The Effects of Weather on Recreational Fishing Demand and Adaptation: Implications for a Changing Climate

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Abstract: Outdoor recreation is one of the most popular leisure activities in the United States, yet the potential impacts of climate change on the non-market aspects of this activity are largely unknown or poorly understood. We estimate the non-linear effect of temperature and precipitation on the demand for a significant segment of the outdoor recreation economy – shoreline marine recreational fishing in the Atlantic and Gulf Coast regions – from 2004-2009. Our econometric estimates suggest extreme heat significantly reduces recreation participation. We find declines in participation (up to 15 percent) and welfare (up to $312 million annually) over a range of predicted climate futures. These impacts vary spatially and temporally, with warmer locations and times of year experiencing significant losses and gains possible in cooler areas. We also find evidence of climate-averting behavior as anglers shift their activities to nighttime rather than fish less frequently to mitigate the negative impacts from extreme heat. (JEL Q26, Q51, Q54)

Keywords: climate change, recreation demand, temporal adaptation, fishing, extreme heat

When and where to recreate outdoors is a decision made by millions of people each day in the United States (U.S.) and around the world. These decisions are economically significant, with outdoor recreation activities contributing $412 billion (2016 USD), or 2.2 percent, to U.S. gross domestic product annually - more than double the contribution of agriculture (BEA 2018). This statistic likely underestimates the total economic value of recreation, as it is a measure of only

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market transactions and does not include non-market values. As an example, a conservative estimate of the annual non-market value for a single type of outdoor recreation - marine recreational fishing - exceeded $1.69 billion in 2016 for just the East and Gulf coast regions (NMFS 2018).[1] Given the size of this sector of the economy and the inextricable link of these activities to weather and climate, we seek to estimate the impact of weather on demand and assess the welfare implications of climate change on the non-market aspect of these activities.

We hypothesize that a primary driver of recreational behavior is weather and its impact on overall comfort during an outdoor experience. Recent evidence suggests general preferences for daily average temperatures near 65°F (Albouy et al. 2016) and for outdoor activity around 82°F (Obradovich and Fowler 2017). Deviations from these temperatures are likely to affect the marginal utility gained from a recreational trip, which may have important welfare implications as temperatures increase due to climate change. The net effect of these changes is an open empirical question, as moving colder days into more moderate temperatures could improve welfare (e.g., Mendelsohn and Markowski 1999; Loomis and Crespi 1999) while increasing the number of days with extreme heat could discourage outdoor recreation and cause welfare to decline.

To address this question, we investigate the effect of weather on the demand for a specific activity representing a sizeable share (~10 percent) of the outdoor recreation economy - shoreline marine fishing.[2] We focus on the behavioral factors leading to recreational participation and site choice. Weather, especially temperature, is likely to directly influence these choices. We adopt a flexible modeling approach that can detect nonlinearities in the effect of temperature on the participation choice. Combining this method with a dataset of individual decisions across time and space allows us to credibly identify the impact of temperature extremes on recreation demand. We maintain our temporally and spatially explicit framework through our predicted future climate scenarios, using downscaled 1/8 degree climate predictions from 132 unique general circulation model (GCM) outputs.[3] We find that the decline in participation due to extreme heat outweighs the potential positive impact of more days with moderate temperatures. This finding fills a

[1] Author calculation multiplying the number of trips estimated by NOAA in 2016 (56.4 million) by an average non-market value per trip of $30 based on meta-analyses of Johnston and Moeltner (2014) and Moeltner and Rosenberger (2014).
[2] NOAA estimates that the 9.8 million marine anglers in the U.S "supported 472,000 jobs…" and "…generated about $67.9 billion in sales impacts, $24.3 billion in income impacts and $38.7 billion in value-added impacts." (NMFS 2018, p. 11).
[3] See table A.1 in the online-only appendix for a full list of the models used (Reclamation 2013). GCMs are numerical models that represent physical processes in the atmosphere, ocean, and land surface simulate the response of the global climate system to increasing greenhouse gas concentrations. The IPCC uses Representative Concentration Pathways (RCPs) where RCP2.5 (4.5, 6.0) assumes greenhouse gas (GHG) emissions peak in 2020 (2040, 2080) and then decline. RCP8.5 assumes GHG emissions continue unabated in a "business-as-usual" scenario.

significant gap in economists' understanding of potential climate impacts on recreation as we reveal a previously difficult-to-identify pathway for temperature to affect the choice decision. Graff-Zivin and Neidell (2014) noted the critical nature of exploring the tails of the distribution and found a qualitatively similar impact of extreme heat on self-reported outdoor leisure time, though the impact was not statistically significant. Furthermore, our concentration on individual recreation decisions allows us to model an economically significant climate-averting behavior whereby people shift recreation from day to night. We show that the choice to fish at night is a behaviorally relevant, intensive margin adaptation to increased temperatures, and climate change forecasts combined with our econometric results indicate that more angling will occur in the after-dark evenings and pre-dawn mornings.

