in nature, so one can calculate dose-responses and consumer surplus separately, then overlay this approximation to derive welfare estimates. Moreover, the data and information burdens are low, requiring only the original demand curve and a point estimate for the dose-response function. For example, to evaluate climate impacts on recreation demand, one can estimate a climate–recreation dose-response function and couple this with existing measures of recreation surplus from the environmental valuation literature.

Our method for approximating welfare changes is not novel in and of itself, as it is featured in several prior works estimating recreation demand (for example, see Mendelsohn and Markowski (1999) and Loomis and Crespi (1999)). However, this approach has been used primarily as a matter of convenience, given its modest data requirements, and its underlying assumptions and potential shortcomings have been left unexamined. Thus, it is unclear how well it accords with welfare theory, raising questions about the reliability of resultant estimates.

Despite the simplicity of this approximation, we demonstrate that its theoretical soundness through a series of propositions and proofs. We examine the relevant underlying assumptions and analyze potential bias, showing that any bias will tend to attenuate welfare estimates. We also provide several illustrations that highlight the usefulness of our approach. In one application, we use this technique to value recreation site quality changes from an existing study. Our approximation succeeds in reproducing prior estimates with only minimal (0.2%) error, and the direction of bias accords with our theoretical predictions by (modestly) underestimating the true welfare change. In a second application, we use our approach to predict future impacts of climate change on participation in a suite of outdoor recreation activities, ranging from swimming to hiking to skiing. Drawing on nationally representative time-use survey data, 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 warm-weather and cold-weather activities (e.g., swimming versus skiing) will respond differently to the changing climate, we find that future warming will tend to stimulate outdoor recreation on net, consistent with complementary work using alternative data sources and identifying variation (Chan and Wichman, 2017).

This paper brings together two primary lines of inquiry in environmental economics. First, we draw from prior work on environmental valuation. There have been extensive efforts to understand the welfare implications of environmental quality changes, including water quality (e.g., Whitehead et al., 2000; Hanley et al., 2003), recreational amenities (e.g., Eiserwerth et al., 2000; Morey et al., 2002), and cost of access to recreation sites (e.g., Englin and Cameron, 1996).

Second, our research relates closely with the quickly growing literature on estimating weather-response functions to identify climate impacts. Prior work has used this technique to investigate how climate will influence labor productivity (Graff Zivin and Neidell, 2014), agriculture (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Burke and Emmerick, 2016), economic growth (Burke et al., 2015; Dell et al., 2012), 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 translate these impacts into welfare consequences.

Our research lies at the interface of these two literatures. We tie together classic environmental valuation techniques and the more recent wave of reduced-form climate identification research, providing a crucial link between reduced-form estimates and welfare. Our approach has several attractive features. First and foremost, our technique is transparent, easy to understand, and simple to implement. Second, it is versatile and can be applied to a wide range of nonmarket activities. Candidate applications include climate impacts on human health, mortality, and morbidity; outdoor recreation; ecosystems, habitats, and biological diversity; and nonuse values for pristine wildernesses, flora, and fauna. Third, it is readily scalable because it takes a modular approach; it draws from, and can be easily combined with, existing analyses of climate responses and nonmarket values. Lastly, as we show, it has desirable theoretical properties, offering conservative or exact estimates of surplus changes in most standard cases.

In the next section, we model consumer behavior and construct our welfare measure. Using a series of propositions and proofs, we show how our measure performs under common

functional forms for demand. We find that our measure will typically offer conservative or exact estimates of true consumer surplus changes, and we verify this finding by reproducing 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 Basic model

In what follows, we begin from first principles to construct our consumer surplus approximation. The measure can be used for any specification of demand, although its performance will vary depending on the form of demand and the manner in which demand shifts in response to quality changes. We characterize the bias from our measure under several common specifications for demand, and we also provide general propositions that cover two overarching classes of demand models.

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 . We will focus primarily on W as a (vector of) weather variable(s), but it could stand in for any environmental quality dimension that is a weak complement for y , such as air quality, water quality, or availability of fish.¹ We can write the consumer's problem as

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

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 denote 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 . Assume without loss of generality that $W_1 > W_0$ and that W_1 represents more favorable conditions, so that $\bar{p}_0 \leq \bar{p}_1$. For any prevailing price p^* , we can calculate consumer surplus as

¹For helpful discussions of weak complementarity, see Bockstael and McConnell (2007), Freeman et al. (2014), and Phaneuf and Requate (2017).

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

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. The area between these two curves represents ΔCS . Thus, the welfare change is simple to calculate in principle: one need only integrate between the demand curves over the appropriate range. Equivalently, if the “quality shift function” $\sigma(W, p)$ were known—that is, the translation that would transform $y_0(p)$ into $y_1(p)$ according to $y_1(p) = y_0(p) + \sigma(W, p)$ —one could simply integrate that quality shift function from p^* to \bar{p}_1 to measure the surplus change.

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 $y_0(p)$ (or a baseline consumer surplus measure CS_0) and a single point on $y_1(p^*)$ corresponding with current price p^* . The former can be estimated 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.

We propose the following approximation:

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

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 approximate 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 biases that may arise from it.²

Mathematically, this approach is equivalent to approximating the shifted demand function as $\hat{y}_1 = \frac{y_1^*}{y_0^*} y_0(p)$ and the resultant CS 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 an intuitive graphical depiction of \hat{y}_1 and $\widehat{\Delta CS}$.

2.1 Quantifying bias

The bias from our approximation is

$$\begin{aligned}
\widehat{\Delta CS} - \Delta CS &= \frac{y_1^*}{y_0^*} CS_0 - CS_0 - (CS_1 - CS_0) \\
&= \frac{y_1^*}{y_0^*} CS_0 - CS_1.
\end{aligned} \tag{1}$$

²In 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. Our approximation 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.

We will have an exact measure of welfare changes if $CS_1 = \frac{y_1^*}{y_0^*} CS_0$, which will hold with certainty in the special case where

$$y_1(p) = \frac{y_1^*}{y_0^*} y_0(p). \quad (2)$$

Meanwhile, $\widehat{\Delta CS}$ 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 $p^* \leq p \leq \bar{p}_0$,

$$\begin{aligned} y_1(p) &\geq \frac{y_1^*}{y_0^*} y_0(p) \\ \frac{y_1(p)}{y_0(p)} &\geq \frac{y_1^*}{y_0^*}, \end{aligned} \quad (3)$$

By definition, this expression holds with equality at p^* . Thus, to ensure that $\widehat{\Delta CS}$ 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 3 will be satisfied.

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

$$y = f(p) + \sigma(W, p) \quad (4)$$

$$\log(y) = f(p) + \sigma(W, p), \quad (5)$$

where $f(p)$ captures the basic demand (price-quantity) relationship and $\sigma(W, p)$ is a “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.³ 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 Equation 4 as demand “in levels” and Equation 5 as demand “in logs” or a “semilog” specification.

³Recall, however, that $\sigma(W, p)$ can only be estimated at $p = p^*$ given typical data constraints.

The performance of this approximation will depend on the demand specification and the manner in which demand shifts. We will show that our measure *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 our approximation will be exact 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.

Demand in levels

Consider the demand function

$$y(\cdot) = f(p) + \sigma(W, p), \quad (6)$$

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

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

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

$$\begin{aligned} \frac{\partial \sigma}{\partial p} f(p) &> \sigma(W_1, p) f'(p) \\ \frac{p}{\sigma} \frac{\partial \sigma}{\partial p} &> \frac{p}{f(p)} f'(p) \\ \varepsilon_{\sigma, p} &> \varepsilon_{f, p} \end{aligned} \quad (7)$$

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. 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; however, even if it does fail to hold in certain unusual cases, $\widehat{\Delta CS}$ may *still* underestimate true CS changes, and the result will depend on the quantitative tradeoff presented in Figure 3. \square

Proposition 1 applies to any demand function of the form described in Equation 6. 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 $\widehat{\Delta CS}$ 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. \square

Thus, if the demand shift is linear in W , $\widehat{\Delta CS}$ 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 $\widehat{\Delta CS}$

will underestimate 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

$$\begin{aligned} \theta f(p) - f'(p)(\gamma + \theta p) &> 0 \\ \theta f(p) &> f'(p)(\gamma + \theta p) \\ \frac{\theta p}{\gamma + \theta p} &> \frac{p}{f(p)} f'(p) \equiv \varepsilon_{f,p} \end{aligned} \tag{8}$$

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. \square

Notice that as $\theta \rightarrow 0$, 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 Figure 3.

Demand in logs

Consider the general class of semilog demand specifications of the form

$$\log(y) = f(p) + \sigma(W, p), \tag{9}$$

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

Proposition 2. If the quality shift function increases (decreases) in p , then $\widehat{\Delta CS}$ will underestimate (overestimate) ΔCS . If the quality shift function is constant in p , then $\widehat{\Delta CS}$ 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 $\widehat{\Delta CS}$. 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 $\widehat{\Delta CS}$ will underestimate ΔCS . Lastly, if $\frac{\partial \sigma}{\partial p} < 0$, then $\hat{y}_1 > y_1$, and $\widehat{\Delta CS}$ will overestimate ΔCS . \square

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 $\widehat{\Delta CS} = \Delta CS$. If the scaling factor varies in p , then $\widehat{\Delta CS}$ will systematically under- or overestimate ΔCS . It is worth noting that 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).