Previous literature assessing the climate impacts on recreation took a broad approach by attempting to estimate the overall effect on a variety of popular recreation activities (Mendelsohn and Markowski 1999; Loomis and Crespi 1999). Mendelsohn and Markowski (1999) adopt a cross-sectional approach to estimate how annual recreation days correlate with average summer and winter temperature using a single year of state-level data for seventeen different recreational activities. Their results suggest a net gain from climate change to recreation in the range of $3 to $25 billion (1991 USD), with the largest gains arising with fishing. Loomis and Crespi (1999) also find benefits from increasing recreation days of up to $2.7 billion (1992 USD) with similarly aggregated data and models. More recently, Whitehead and Willard (2016) used a comparable approach with state-level data and predicted large increases in marine recreational fishing days (27 percent) and welfare gains ($2.5 billion annually, 2010 USD) attributable to climate change. Each approach above suggests welfare improvements for recreation with climate change, but these results: 1) are based on highly aggregated data and models reliant on average temperature that may obfuscate the temperature impact if the relationship is nonlinear (e.g., Schlenker and Roberts 2009); 2) rely on questionable identification strategies; and 3) do not structurally model recreation behavior. Alternatively, two other studies investigate the ecological impact of climate in freshwater fishing applications by modeling angler behavior within a random utility maximization (RUM) framework. Pendleton and Mendelsohn (1998) model the ecological effects of climate on catch rates in the northeastern U.S and find a range of welfare implications from a $4.6 million loss to $20.5 million gain (1990 USD). Ahn et al. (2000) use a cross-sectional survey with 546 respondents to estimate the impact of expected habitat loss from climate change and find a negative impact on angler consumer surplus of 2 to 20 percent for trout fishing in western North Carolina. Both studies utilize a single year of data with limited geographic range.

Our paper brings new evidence to bear on the question of weather and climate impacts on recreation and contributes to the literature in several ways. We are the first study to identify and quantify the impacts of extreme heat that may cause discomfort while recreating outdoors. To accomplish this, we use one of the largest recreation datasets currently available, utilizing site intercept data from nearly 200,000 anglers and participation data from 1.6 million households over six years (2004 - 2009) across seventeen U.S. states in four regions.[4] Our primary econometric result suggests that participation declines with extreme heat (>=95° F) and cold (<= 40° F), implying an inverted U-shape for our temperature-response function.[5] This highlights a clear distinction from previous work finding only a positive overall effect from moving colder days into more pleasant temperature ranges. These previous studies were limited by data constraints common historically with recreation data.

We then use our estimated weather response functions to predict potential impacts of climate change. We estimate declines in participation and welfare from the increasing incidence of days with extreme heat (>= 95° F) are larger than gains from shifting colder days to more moderate temperatures. Specifically, our simulation results suggest overall participation declining between 1.1 to 15.1 percent and welfare losses up to $312 million annually. These estimates are identified assuming temperature is exogenous after nonparametrically controlling for spatial and temporal factors (Auffhammer et al. 2013; Hsiang 2016), bringing our non-market estimates of climate impacts on recreation into comparable terms with market-based estimates in agriculture (Schlenkler and Roberts 2009), labor (Graff-Zivin and Neidell 2014), income (Deryugina and Hsiang 2014), and mortality (Heutel et al. 2017). Furthermore, our focus on the impacts on local outdoor recreation decisions is an important conduit through which climate change may affect the quality of life and associated non-market amenities (e.g. Albouy et al. 2016). Recreation was a clear missing sector in the broad analysis by Hsiang et al. (2017) of economic damages from climate and quantification of these impacts has been noted elsewhere as a needed research direction in the refinement of social cost of carbon estimates (Burke et al. 2016). The scope of our data also

[4] The spatial extent of our study area includes a large majority (>95 percent) of the estimated marine recreational fishing trips taken in the U.S. (excluding the West Coast) recorded by NOAA (NMFS 2018).