2.2 A test of our approximation using prior work

Here, we assess our measure $\widehat{\Delta CS}$ by applying it to prior work on valuation of environmental quality changes. First, we should note that most authors implicitly 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, our approximation $\widehat{\Delta CS}$ will be an exact measure of ΔCS if true demand is semilog; meanwhile, our measure 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 $\widehat{\Delta CS} = \Delta y \times \overline{CS}_0$.^{4,5} 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., $\frac{\partial \sigma}{\partial p} \neq 0$). 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.

Whitehead et al. (2000) report consumer surplus values of \$64.14 per trip under current quality and \$84.99 per trip under improved quality, with the predicted number of trips per person rising from 1.88 to 2.49 with the quality change. This amounts to a change in consumer surplus of $\Delta CS = \$20.85$. Given their estimates of the quality-price interaction ($\frac{\partial \sigma}{\partial p} > 0$), we should expect our approximation to yield a downwardly biased estimate of true CS changes. Using our approximation, we calculate $\widehat{\Delta CS} = \frac{2.49}{1.88} 64.14 - 64.14 = \20.81 . This underestimates the true change in surplus by \$0.04, an error of less than 0.2 percent. Thus, not only does this exercise confirm the theoretical results regarding underestimation of true surplus changes, it also demonstrates that this downward bias can be exceedingly small, at least for this particular application.

We should not rely too heavily on any particular empirical application to validate our approach; rather, we intend for the calculations above to be illustrative. Meanwhile, our theoretical framework assures us that bias from our approximation will be minimal in many cases, as it is for the Pamlico Sound application. Specifically, as long as the “shift elasticity” ($\frac{\partial \sigma}{\partial p}$) is sufficiently small, our approximation will tend to give precise estimates that are only modestly biased.

⁴For example, 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 $\widehat{\Delta CS} = \Delta y \times \overline{CS}_0$ according to our framework gives a consumer surplus change of \$11.62 per foot of water level increase, exactly equal to their results (with a slight discrepancy due to rounding error).

⁵This exact match is simply an artifact of the assumed semilog function. We should note that the analyst’s assumption of a semilog function does not guarantee that the semilog function actually matches the underlying data-generating process. In such cases, our theoretical exposition above remains useful as a mean for characterizing the bias that arises from misspecification.

2.3 Two points of clarification

Two finer details underlying our framework merit clarification, as they are frequent sources of confusion and can undermine the theoretical consistency of welfare calculations in practice.

First, we have focused on how climate change or environmental quality changes will affect demand for good y . However, as consumption of y changes, so too will consumption of other goods and activities. At first glance, this appears to complicate welfare calculations. How does welfare change in net? Should we calculate consumer surplus changes for y in addition to all other goods that may be affected by changes in y ? If so, estimation of net welfare changes verges on infeasibility because of the sheer number of activities that must be studied.

Fortunately, CS_0 values taken from prior work already embed the value of other forgone opportunities. For example, consumer surplus values derived from the travel cost method will be net of opportunity costs; travel cost studies model the “price” of recreation as the sum of admission fees, travel expenditures, *and* the value of time. As a virtue of this, it is not necessary to catalog and calculate demand changes for all other potential uses of time; instead, those trade-offs are already accounted for in the reported value of CS_0 . This fact remains a frequent source of confusion, even though it can be established via inspection of the CS calculation. Reassuringly, comparative statics for ΔCS will be equivalent whether CS is defined net of all opportunity costs (including competing activities) or CS is defined net of only market prices. We relegate the full discussion, proof, and illustrative graphs to the Appendix.

The main point here is to dispel concerns about changes in *other activities*. When evaluating the impact of environmental quality changes in W , it is sufficient to focus only on the response in y ; one need not catalog gains and losses from other related activities when applying our approximation $\widehat{\Delta CS}$, as they are implicitly accounted for in the baseline CS_0 value. In short, our approximation accords with standard welfare theory, even though, at face, it appears to ignore the value of substitute activities.⁶

Second, some studies use the average wage rate to approximate welfare changes at the margin. The intuition is that the wage rate captures the earnings from one additional hour of work, so someone who enjoys a recreation activity in lieu of work must derive at least that much pleasure from the recreation activity. Other studies use a fraction of the average wage rate, reasoning that many workers have inflexible hours, so the *marginal* hour of work

⁶These arguments are based on partial equilibrium analysis. In general equilibrium, *ceteris paribus* conditions will fail, potentially introducing bias into our welfare measure. However, this problem is not unique to our approximation; it will apply equally to standard approaches to welfare measurement as well. The issue could be addressed by incorporating a more sophisticated benefits transfer model into our approximation technique to capture other changes, a point that we discuss later in the paper.

is unlikely to earn as much as the average hour.

Although this is sound reasoning at the margin, we would advise against using the wage rate for such calculations, as it is not itself an appropriate welfare measure and should not be used as a direct measure of value. The wage rate is a measure of opportunity costs, not benefits. Therefore, it is a mistake to conflate the wage rate with the amount of benefit derived from an activity. True, the wage rate will be exactly equal to benefits at the margin, but this equivalence will fail to hold elsewhere. Instead, consumer surplus, which measures the consumer’s willingness to pay (demand) in excess of opportunity costs (price), is a more appropriate measure.

3 Empirical application

In the previous section, we tested our approximation 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 bias from our approximation, 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 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 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.

3.1 Data

We use annual 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. For each survey respondent, we calculate the total amount of

time spent engaged in recreational activities. The activities of interest are summarized in Table 1. 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 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. 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. 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 climate (i.e., changes in environmental quality complementary to recreation). 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_{it}^a represent individual i ’s binary choice to participate in recreational activity a at time t . We define our outcome variable as equal to one if time use survey respondents report allocating any amount of time on activity a during their diary day, and zero otherwise.

We specify the following estimating equation

$$R_{it}^a = \alpha + f(W_{it}|\Theta) + \beta X_i + C_i + S_t + \tau_t + \varepsilon_{it} \quad (10)$$

where $f(W_{it}|\Theta)$ is a flexible function of prevailing weather conditions parameterized by Θ , X_i is a vector of individual-specific attributes, C_i are climate-region fixed effects, S_t are season fixed effects, and τ_t are year dummies. The error term ε_{it} is adjusted for correlation within states. We estimate equation 10 using logistic regression weighted to account for the nationally representative survey sampling design.

Reduced-form climate impact studies seek to estimate the coefficient vector Θ , and we follow suit. 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

$$f(W_{it}|\Theta) = \sum_{s=1}^S \gamma_s 1[T_{it} = s] + \sum_{q=S+1}^Q \gamma_q 1[P_{it} = q] + \eta_1 \text{Snowfall}_{it} + \eta_2 \text{Snow Depth}_{it} \quad (11)$$

where the first summation over s indicates a set of S 5° Celsius temperature bins that equal one if observed daily average temperature falls in bin s and zero otherwise. In our primary models, we use average daily temperatures, defined as the simple average of maximum and minimum temperatures. Likewise, the second summation over q indicates a set of Q 10-millimeter precipitation bins that equal one if observed daily precipitation falls in bin q and zero otherwise. Snowfall and Snow Depth linearly summarize snowfall and snow depth patterns in millimeters.⁷

Upon estimating the model in Equation 10, 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 temperature changes and percentage changes in precipitation for the period 2070–2099. Within each climate region, we assume that temperature changes are additively constant and that precipitation changes are proportionally constant. We approximate temperature and precipitation changes at the climate-region level using the multimodel mean statistics for each of the CMIP5 Representative Concentration Pathways (RCP) scenarios reported in Sun et al. (2015). We assume no change in snowfall; 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 4, and these values correspond with W_0 and W_1 from our theoretical model.

⁷Note that the model for “running” did not converge; rather, we report coefficient estimates after 15 iterations.

3.3 Results

3.3.1 Responsiveness to weather

We present coefficients from our primary estimation results in Table 3. As shown, temperatures below the omitted temperature bin (16–20°C) are generally negative 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.

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

To put these coefficients into context, we illustrate the weather-response relationship for each of our activity categories. We center 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 Figures 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, and in warmer bins, confidence intervals overlap with zero, suggesting no significant change with respect to the warmest temperatures. For our limited set of aggregate recreation activities (defined in Table 1), we continue to see positive responses of about 15–25 percent increases in recreation for days above 30°C relative to more moderate temperatures. For precipitation, recreators appear willing to tolerate a small amount of rain 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 Figure 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 mirrors the shape of our nonsport aggregate measure of recreation quite closely, albeit with slightly larger magnitudes on the cold end of the temperature distribution. The results for hiking suggest that hikers dislike extremely hot

temperatures and rainy days but can tolerate cold temperatures fairly well.

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 is almost universally bad for participating in recreational activities. 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 more participation in recreational activities.

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 2070–2099. The four RCP climate scenarios characterize four possible climate futures, with RCP 2.6 being the most optimistic and RCP 8.5 being the most pessimistic. For our purposes, we are interested in the spatially explicit multimodel mean change in temperature and precipitation within each scenario.

By scaling observed temperature and precipitation by anticipated changes in 2070–2099, we can predict likely changes in recreation participation using the estimated relationships in Table 3. First, we predict participation under 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 outdoor recreation, which corresponds with Δy from our welfare estimation model. 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 2070–2099 on the

order of 1.6–9.6 percent. This result is consistent with the central estimate of a 5.5 percent increase in outdoor recreation that Chan and Wichman (2017) find using bike-share micro data.

Climate impacts for specific activities are mixed. For running, cycling, and water sports, we estimate large positive impacts of climate change on participation. For hiking, hunting, and skiing, we see increasingly negative impacts on participation. The effects for boating 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 Equation 10 and anticipated changes in weather due to climate. To do so, we simply calculate the expected change in recreation participation in person days per year and multiply this value by average consumer surplus (CS) 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 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, 2006).

Our results are presented in Table 6. Taking an average CS value for all outdoor recreation, we can approximate a net effect for our aggregate recreation measures. This value ranges from \$9.8 billion to \$37.6 billion per year depending on the variable and climate scenario. Of note is how closely our estimate for all outdoor recreation in RCP 4.6 is to the estimates of Chan and Wichman (2017) for 2060 (\$20.7 billion per year) and Mendelsohn and Markowski (1999) for 2060 under a 5°C scenario (\$14.4 billion to \$26.5 billion per year), even though 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. Further, we value the extensive margin of the participation decision, whereas Chan and Wichman (2017) value the intensive margin for a similar set of activities. Despite these differences, our projected welfare changes are quite similar.

For activity-specific results, we find the largest welfare gains for cycling, running, and water sports, totaling (respectively) \$1.8 billion, \$4.5 billion, and \$4.6 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 \$1.6 billion and \$1.4 billion, respectively. Although we do see welfare losses for relatively high value winter sports, these losses are offset entirely 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 ranging from \$3.6 to \$12.4 billion.

Building off our exercise here and existing results in the literature, we posit that climate change will have large net welfare benefits for outdoor recreation in the continental United States by the end of the century.

3.3.4 Caveats

Our empirical exercise is intended to illustrate the value of our conceptual contribution from Section 2. Because of this, we have made several simplifying assumptions for the sake of transparency.

First, we have estimated a relatively simple model to capture the responsiveness of outdoor recreation to changes in weather. 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 Equations 10 and 11. Structural models of recreation participation decisions can be implemented (e.g., Dundas and von Haefen, 2017), although the data requirements are large and the modeling assumptions are relatively strict. Our approach, on the other hand, provides a theoretically consistent way to approximate welfare impacts of climate change on nonmarket activities with few a priori assumptions.

Second, our climate projection is somewhat rudimentary. Although we match the averages of temperature and precipitation with geographic specificity for commonly used climate model ensembles under the full range of scenarios, we do not capture seasonal changes or changes in snowfall, humidity, and other elements important for recreation decisions. For the purposes of this paper, we view these concerns as second order. Our analysis could be augmented by a more detailed climate projection, but it is unlikely that the magnitude of our primary results would change in a meaningful way relative to the host of other uncertainties inherent in 50- to 70-year climate projections.

Third, 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). We 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. Investigating how to incorporate function transfers into our welfare framework would be an interesting avenue for future work.

Finally, like all long-run projections, we cannot anticipate all changes in the US econ-

omy that may affect preferences for recreation or the supply of environmental resources conducive to recreation. Notably, we have a limited understanding of how demand for recreation would change with climate-induced changes in ecosystems or environmental services that complement recreation. Further, advances in technology may reduce the welfare costs of climate change on outdoor recreation. For example, advances in snow-making technology could substantially reduce the losses borne by the skiing industry that we estimate here. Many of these challenges harken back to the seminal work of Krutilla (1967) and warrant further exploration. We leave those deep questions for future research. Notably, our framework here provides a theoretically consistent way to value those very changes in these nonmarket goods and services.

4 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. Our approach draws from and unites two separate literatures on environmental valuation and reduced-form climate damage estimation. It provides a framework for combining techniques and findings from each to develop much-needed welfare estimates of nonmarket climate damages.

In deriving our welfare measure, we investigate its theoretical properties with an eye toward empirical application. Overall, the accuracy of our 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 bias. For many commonly used functional forms, our approach will yield an exact measure of surplus changes.

We use our 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 bias 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 \$9.8 billion to \$37.6 billion annually. We could obtain even more precise estimates by using more refined climate projections, benefits transfer techniques, and additional models of consumer choice. However, for this paper, we seek primarily to demonstrate our measure 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 climate change, it is not immediately clear how to translate these behavior changes into welfare implications, a gap that we attempt to fill here. 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.

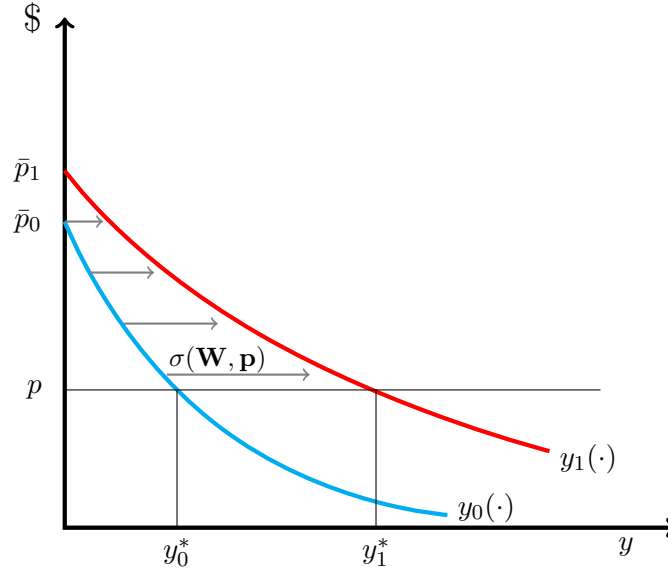
References

- Bockstael, Nancy E. and Kenneth E. McConnell**, “Implementing Weak Complementarity,” in “Environmental and Resource Valuation with Revealed Preferences: A Theoretical Guide to Empirical Models,” Dordrecht: Springer Netherlands, 2007, pp. 67–99.
- Boyle, Kevin J., Nicolai V. Kuminoff, Christopher F. Parmeter, and Jaren C. Pope**, “The Benefit-Transfer Challenges,” *Annual Review of Resource Economics*, 2010, 2 (1), 161–182.
- Burke, Marshall and Kyle Emerick**, “Adaptation to climate change: Evidence from US agriculture,” *American Economic Journal: Economic Policy*, 2016, 8 (3), 106–140.
- , **Solomon M. Hsiang, and Edward Miguel**, “Global non-linear effect of temperature on economic production,” *Nature*, 2015, 527 (7577), 235–239.
- Chan, Nathan W. and Casey J. Wichman**, “The Effects of Climate on Leisure Demand: Evidence from North America,” Working Paper 17-20, Resources for the Future 2017.
- Chetty, Raj**, “Sufficient Statistics for Welfare Analysis: A Bridge Between Structural and Reduced-Form Methods,” *Annual Review of Economics*, 2009, 1 (1), 451–488.
- Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken**, “Temperature shocks and economic growth: Evidence from the last half century,” *American Economic Journal: Macroeconomics*, 2012, 4 (3), 66–95.
- , —, and —, “What do we learn from the weather? The new climate–economy literature,” *Journal of Economic Literature*, 2014, 52 (3), 740–798.
- Deryugina, Tatyana and Solomon Hsiang**, “The Marginal Product of Climate,” Working Paper 24072, National Bureau of Economic Research November 2017.

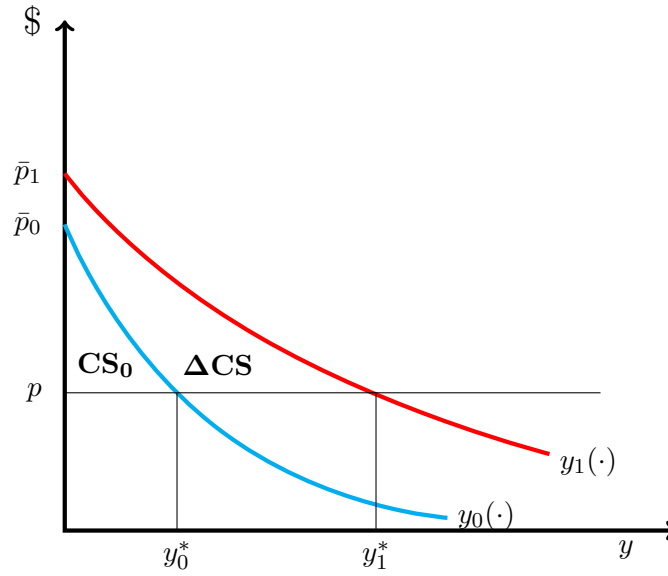
- Deschênes, Olivier and Michael Greenstone**, “The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather,” *American Economic Review*, March 2007, 97 (1), 354–385.
- Dundas, Steven J. and Roger H. von Haefen**, “Weather effects on the demand for coastal recreational fishing: implications for a changing climate,” Working Paper 2017.
- Eiswerth, Mark E., Jeffrey Englin, Elizabeth Fadali, and W. Douglass Shaw**, “The value of water levels in water-based recreation: A pooled revealed preference/contingent behavior model,” *Water Resources Research*, 2000, 36 (4), 1079–1086.
- Englin, Jeffrey and Trudy Ann Cameron**, “Augmenting travel cost models with contingent behavior data,” *Environmental and Resource Economics*, Mar 1996, 7 (2), 133–147.
- Eom, Young-Sook and Douglas M. Larson**, “Improving environmental valuation estimates through consistent use of revealed and stated preference information,” *Journal of Environmental Economics and Management*, 2006, 52 (1), 501 – 516.
- Freeman, A. Myrick, Joseph A. Herriges, and Catherine L. Kling**, *Welfare Measures: Empirical Assessment*, 3 ed., New York, NY: RFF Press, 2014.
- Graff Zivin, Joshua and Matthew Neidell**, “Temperature and the allocation of time: Implications for climate change,” *Journal of Labor Economics*, 2014, 32 (1), 1–26.
- Hanley, Nick, David Bell, and Begona Alvarez-Farizo**, “Valuing the Benefits of Coastal Water Quality Improvements Using Contingent and Real Behaviour,” *Environmental and Resource Economics*, Mar 2003, 24 (3), 273–285.
- Hofferth, Sandra L., Sarah M. Flood, and Matthew Sobek**, “American Time Use Survey Data Extract Builder: Version 2.6,” 2017.
- Johnston, Robert J., John Rolfe, Randall S. Rosenberger, and Roy Brouwer**, “Introduction to Benefit Transfer Methods,” in “Benefit Transfer of Environmental and Resource Values,” Dordrecht: Springer, 2015, pp. 19–59.
- Kling, Catherine L.**, “The Importance of Functional Form in the Estimation of Welfare,” *Western Journal of Agricultural Economics*, 1989, 14 (1), 168–174.
- Krutilla, John V.**, “Conservation Reconsidered,” *The American Economic Review*, 1967, 57 (4), 777–786.
- Loomis, John and John Crespi**, “Estimated effects of climate change on selected outdoor recreation activities in the United States,” in Robert Mendelsohn and James E. Neumann, eds., *The Impact of Climate Change on the United States Economy*, Cambridge:, 1999, chapter 11, pp. 289–314.
- Mendelsohn, Robert and Marla Markowski**, “The impact of climate change on outdoor recreation,” in Robert Mendelsohn and James E. Neumann, eds., *The Impact of Climate Change on the United States Economy*, Cambridge:, 1999, chapter 10, pp. 267–288.