[5] With respect to precipitation, we find a small increase in participation with minimal rainfall (> ¼”), consistent with anecdotal evidence that overcast days tend to increase fishing success, but generally insignificant results for high precipitation levels.

allow us to clearly identify spatial and temporal heterogeneity in the effect of weather. We estimate recreation participation declines in hotter baseline regions (Gulf and Southeast) and months (March through October) and increases with a colder baseline climate (New England) and during cooler months of the year (November through February). The spatial distribution of impacts predicted here for recreation are comparable with recent results estimating total direct economic damages from climate change in the U.S. (Hsiang et al. 2017).

From a methodological perspective, our approach makes three main contributions. First, we develop a strategy for overcoming coverage gaps in our onsite intercept data that are likely present in other recreational data sets due to cost considerations with data collection. In particular, NOAA's Marine Recreational Information Program (MRIP) intercepts anglers at less than half of registered shoreline fishing sites. To account for unsampled sites and more accurately characterize the full range of substitutes available to anglers, we employ a contraction mapping algorithm (Berry 1994) that imputes missing intercept data based on NOAA's best available estimates of aggregate fishing activity at unsampled sites. Second, our structural approach allows for more nuanced welfare calculations that include losses associated with the quality of inframarginal trips - trips that are still taken (i.e., not lost) but diminished in value with climate change. We show that the common approach to estimate welfare changes by multiplying the change in trips by a per-trip unit value systematically biases these estimates towards zero. Our results suggest this effect may be significant, as calculations that ignore these diminished trip impacts would under predict welfare losses by 15 to 49 percent in our application. Third, our overall modeling approach represents a promising and behaviorally consistent framework for estimating the behavioral and welfare effects of climate change on other types of outdoor recreation (e.g., skiing, surfing) with emerging big data sources such as cell phone records and social media application programming interfaces (APIs; e.g., Sonter et al. 2016), and thus more completely characterizes the climate change-recreation nexus.

Lastly, we identify and quantify the value of an intensive margin mechanism for adapting to climate change in the context of recreational participation. Results from a simple logit model suggest anglers respond to extreme heat by shifting the timing of their recreation to nighttime. To illustrate the importance of this behavioral adaptation, we run a counterfactual simulation that predicts welfare change under climate futures where this mechanism is turned off (Hsiang 2016). This exercise demonstrates that shifting recreation activity to cooler times of the day could prevent losses up to $27 million annually from extreme heat. Importantly, we find that the reduction in welfare losses from this adaptation declines from 14.9 percent in 2030 to 8.6 percent by 2080, suggesting the efficacy of this pathway may diminish as temperatures increase in the future.

This article proceeds as follows. Section 1 describes our panel approach to identifying the effects of weather, our repeated discrete choice modeling approach, and the three-step procedure for empirically implementing our model. In section 2, we discuss our primary data sources, including two independent NOAA surveys on recreation and observed and predicted weather outcomes. Next, we discuss results from our structural recreation demand model as well as predicted demand and welfare changes from our climate simulations. Section 4 discusses the potential of temporal substitution as an adaptation pathway and identifies night-fishing as viable intra-day substitution to avoid extreme heat. The final section provides a summary of our findings, limitations to our study, and implications for future research.

1. MODELING APPROACH

Econometric strategies for identifying the impacts of climate on economic activity largely fall into either cross-sectional or panel data approaches (Hsiang 2016; Massetti and Mendelsohn 2018). Cross-sectional approaches examine economic behavior at a single point in time and assume that different economic agents across space have similar preferences and production technologies. Differences in observed behavior are then correlated with differences in climate. The major drawback with this approach is the potential for omitted variables correlated with climate and other observable characteristics to bias estimation results. In contrast, panel methods compare the behavior of the same agents at different points in time, utilizing temporal variation in weather to identify the impacts of climate. This approach diminishes concerns of omitted variable bias by systematically controlling for spatial and temporal unobservables. However, identification of climate impacts relies on the assumption that the estimated effect of a small change in realized weather is the same as the effect of a similar small adjustment in climate, termed the marginal treatment comparability assumption by Hsiang (2016). Potential for bias using a panel approach occurs if economic agents can adapt in the long-run (upward bias) or if short-run adaptation are no longer feasible in the long-run (downward bias).

In this study, we combine a structural model of recreational angling behavior with a pseudo-panel of observed trip data to identify the effects of weather and, in turn, climate on participation in coastal recreational fishing. Our identification strategy has two main advantages. First, our strategy leverages panel data and thus allows us to control for spatial and temporal unobserved factors that would not be possible with purely cross-sectional data. These controls are especially important in our application because our data do not include detailed information on many fishing trip characteristics (e.g., available gear, fish stocks) and thus would be especially vulnerable to omitted variable bias. Assuming the marginal treatment comparability assumption holds, our econometric strategy allows us to credibly identify the effects of climate on fishing participation. Second, by adopting a structural approach, we can quantify welfare changes associated with changes in the quantity of trips as well as changes in the quality of inframarginal trips. This differs from more commonly used back-of-the-envelope strategies in the climate damage literature that monetize only the quantity change by multiplying a change in the economic variable of interest (e.g., premature deaths) by a unit value measure (the value of a statistical life). By monetizing the losses or gains associated with inframarginal trips, our approach generates a more comprehensive welfare measure that avoids the inherent biases with unit-value approaches.

Our structural model employs the repeated discrete choice framework, which was first introduced by Morey et al. (1993) and has subsequently been used widely in recreation (e.g., English et al. 2018) and other fields of applied demand analysis (Nevo 2001). The framework assumes that the time horizon of choice can be decomposed into independent choice occasions, whereby individuals make repeated decisions of whether to purchase a good (i.e., trip) and, if so, which discrete variety (or site) to consume. As such, the framework can be used to model both recreation participation and site choice in a behaviorally consistent manner that permits welfare measurement. Although the framework can in principle incorporate temporal linkages such as habit formation and variety seeking behavior, data limitations typically preclude modeling such dynamic behavior. Our pseudo-panel data environment suffers from these limitations,[6] and thus like English et al. (2018) and Nevo (2001), our model should be interpreted as static in nature.

For the site choice decision, we assume individual *i's* preferences for visiting site *j* on choice occasion *t* can be specified in general terms as:

$$V_{ijt} = U(m_{it} - c_{ij}, \mathbf{X}_j, \varepsilon_{ijt}) \tag{1}$$

[6] Since we do not observe choices for the same respondents over a long time horizon but instead observe only behavior over two-month periods, detecting dynamic behavior in our application is confounded by the changing characteristics of the sample. As discussed in English et al. (2018), the evidence from the literature does not suggest a clear direction of bias from this omission, with some studies finding modestly larger welfare effects from dynamic models and others finding modestly smaller ones.

where m_{it} is income, c_{ij} is travel cost, $\mathbf{X}_j$ is a vector of site characteristics, and ε_{ijt} captures idiosyncratic factors.[7] These factors are by assumption known to the individual but unobserved and random from the analyst's perspective. Consistent with the RUM framework (McFadden 1974) and conditional on taking a trip, a rational individual selects the site that generates the highest utility, i.e., site *j* is chosen if and only if $V_{ijt} \geq V_{ikt}, \forall k \neq j$. Assuming a joint probability density function for ε_{ijt}, the probability of selecting site *j* on choice occasion *t* is represented by:

$$\Pr_{it}(j \mid Trip) = \Pr[V_{ijt} \geq V_{ikt}\,,\ \forall\ k \neq j]. \tag{2}$$

To endogenize participation, we introduce a "no fishing trip" alternative, which represents the angler's utility when choosing not to fish:

$$V_{i0t} = U(m_{it}, \boldsymbol{Z}_i, \varepsilon_{i0t}), \tag{3}$$

where $\boldsymbol{Z}_i$ includes observable factors that influence participation and ε_{i0t} captures unobserved determinants of choice that are by assumption random draws from a known probability distribution. If V_{it}^{Trip} represents the maximum utility of taking a trip on choice occasion *t*, then the probability that individual *i* chooses to take a trip is:

$$\Pr_{it}(Trip) = \Pr[V_{it}^{Trip} > V_{i0t}]. \tag{4}$$

If there are *C* choice occasions over the specified time horizon, the predicted number of trips for individual *i* to site *j* equals $C \times \Pr_{it}(Trip) \times \Pr_{it}(j \mid Trip)$.

1.1 Empirical Implementation of the Model

As discussed in more detail in the next section, a complication with our empirical application is that the participation and site choice data were collected by separate and independent surveys. As such, we observe either participation or site choice decisions over a two-month period for each individual in our data, but not both. This limitation requires that we employ an econometric specification that permits separate estimation of each margin of choice. With this in mind, we follow Dundas et al. (2018) and English et al. (2018) and employ a two-level nested logit specification of the repeated discrete choice model. As discussed in Morey et al. (1993), the two-