- Morey, Edward R.**, “What is consumers surplus per day of use, when is it a constant independent of the number of days of use, and what does it tell us about consumers surplus?,” *Journal of Environmental Economics and Management*, 1994, *26* (3), 257 – 270.
- , **Terry Buchanan, and Donald M. Waldman**, “Estimating the benefits and costs to mountain bikers of changes in trail characteristics, access fees, and site closures: choice experiments and benefits transfer,” *Journal of Environmental Management*, 2002, *64*, 411 – 422.
- Oregon State University**, “Recreational Use Values Database,” 2006. data accessed: 4 September 2017, <http://recvaluation.forestry.oregonstate.edu/>.
- Phaneuf, Daniel and Till Requate**, *Revealed Preference Methods*, 1 ed., New York, NY: Cambridge University Press, 2017.
- Schlenker, Wolfram and Michael J. Roberts**, “Nonlinear temperature effects indicate severe damages to US crop yields under climate change,” *Proceedings of the National Academy of Sciences*, 2009, *106* (37), 15594–15598.
- Sun, L., K. E. Kunkel, L. E. Stevens, A. Buddenberg, J. G. Dobson, and D. R. Easterling**, “Regional Surface Climate Conditions in CMIP3 and CMIP5 for the United States: Differences, Similarities, and Implications for the U.S. National Climate Assessment,” 2015. NOAA Technical Report NESDIS 144, 111.
- Whitehead, John C., Timothy C. Haab, and Ju-Chin Huang**, “Measuring recreation benefits of quality improvements with revealed and stated behavior data,” *Resource and Energy Economics*, 2000, *22* (4), 339 – 354.

Figures



(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 .

Figure 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.

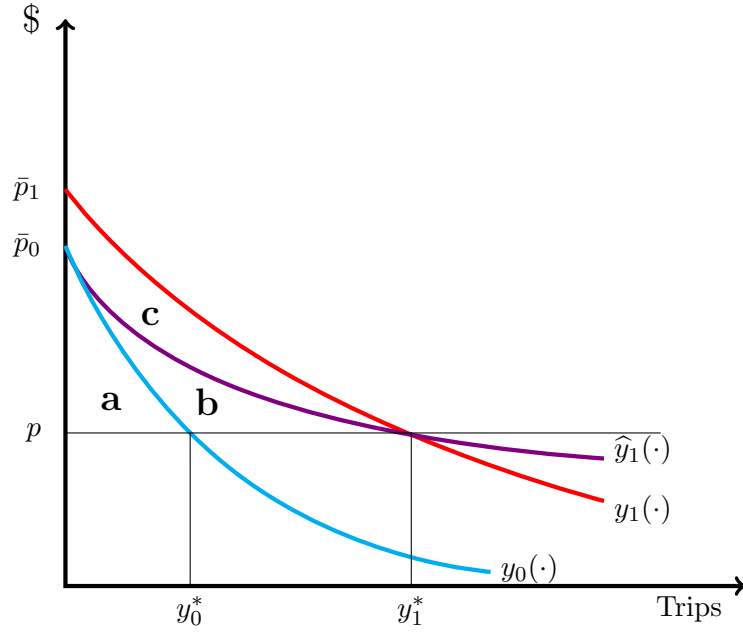


Figure 2: Exact CS change compared with authors' approximation. Changing weather shifts demand from $y_0(\cdot)$ to $y_1(\cdot)$. The original consumer surplus is $CS_0 = a$ but the new consumer surplus is $CS_1 = a + b + c$, yielding $\Delta CS = b + c$. In the absence of the full demand curve, we approximate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

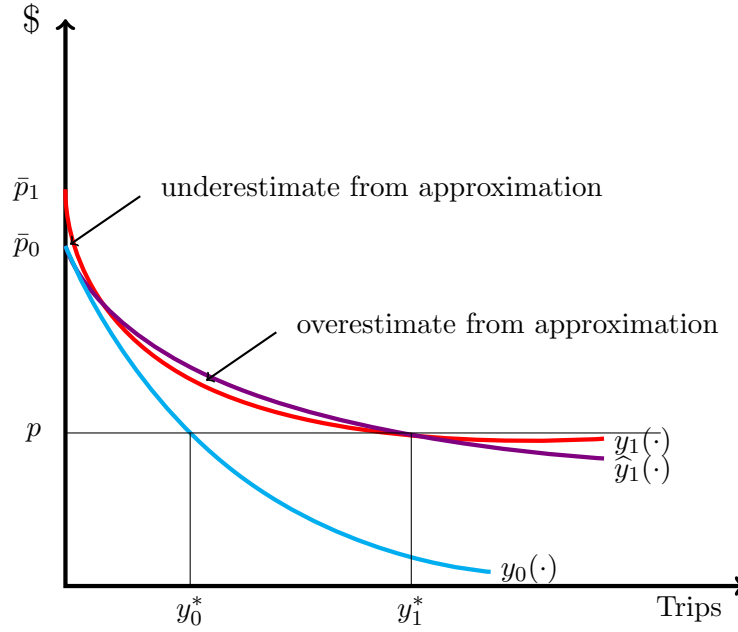
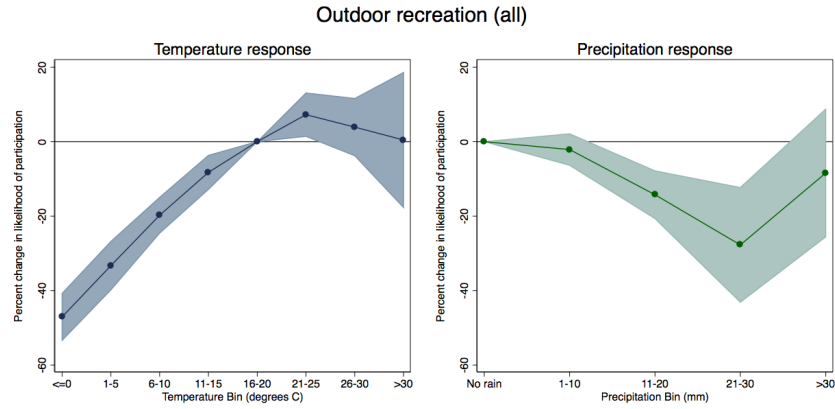
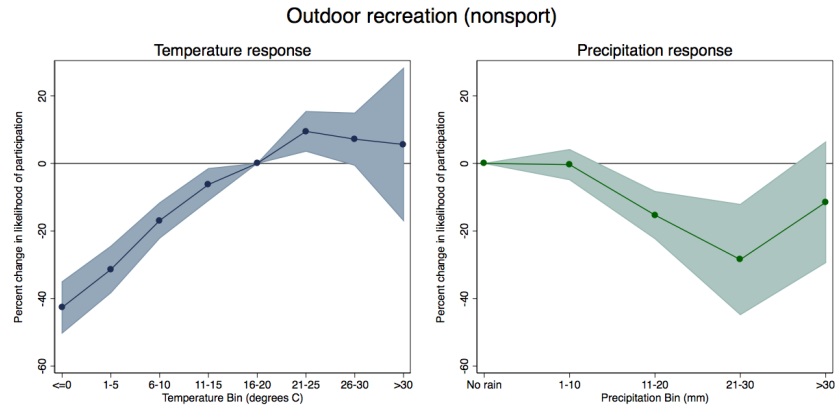