[7] In a static repeated discrete choice model, choice occasions do not necessarily have a temporal interpretation and should be viewed as a modeling device for endogenizing participation. How one specifies choice occasions in this context is somewhat arbitrary, but past research with other datasets (e.g., English et al. 2018) and similar analyses with ours suggest that welfare measures differ by less than one percent across alternative plausible specifications. It should be noted, however, that the number of choice occasions must exceed the number of trips taken by every respondent for the model to predict fully observed behavior.

level nested logit model assumes the unobserved determinants of choice are jointly drawn from a generalized extreme value (GEV) variant of the Type I extreme value distribution. The model in essence allows us to introduce a common random factor that enters the site-specific unobserved determinants of choice on each choice occasion and induces correlations among site utilities and more reasonable substitution patterns relative to standard logit models. And importantly for our application, the two-level nested logit model permits sequential estimation of the parameters entering the site choice and participation decisions.

In our econometric specification, we assume all conditional indirect utility functions are linear and additive in the unobserved determinants of choice:

$$V_{ijt} = v_{ijt} + \varepsilon_{ijt},\ j = 0,...,J\ , \tag{5}$$

where the v_{ijt} contains the systematic, observable components of utility. Under our maintained GEV distributional assumption, the probability that individual *i* chooses site *j* on choice occasion *t*, P_{ijt}, is:

$$P_{ijt} = P_{it}(j\,|\,trip) \times P_{it}(trip) = \frac{e^{\left(v_{ijt}/\lambda\right)}}{\sum_{j=1}^{J} e^{v_{ijt}/\lambda}} \frac{\left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda}}{e^{v_{i0t}} + \left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda}} = \frac{e^{\left(v_{ijt}/\lambda\right)}\left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda-1}}{e^{v_{i0t}} + \left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda}}, \tag{6}$$

where λ is the nested logit's dissimilarity coefficient, which, for consistency with the RUM hypothesis, is bounded between zero and one (Herriges and Kling 1997). Similarly, the probability of not taking an angling trip, P_{i0t}, is then:

$$P_{i0t} = \frac{e^{v_{i0t}}}{e^{v_{i0t}} + \left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda}}. \tag{7}$$

The above nested logit structure facilitates a sequential estimation strategy (see, e.g., Ben-Akiva and Lerman 1985, pp. 295-299), whereby all parameters entering the site choice model can be estimated first, and the remaining parameters entering the participation model can then be estimated conditionally. At both stages of estimation, standard maximum likelihood estimation techniques for logit models can be used. Although this two-step estimator implies some efficiency loss relative to full-information maximum likelihood estimation, the large size of our data suggests that this is relatively small price to pay.

We specify the conditional indirect utility from visiting site j on choice occasion t as follows:

$$v_{ijt} = \eta c_{ij} + \delta_j \,, \tag{8}$$

where η is the travel cost coefficient (or the negative of the marginal utility of income under the standard linear-in-income specification), and δ_j is an alternative specific constant (ASC) for site j that we allow to vary by year. These site constants nonparametrically control for unobserved characteristics like parking, restrooms and catch rates that vary across sites and years. Spatial heterogeneity in travel costs is accommodated by allowing the travel cost coefficient to vary across four origin regions (New England, Mid-Atlantic, Southeast and Gulf).

The first-stage site choice estimation generates consistent estimates for the travel cost coefficient (normalized by λ), but as discussed in Ben-Akiva and Lerman (1985), it does not generate consistent estimates for the ASCs due to the sampling properties of the MRIP data. Specifically, NOAA only samples a fraction of shoreline fishing sites (up to 40%) in every year/wave, which implies that our site choice data suffers from choice-based sampling bias. Moreover, for sites not sampled in a particular year/wave, the ASCs are not identified. To resolve this issue, we follow Dundas et al. (2018) and use auxiliary fishing pressure data for every recreation site to recover calibrated ASC estimates. To simplify the calibration, we employ Berry's (1994) contraction mapping, which iteratively solves for the ASCs that imply aggregate demand predictions that match trip frequency information from NOAA's site registries for all 2,473 fishing sites. With the calibrated ASCs in hand, we then construct the following inclusive value index:

$$IV_i = \ln\left(\sum_{k=1}^{J} e^{\left(\widehat{\eta/\lambda}_{ik} + \tilde{\delta}_k\right)}\right), \tag{9}$$

where $\widehat{\eta/\lambda}$ is estimated with the site choice model and $\tilde{\delta}$ is estimated in our calibration step. IV_i can loosely be interpreted as the expected utility of a trip (Hausman et al. 1995) and is used in the third and final step to consistently link the site choice and participation models.

The participation model describes how individuals residing in coastal counties in our study area choose the quantity of angling trips to take over a two-month time period or wave.

Contemporaneous temperature and precipitation are assumed to influence these decisions. It is also plausible that contemporaneous weather plays a role with site choice, but we do not consider this possibility for two reasons. First, the vast majority of angling trips in the MRIP data have durations of a single day or less and occur at sites within a short drive of each survey respondent's residence. For these trips, variation in weather across local substitute sites is likely to be small, so we suspect that weather operates more so on the decision of whether to take a trip. Second, given that our weather data must be aggregated over two-month waves to match the temporal scale of our participation data, the day-to-day variation in weather at different sites that might explain why an individual fishes at a particular site on a given day is largely lost, leaving relatively thin spatial variation in temperature and precipitation across sites compared to the more substantial temporal variation across waves.

Following current empirical practice, we characterize temperature and precipitation using a binning approach (Hsiang 2016). In particular, for the two-month wave corresponding to each individual's reporting period, we calculate the number of days where the maximum temperature at nearby coastal areas (defined in section 2.3) falls into one of 15 bins, ranging from <= 30° F to >= 95° F in 5° F increments. Similarly for precipitation, we calculate the number of days where total rainfall fell into one of 10 bins ranging from no precipitation to > 2 inches in ¼-inch increments. For identification purposes, we omit the 70° - 75° F bin and the no precipitation bin in estimation. Hereafter we refer to these individual-specific binned weather variables as $\boldsymbol{T}_i$ and $\boldsymbol{P}_i$, respectively, where we drop the implicit wave and year subscripts to simplify notation.

As suggested in equation (4), the participation decision on each choice occasion boils down to a comparison of the utilities from taking a fishing trip ($V_{it}^{Trip} = v_{it}^{Trip} + \varepsilon_{it}^{Trip}$) and not taking a fishing trip ($V_{i0t} = v_{i0t} + \varepsilon_{i0t}$). In this case, the individual's decision rule on choice occasion *t* can be rewritten as:

$$\text{Take trip } \textit{iff} \quad \Delta V_{it} = V_{it}^{Trip} - V_{i0t} = \Delta v_{it} + \Delta\varepsilon_{it} > 0, \tag{10}$$

which, given our distribution assumptions, implies a simple logit probability for taking a trip. In our empirical specification, we assume:

$$\Delta v_{it} = \beta \boldsymbol{T}_i + \mu \boldsymbol{P}_i + \lambda IV_i + \psi_y + \tau_{w\times r} + \chi_i, \tag{11}$$

where $\boldsymbol{T}_i$ and $\boldsymbol{P}_i$ are the weather variables defined above, IV_i is the inclusive value defined in (9), and $(\psi_y, \tau_{wxr}, \chi_i)$ are, respectively, year fixed effects that control for aggregate (e.g., economic) shocks, wave-by-region fixed effects that control for seasonal effects specific to the four coastal regions (e.g., popular fish runs), and origin fixed effects that control for unobserved factors common to individuals residing in one of 66 different spatial regions (see section 2.2 for details). Since we observe the number of trips taken per wave by each sampling unit, we can use the random realizations of weather in the nearby coastal area in each wave that deviate from the underlying distribution of daily maximum temperature and precipitation to infer how anglers respond to weather. In other words, the average weather distribution is absorbed by our fixed effects and we are identifying the effect of weather off of the within-wave deviations relative to the mean. A visualization of our strategy for identifying the effect of weather on participation in coastal recreational fishing is provided in figure A.1 of the online appendix.

2. DATA

Our recreation data are obtained from the NOAA National Marine Fisheries Service (NMFS) MRIP, formerly the Marine Recreational Fishery Statistics Survey (MRFSS). The data include a point-of-access Angler Intercept Survey (intercept data) and the Coastal Household Telephone Survey (phone data). Our analysis uses six years (2004-2009) of intercept data to estimate site choice model and the same six years of phone data to estimate the participation model.[8] The data are restricted to shoreline intercepts for individuals participating in localized recreation where the primary mode of transportation is driving and the angler's county of residence is included in the sampling frame for the phone survey. These restrictions imply that the vast majority of observed trips are likely to be contained within a single day. The data are compiled in two-month intervals, resulting in six waves per year.