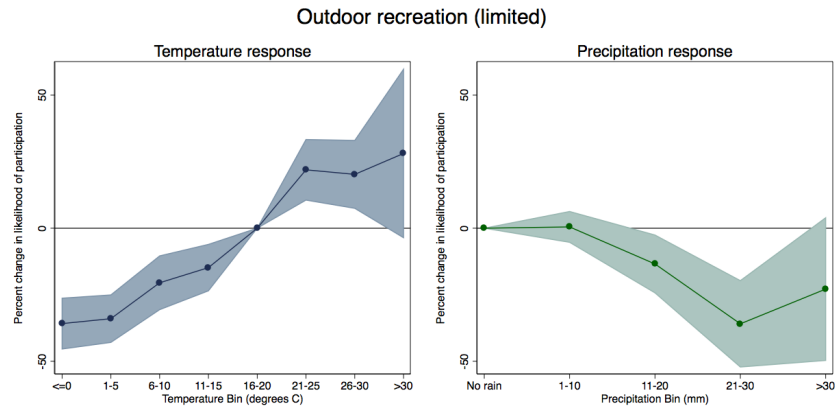
Figure 3: Welfare change from weather changes. Changing weather shifts demand from $y_0(\cdot)$ to $y_1(\cdot)$. Approximating the change in consumer surplus as $\Delta CS \approx \frac{y_1^*}{y_0^*} CS_0 - CS_0$ may have countervailing biases when there is an interaction between the demand shift and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



(a) Percentage change (and 95% CI) in participation for all outdoor recreation due to changes in daily average temperatures and daily precipitation



(b) Percentage change (and 95% CI) in participation for nonsport outdoor recreation due to changes in daily average temperatures and daily precipitation



(c) Percentage change (and 95% CI) in participation for limited outdoor recreation due to changes in daily average temperatures and daily precipitation

Figure 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.

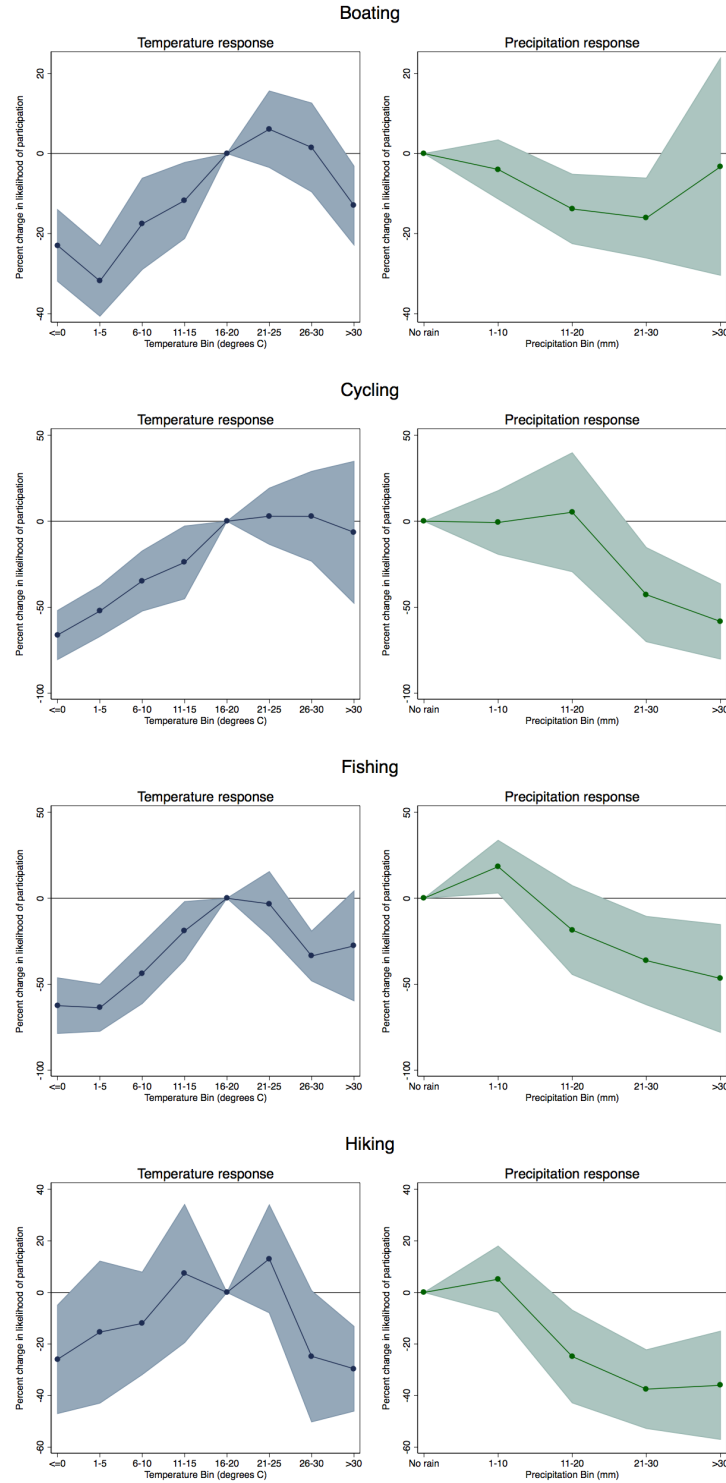


Figure 5: Activity-specific relationship between recreation and daily weather. Percentage changes (and 95% CI) are calculated as the marginal effect from logistic regression, centered at the sample mean of each covariate, divided by the weighted sample mean of the dependent variable.

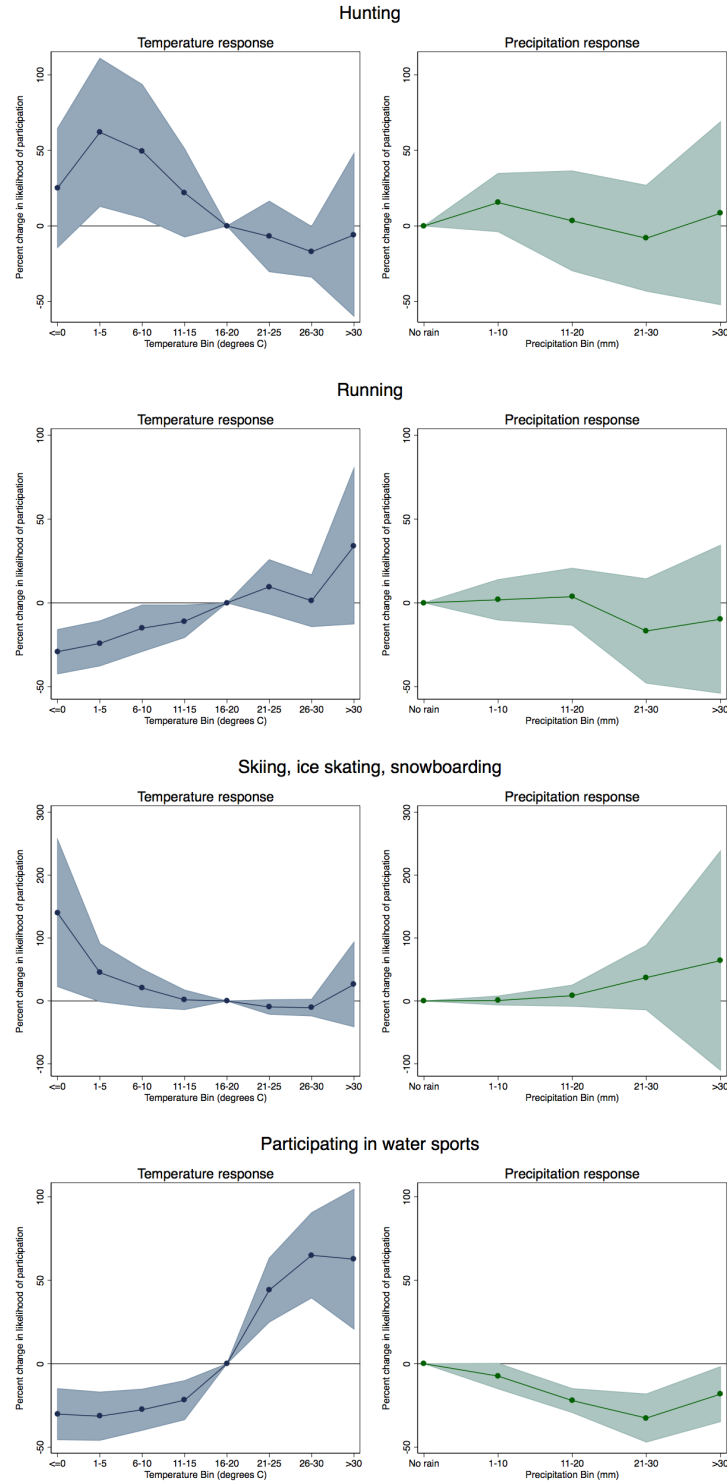


Figure 5 (cont.): Activity-specific relationship between recreation and daily weather. Percentage changes (and 95% CI) are calculated as the marginal effect from logistic regression, centered at the sample mean of each covariate, divided by the weighted sample mean of the dependent variable.

Tables

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

Notes: 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.

Table 2: Summary statistics for participation in recreational activities

	Mean	SD	Average 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	
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	3,464	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	3,340	107.49	27.79

Notes: 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.