2.1 Intercept Data

The intercept survey includes trip data from intercepted shoreline recreators in coastal areas from Maine to Louisiana. For our analysis, the variables of particular interest include the intercept location and the zip code of residence for each survey respondent. There are 2,473 intercept sites

[8] Other researchers using MRIP data (e.g., Alvarez et al. 2014) have modeled participation using the self-reported 2-month and 12-month total trip information contained in the intercept survey. In our application, it is important to model the participation decisions for the full population (as opposed to just current anglers), as climate change may induce individuals who do not currently fish in coastal waters to do so.

along the Atlantic and Gulf Coast and nearly 14,000 origin zip codes that have been geocoded for inclusion in our analysis. The restriction of the analysis to localized recreation and shoreline fishing yield a sample size of 186,643 trips across six years and 36 waves.

The survey is stratified by site, state, mode, year and wave. Due to cost, the NMFS does not sample at every site, but instead randomly selects sites using expected "fishing pressure" data in each state, year and wave. It then samples at selected sites in proportion to expected fishing pressure. This sampling design is choice-based (Ben-Akiva and Lerman 1985) and therefore raises challenges for consistent estimation of model parameters. Hindsley et al. (2011) develop innovative methods to address this issue, but beginning in 2012, the NMFS published design-based weights dating back to 2004 that correct for the non-randomness of the sampling design and can be used to generate unbiased estimates of angler effort (Breidt et al. 2012). Moreover, using these weights in estimation allows us to recover consistent estimates of the normalized travel cost coefficients in our first-stage estimation. Since the weights are only available back to 2004, we use only post-2004 data in our analysis.

We used the program *PC*Miler* to calculate the round-trip travel distance, travel time, and tolls from the centroid of all origin zip codes in coastal counties to all sites in each choice set. We assume that any site within 300 miles (roughly a six-hour drive one-way) of each origin zip is in the respondent's choice set. This assumption is based on the notion that 300 miles represents the furthest an individual would likely be able to travel for a single day of localized recreation, which is the focus of our analysis.[9] We collect additional data to calculate travel costs. We use national averages for fleet fuel economy from the U.S. Department of Transportation and automobile per-mile operation costs including tires, depreciation and maintenance from AAA, state-level gas prices from the U.S. Energy Information Administration, and zip code-level median household income from the U.S. Census Bureau. The opportunity cost of time is derived using the common assumption that it is 1/3 of the wage rate, where the wage rate is estimated as annual household income divided by 2080 hours.[10] Costs that can be shared by all persons on a given trip (e.g. tolls,

[9] Similar assumptions are typical in recreation demand analysis (e.g. Dundas et al. 2018). Moreover, most non-local trips involve significant expenditures and advanced planning, and thus short-run, unanticipated fluctuations in weather are less likely to generate significant behavioral responses.

[10] The scale of variable construction for our travel cost estimate is not likely to significantly influence our results as accounting for greater spatial variation in gas prices, fuel economy or operation costs are likely to average out. However, our results are sensitive to our treatment of the opportunity cost of travel time. Assuming a value of travel time equal to one-third of the average wage rate is consistent with recent, state-of-the-art travel cost studies (English et al. 2018), but may be interpreted as conservative given recent evidence by Fezzi et al. (2014).

gas, and mileage) are divided by the average number of individuals in each party (2.73) from the intercept data.

2.2 Phone Data

Using county stratified, random-digit-dialing (RDD) from households in coastal counties, the phone survey collects data on the frequency of fishing trips in the preceding two months. The data compiled from this survey include the state and county where the trip occurred and, importantly, the number of anglers who had taken trips and the count of trips taken by each angler in the previous two months. For the geographic areas in this study, the phone survey pulls from 12,075 six-digit phone exchanges in 328 coastal counties as the spatial unit of analysis (figure 1, panel a). To construct the pseudo-panel we use in estimation, we aggregate the individual-level repeated cross-sectional data up to the six-digit phone exchange level.

Our final estimation data set consists of 372,657 observations corresponding to phone exchange/year/wave combination where sampling occurred from 2004-2009. These observations are constructed from interviews for 1,558,635 households, 186,609 of which report taking a trip during the most recent wave. These respondents took a total 1,057,413 trips, or 5.67 per angling household. For non-fishing households, one limitation of the MRIP data set is that it only reports the county of residence, not the six-digit phone exchange. To allocate these households to exchanges, we follow the approach developed in Dundas et al. (2018) that relies on the RDD design of the phone survey. A key advantage to modeling participation using the phone survey with data on both fishing and non-fishing households is avoiding potential biases related to endogenous stratification and truncation present in the intercept data (see Alvarez et al. 2014).