Table 3: Estimation results from logistic regression

	Outdoor recreation			Cycling	Boating	Fishing	Hiking	Hunting	Running	Skiing	Watersports
	(all)	(nonsport)	(limited)								
Temp. Bin: <0°C	-0.71 (0.06)	-0.62 (0.07)	-0.55 (0.09)	-1.50 (0.26)	-1.93 (0.66)	-1.49 (0.30)	-0.77 (0.44)	0.56 (0.36)	-0.56 (0.16)	2.79 (0.44)	-0.73 (0.24)
Temp. Bin: 1-5°C	-0.47 (0.06)	-0.43 (0.06)	-0.52 (0.09)	-1.04 (0.22)	-3.80 (1.03)	-1.54 (0.26)	-0.40 (0.44)	1.08 (0.28)	-0.44 (0.15)	1.67 (0.44)	-0.77 (0.24)
Temp. Bin: 6-10°C	-0.26 (0.04)	-0.22 (0.04)	-0.28 (0.08)	-0.58 (0.18)	-1.16 (0.50)	-0.84 (0.22)	-0.30 (0.28)	0.94 (0.30)	-0.26 (0.13)	1.07 (0.49)	-0.63 (0.17)
Temp. Bin: 11-15°C	-0.10 (0.03)	-0.08 (0.03)	-0.20 (0.06)	-0.37 (0.19)	-0.66 (0.31)	-0.31 (0.16)	0.16 (0.27)	0.51 (0.28)	-0.18 (0.08)	0.14 (0.58)	-0.47 (0.15)
Temp. Bin: 21-25°C	0.09 (0.03)	0.11 (0.03)	0.26 (0.06)	0.04 (0.11)	0.26 (0.19)	-0.05 (0.14)	0.27 (0.20)	-0.21 (0.38)	0.14 (0.12)	-1.02 (0.77)	0.66 (0.12)
Temp. Bin: 25-30°C	0.05 (0.05)	0.08 (0.05)	0.23 (0.07)	0.04 (0.18)	0.07 (0.25)	-0.61 (0.18)	-0.72 (0.52)	-0.59 (0.35)	0.02 (0.12)	-1.33 (1.29)	0.85 (0.12)
Temp. Bin: >30°C	0.01 (0.11)	0.07 (0.13)	0.31 (0.16)	-0.09 (0.32)	-0.88 (0.47)	-0.51 (0.38)	-1.05 (0.47)	-0.18 (0.90)	0.43 (0.25)	1.15 (0.91)	0.78 (0.19)
Prcp. Bin: 1-10mm	-0.03 (0.03)	-0.00 (0.03)	0.01 (0.04)	-0.01 (0.13)	-0.18 (0.16)	0.28 (0.12)	0.12 (0.15)	0.46 (0.31)	0.03 (0.10)	0.06 (0.30)	-0.13 (0.07)
Prcp. Bin: 11-20mm	-0.18 (0.05)	-0.20 (0.05)	-0.18 (0.08)	0.07 (0.23)	-0.92 (0.40)	-0.31 (0.26)	-0.76 (0.42)	0.09 (0.43)	0.06 (0.13)	0.53 (0.43)	-0.50 (0.11)
Prcp. Bin: 21-30mm	-0.39 (0.13)	-0.40 (0.14)	-0.59 (0.17)	-0.87 (0.43)	-1.28 (0.75)	-0.74 (0.38)	-1.71 (1.00)	-0.26 (0.64)	-0.30 (0.33)	1.40 (0.57)	-0.90 (0.29)
Prcp. Bin: >30mm	-0.11 (0.12)	-0.15 (0.12)	-0.34 (0.23)	-1.57 (0.67)	-0.16 (0.74)	-1.11 (0.67)	-1.59 (1.02)	0.21 (0.70)	-0.16 (0.41)	1.83 (1.23)	-0.41 (0.23)
Snowfall (mm0	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.01 (0.00)	-0.01 (0.02)	-0.01 (0.01)	-0.02 (0.02)	0.01 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Snow depth (mm)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Edu ≥ college (=1)	0.31 (0.02)	0.40 (0.02)	0.35 (0.04)	0.71 (0.08)	0.14 (0.15)	-0.78 (0.13)	0.98 (0.19)	-1.29 (0.20)	0.61 (0.08)	0.72 (0.19)	0.32 (0.07)
Race nonwhite (=1)	-0.17 (0.05)	-0.24 (0.07)	-0.58 (0.11)	-0.41 (0.10)	-1.37 (0.43)	-0.34 (0.10)	-1.14 (0.26)	-1.30 (0.35)	-0.31 (0.11)	-1.36 (0.34)	-0.83 (0.20)
Age ≥ 70 (=1)	-0.06 (0.05)	-0.03 (0.05)	-0.54 (0.10)	-0.22 (0.19)	-1.54 (0.33)	-0.67 (0.20)	-0.98 (0.33)	-1.16 (0.35)	-1.25 (0.36)	-0.32 (1.13)	-0.31 (0.13)
Income <25k (=1)	-0.27 (0.06)	-0.20 (0.06)	-0.39 (0.07)	-0.55 (0.18)	-0.68 (0.34)	-0.38 (0.20)	-0.73 (0.27)	0.77 (0.31)	-0.35 (0.13)	-0.38 (0.63)	-0.41 (0.10)
Income 25-50k (=1)	-0.15 (0.05)	-0.14 (0.05)	-0.12 (0.07)	-0.33 (0.19)	0.03 (0.27)	-0.28 (0.16)	0.07 (0.24)	1.28 (0.29)	-0.20 (0.13)	0.50 (0.51)	-0.13 (0.12)
Income 50-75k (=1)	-0.00 (0.05)	-0.03 (0.06)	0.14 (0.07)	-0.14 (0.15)	-0.01 (0.32)	-0.09 (0.18)	0.06 (0.24)	1.07 (0.29)	0.20 (0.12)	0.48 (0.55)	0.27 (0.14)
Income 75-100k (=1)	0.10 (0.04)	0.08 (0.05)	0.24 (0.09)	0.01 (0.18)	0.44 (0.28)	-0.03 (0.22)	-0.55 (0.28)	1.34 (0.30)	0.36 (0.15)	0.64 (0.50)	0.32 (0.16)
Income >100k (=1)	0.27 (0.05)	0.21 (0.05)	0.40 (0.08)	0.15 (0.18)	0.48 (0.27)	-0.29 (0.22)	0.16 (0.35)	0.93 (0.37)	0.62 (0.13)	0.49 (0.50)	0.42 (0.13)
Employed (=1)	-0.55 (0.03)	-0.34 (0.03)	-0.36 (0.04)	-0.46 (0.14)	0.22 (0.15)	-0.08 (0.11)	-0.35 (0.24)	1.03 (0.19)	-0.38 (0.08)	-0.44 (0.29)	-0.62 (0.08)
Retired (=1)	-0.05 (0.04)	0.17 (0.04)	-0.46 (0.07)	-0.14 (0.14)	0.53 (0.24)	0.26 (0.21)	0.01 (0.37)	0.94 (0.40)	-1.71 (0.23)	-2.12 (0.93)	-0.45 (0.10)
Observations	171,780	171,780	171,780	171,780	171,319	171,780	171,780	171,319	171,780	171,780	171,780
Pseudo-R sq.	0.0324	0.0318	0.0504	0.0491	0.124	0.0551	0.100	0.129	0.0612	0.216	0.111
Log pseudolikelihood	-4.0e+11	-3.6e+11	-2.0e+11	-3.9e+10	-1.3e+10	-3.3e+10	-1.3e+10	-1.8e+10	-8.2e+10	-7.3e+09	-7.5e+10

Notes: Dependent variable is whether a household participated in a given activity. All models include climate-region fixed effects, season fixed effects, 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.

Table 4: Temperature and precipitation change projections by climate region for 2070–2099

Climate region:	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. (%)
Ohio Valley	1.4	2.5	2.5	5.0	2.8	5.0	4.7	7.5
Upper Midwest	1.4	5.0	2.8	7.5	3.1	7.5	5.3	7.5
Northeast	1.4	7.5	2.5	7.5	3.1	7.5	5.0	12.5
Northwest	1.4	2.5	2.2	2.5	3.1	2.5	4.2	2.5
South	0.8	0.0	1.9	-2.5	2.5	-5.0	4.4	-7.5
Southeast	0.8	5.0	1.9	7.5	2.5	2.5	3.6	2.5
Southwest	1.4	0.0	3.1	-2.5	2.8	-5.0	5.0	-7.5
West	1.1	0.0	2.2	-2.5	2.5	-2.5	4.2	-2.5
Northern Rockies and Plains	1.4	2.5	2.5	2.5	3.1	2.5	4.7	2.5

Notes: Temperature changes (in degrees C) and precipitation changes (in percentages) are applied uniformly within the climate region. Climate-region averages are approximated as the multimodel mean from CMIP5 running the given scenario. Representative Concentration Pathways (RCP) scenarios are reported in Sun et al. (2015).

Table 5: Climate impacts on activity-specific participation rates by RCP scenario, 2070–2099

	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
Outdoor recreation (all)	1.6	3.0	3.5	5.3
Outdoor recreation (nonsport)	1.6	3.0	3.6	5.6
Outdoor recreation (limited)	2.6	5.0	6.0	9.6
Boating	1.4	0.8	0.2	-3.5
Cycling	3.5	6.3	7.5	11.3
Fishing	0.8	1.4	1.8	2.6
Hiking	-0.9	-2.8	-2.9	-6.3
Hunting	-4.6	-9.0	-10.8	-17.3
Running	2.2	4.7	5.9	10.3
Skiing, ice skating, snowboarding	-11.5	-21.1	-25.0	-37.5
Participating in water sports	6.3	11.6	13.6	20.5

Notes: All statistics are percentage changes in participation rates from their weighted sample means. Representative Concentration Pathways (RCP) scenarios are reported in Sun et al. (2015).

Table 6: Annual welfare impacts of climate change on recreation activities by RCP scenario, 2070–2099 (consumer surplus estimates in billions of 2016 USD)

	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
Outdoor recreation (all)	11.43	20.93	24.82	37.56
Outdoor recreation (nonsport)	9.79	18.11	21.75	33.33
Boating	0.19	0.11	0.02	-0.46
Cycling	0.82	1.47	1.76	2.65
Fishing	0.24	0.43	0.55	0.81
Hiking	-0.10	-0.31	-0.32	-0.70
Hunting	-0.69	-1.35	-1.62	-2.59
Running	1.69	3.60	4.49	7.87
Skiing, ice skating, snowboarding	-0.65	-1.20	-1.42	-2.12
Participating in water sports	2.14	3.94	4.61	6.95
Outdoor recreation (limited)	3.62	6.69	8.08	12.41

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).

A Appendix for Online Publication

A.1 Quantifying welfare changes from other goods

Consider a consumer with utility $U(x, y, z; W)$, where x is a numeraire, y is the activity of interest, and z is an alternative activity. The consumer faces a standard money budget ($x + p_y y + p_z z = I$) as well as a time budget ($y + z = \tau$, where τ is total available time). To simplify exposition, consider the linearly separable form $U(x, y, z; W) = x + f(y) + g(z)$. Then the consumer's maximization problem in Lagrangian form is

$$\max_{x, y, z} U(x, y, z; W) - \lambda_1(x + p_y y + p_z z - I) - \lambda_2(y + z - \tau),$$

which gives the first-order conditions

$$\lambda_2 = f'(y) - p_y = g'(z) - p_z$$

along with the money and time budget constraints. Given the quasilinear form of utility, $MB_y(y) \equiv f'(y)$ and $MB_z(z) \equiv g'(z)$ are the inverse demand (marginal benefit) functions for y and z , respectively.

Now we turn to calculating changes in consumer welfare from a change in W . We can do so in either of two ways.

Calculating consumer surplus: Method 1

The first is to directly measure the consumer surplus for each activity, y and z , and sum across the activities. That is, we could calculate

$$\begin{aligned} CS &= CS_y + CS_z \\ &= \int_0^{y^*} MB_y(y) - p_y dy + \int_0^{z^*} MB_z(z) - p_z dz. \end{aligned} \tag{A.1}$$

Figure A.1 provides an intuitive graphical depiction of how consumer surplus can be calculated independently for the two markets, with the overall consumer surplus being the sum of the two. The binding time constraint creates an opportunity cost of time, so consumption does not follow the standard $p = MB$ rule.

Figure A.2 offers a different but equivalent graphical representation, where the demand curve for z is transformed into a function of y using the correspondence between y and z implied by the time budget; moreover, the curves shown are shifted so that they represent the marginal benefits *net of* price. As such, the net demand curves and consumer surplus areas can be visualized on the same axes. Increases or decreases in available time will cause a horizontal translation of the demand curve for z . Intuitively, the equilibrium occurs where the net demand curves cross, adhering to the equimarginal principle.

A change in W will yield a change in welfare $\Delta CS = CS_1 - CS_0$. This will have multiple effects: it will shift $MB_y(\cdot)$, which will in turn change the optimal y^* and z^* to y' and z' , thus altering the bounds of the integral above. For empirical applications, one must observe prices for y and z and measure how y^* and z^* each respond to changes in W to calculate consumer surplus in this way.

Calculating consumer surplus: Method 2

As an alternative measure of surplus, we can focus only on y , accounting for z as an implicit cost to consuming y . That is, for each unit of y consumed, the individual must forgo a unit of z because of the time constraint. Then the full cost of consuming y is $p_y + \widehat{MB}_z(y) - p_z$, where the first term is the monetary cost (price) and the later two terms constitute the surplus from forgone units of z as a function of y .

In this case, we can calculate consumer surplus as

$$\begin{aligned} CS &= \int_0^{y^*} MB_y(y) - (p_y + \widehat{MB}_z(y) - p_z) dy \\ &= \int_0^{y^*} MB_y(y) - p_y dy - \int_0^{y^*} \widehat{MB}_z(y) - p_z dy. \end{aligned} \quad (\text{A.2})$$

A graphical representation is provided in Figure A.3. Here, the full opportunity cost of consuming a unit of y is the price p_y plus $\widehat{MB}_z(y) - p_z$, the forgone surplus from a unit of z . The overall consumer surplus will be the area below the demand curve for y and above the full opportunity cost curve.

To use this calculation in empirical applications, one needs information only on the opportunity cost of time and the response of y^* to changes in W ; this formulation captures z^* implicitly via the time constraint.

Calculating consumer surplus: Synthesis

We can now compare the two different methods for calculating consumer surplus. Let us return to Expression A.1. Taking advantage of $y + z = \tau$, we can employ a change of variables to write $\widehat{MB}_z(y)$, so that the (inverse) demand for z is a function of y , and therefore on the same axes as the $MB_y(y)$ function. To do so, we define $z = \tau - y$ and $\widehat{MB}_z(y) = MB_z(\tau - y)$, giving $dz = -dy$ and limits of integration τ and y^* .

$$CS = CS_y + CS_z \quad (\text{A.3})$$

$$\begin{aligned} &= \int_0^{y^*} MB_y(y) - p_y dy + \int_0^{z^*} MB_z(z) - p_z dz \\ &= \int_0^{y^*} MB_y(y) - p_y dy + \int_{y^*}^{\tau} \widehat{MB}_z(y) - p_z dy. \end{aligned} \quad (\text{A.4})$$

Note that the first term in Expression A.2 is identical to the first term in Expression A.3. However, the second terms of these expressions differ by a normalization. Thus, calculating consumer surplus in these two ways will yield different quantitative results. This fact is readily apparent when Figures A.2 and A.3 are examined side by side.

At first glance, this may seem problematic. However, it is not critical that the consumer surplus calculations match up exactly; rather, what is important is that the *changes* in consumer surplus (i.e., comparative statics) with respect to W are consistent across the two methods.

We seek to verify that ΔCS is the same regardless of which method we use to calculate consumer surplus. In comparing the two formulations of CS , we can dispose of the first

term $\int_0^{y^*} MB_y(y) - p_y dy$ because it is the same in each instance. Thus, we only need to verify the (change in) the second term is identical across cases. Letting Δ imply a change from y^* to y' , we have:

$$\begin{aligned} \Delta \left[\int_{y^*}^{\tau} \widehat{MB}_z(y) - p_z dy \right] &= -\Delta \left[\int_0^{y^*} \widehat{MB}_z(y) - p_z dy \right] \\ \left[\int_{y'}^{\tau} \widehat{MB}_z(y) - p_z dy \right] - \left[\int_{y^*}^{\tau} \widehat{MB}_z(y) - p_z dy \right] &= \\ \left[\int_0^{y^*} \widehat{MB}_z(y) - p_z dy \right] - \left[\int_0^{y'} \widehat{MB}_z(y) - p_z dy \right] &= \\ \widehat{TB}_z(y^*) - \widehat{TB}_z(y') + p_z y' - p_z y^* &= \widehat{TB}_z(y^*) - \widehat{TB}_z(y') + p_z y' - p_z y^*, \end{aligned}$$

where $\widehat{TB}_z(\cdot)$ is the total benefit function, which is simply the integral of $\widehat{MB}_z(\cdot)$ from 0 to the specified value of y . Thus, either way of calculating consumer surplus changes will give equivalent results. Figure A.4 illustrates this point graphically. For many applications, the CS_0 value reported in the literature is calculated net of opportunity costs, implying that Method 2 can be used, and explicit treatment of z is not necessary.

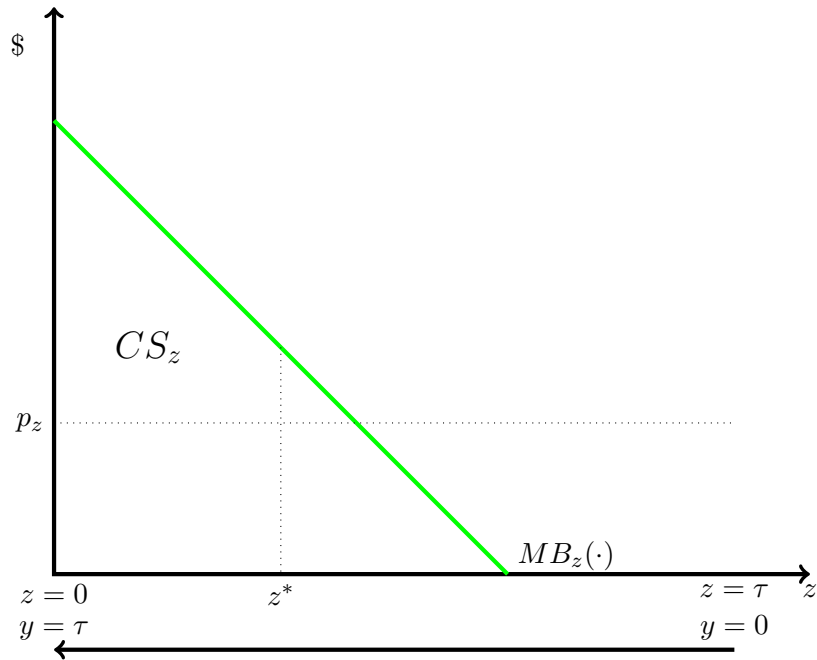
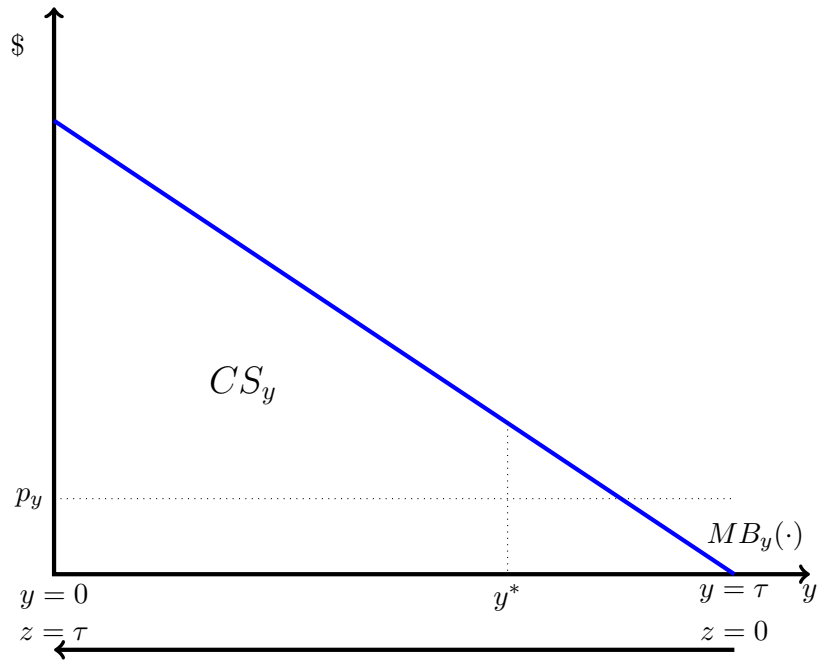


Figure A.1: Consumer surplus calculation: Method 1. Consumer surplus can be calculated in each market independently; the results are then summed to obtain the overall consumer surplus enjoyed by the consumer. Note that optimal consumption levels are *not* where $p = MB$; this is because of the binding time constraint.

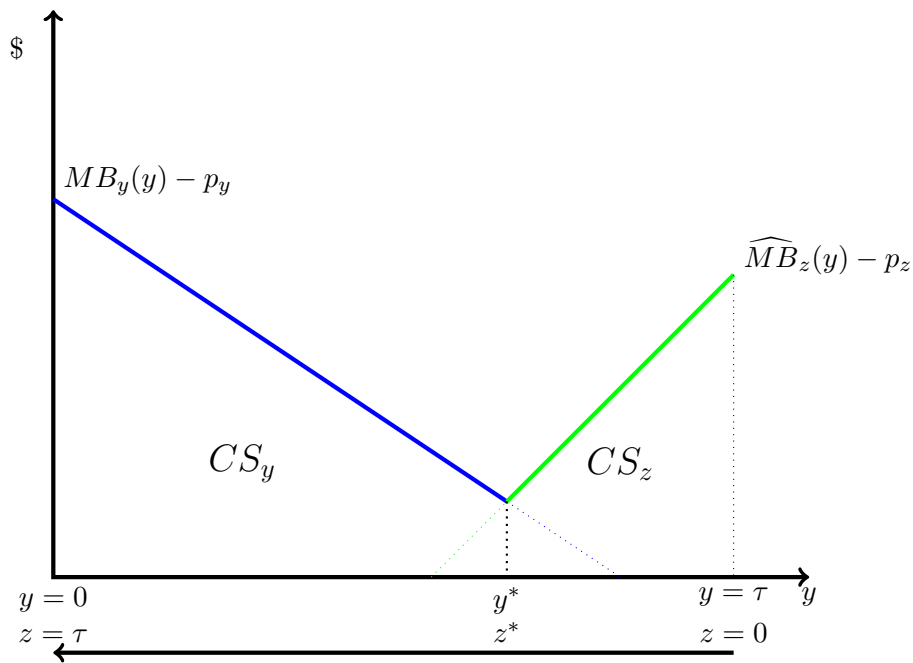


Figure A.2: Consumer surplus calculation: Method 1 (alternative view). The curves are marginal benefit curves *net of* prices. The demand curve for z has been transformed into a function of y using the time constraint $y + z = \tau$, allowing it to be graphed on the same axes as the demand for y . The intersection of the two net demand curves yields the equilibrium quantities, which satisfy the equimarginal principle.

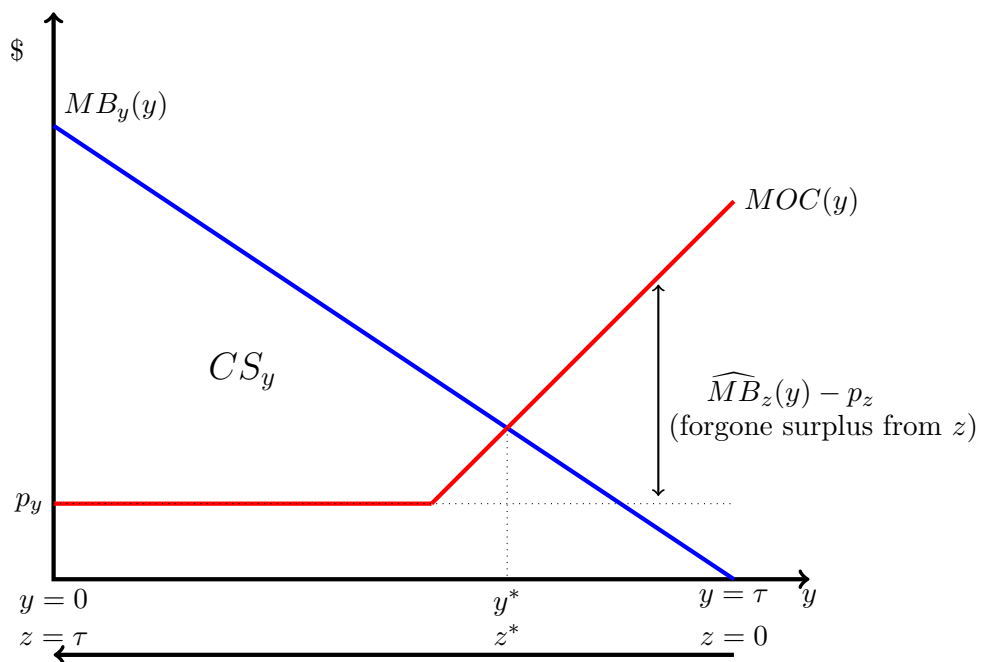


Figure A.3: Consumer surplus calculation: Method 2. $MOC(y)$ is the marginal opportunity cost of consuming y , which includes the monetary cost embodied in the price p_y as well as implicit costs from forgone consumption of z .

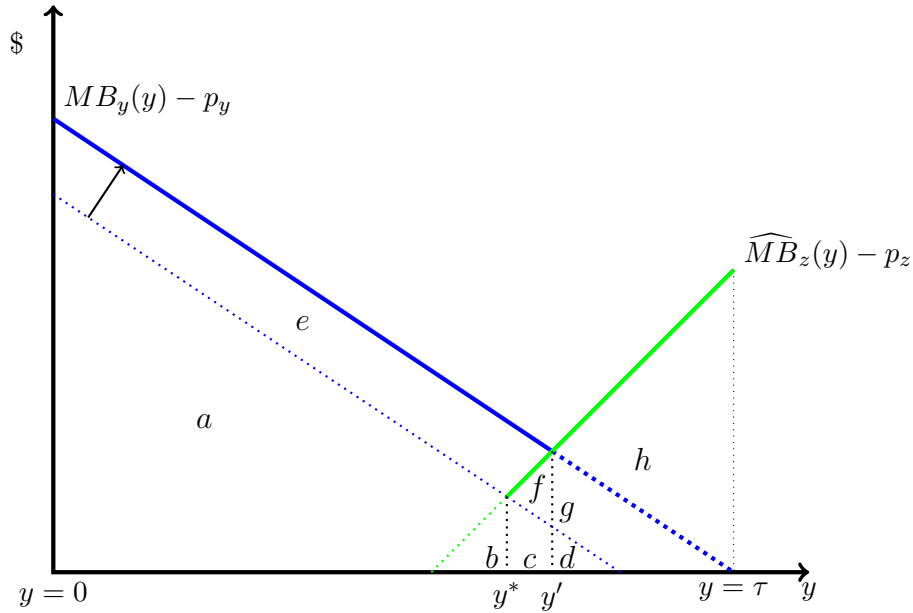


Figure A.4: Consumer surplus can be calculated using either of the two methods described above. The first method calculates consumer surplus directly in each market, whereas the second method focuses on a single market, calculating consumer surplus *net of* forgone opportunities. The numerical value of CS will differ between the two methods; however, the *change* in consumer surplus from a demand shift will be equivalent across the two methods. This fact is depicted graphically and in the calculations below.

Method 1	Original	Shifted	Gain/loss
CS_y	a+b	a+b+c+e+f	c+e+f
CS_z	c+d+f+g+h	d+g+h	-c-f
CS^{total}	a+b+c+d+f+g+h	a+b+c+d+e+f+g+h	e

Method 2	Original	Shifted	Gain/loss
CS^{total}	a	a+e	e