2.3 Weather and Climate Data

Observed weather in the local coastal area is linked to the origin of each observation in our participation data. Daily temperature and precipitation data are generated from the Parameter-elevation Regressions on Independent Slopes Model (PRISM 2009). The PRISM model divides the contiguous U.S. into 2.5 x 2.5 mile grids and uses daily weather station data, while also accounting for factors such as elevation and wind direction, to interpolate weather measures for each grid location. For each bi-monthly wave, we construct a set of variables with the count of days in each of our 15 temperature and 10 precipitation bins by averaging ten PRISM grid locations in the coastal area nearest to each origin six-digit phone exchange (covering ~ 62.5 mi^2) to represent weather conditions along the shoreline at the time of the participation decision. Panel (b) of figure 1 shows a visual representation of this variable assignment.

For our climate simulations, we use daily bias-corrected and downscaled (1/8 degree) CMIP5 temperature and precipitation projections for over 750 locations in our study area from 20 different GCMs from 2020 to 2099 (Reclamation 2013). We use the daily projections to construct temperature and precipitation bin variables in the same manner as our observed weather data in three future time-horizons: 1) 2020-2049; 2) 2050-2079; and 3) 2080-2099. Data are included for multiple runs per model and projections are generated under four IPCC Representative Concentration Pathways, or RCPs (2.6, 4.5, 6.0 and 8.5). In total, we use data from 132 unique climate projections in order to characterize how climate uncertainty may impact our simulation results.

3. RESULTS

First-stage estimation results of the conditional site choice model conform to prior expectations for travel cost. The coefficients are negative and robust across all years and regions (table 1). The precision of the estimates is evident from the large t-statistics. Individuals in the Gulf are more responsive to travel costs associated with a shoreline fishing trip than those in other regions.

Turning now to the second-stage participation model, we briefly discuss a practical issue relating to standard errors before presenting the empirical results. To consistently link the site choice and participation models within the nested logit framework, we construct inclusive values (equation 9) that combine the estimated travel cost parameters from the first stage with the calibrated ASCs for all 2,473 sites. Because the inclusive values are generated regressors that enter the second-stage model, some bias is introduced into the participation model's standard errors (Ben-Akiva and Lerman 1985). However, the precision of the travel cost estimates imply that the covariance matrix of the second-stage estimator should not contain significant noise induced by the first-stage estimates. Therefore, we do not correct the second-stage standard errors as is typically done with sequential estimators, as doing so would involve considerable computational effort given the size of our data.

The second-stage model estimates the effects of weather on recreational participation. We estimate a pooled model using data across all regions and waves, with few exceptions due to MRIP sampling constraints. Parameter estimates for the temperature and precipitation bins are displayed in table 2. A simple specification including year and wave fixed effects (model 1) and a second model with the addition of spatial fixed effects (model 2) both show the impact of an additional day per wave relative to the omitted category (70° - 75° F) in extreme (hot or cold) temperature bins will have a negative impact on participation. Our preferred specification (model 3) adds a wave-by-region fixed effect to flexibly control for common seasonal trends that may vary across regions (e.g., fish runs and derbies, alternative recreation activities). Figures 2 and 3 display the estimated non-linear temperature-response and precipitation-response functions. In the former, we see an inverted U-shape indicating that participation in coastal recreational fishing is negatively impacted at the extremes – cold (< 50° F) and very hot (> 95° F) temperatures. Specifically, for each additional day per wave with extreme heat, our estimates suggest that the odds of taking a recreational trip is reduced by approximately 2 percent. This has important implications since climate change forecasts overwhelmingly suggest the realized temperature distribution in any given future time period is likely to shift to the right (i.e., hotter than usual).

For precipitation, the odds of taking a trip increase by 0.3 percent with an additional day with light precipitation (< ¼"), consistent with anecdotal evidence that overcast days tend to increase fishing success. We also find a significant decrease in the odds of taking a trip by about 1 percent for an additional day in the next bin (days with between ¼" and ½" of precipitation) suggesting discomfort related to fishing in heavier rain outweighs a potential increase in fishing success. With daily precipitation greater than ½", the direction of the impacts become noisy and the precision of the estimates declines.

Lastly, the parameter estimates for the dissimilarity coefficients fall within the unit interval, a sufficient condition for consistency with the RUM model (Herriges and Kling 1997), but the values are quite small. This suggests a very strong correlation in the unobserved portions of utility for alternatives in each nest. As argued elsewhere (Dundas et al. 2018), we suspect that this finding is driven by the imprecise nature of the trip origin information in the phone survey data. In particular, the phone data only includes the respondent's phone exchange or county of residence, not a more geographically precise origin such as a zip code. As a result, measurement error is introduced into inclusive values which in turn likely generates attenuation bias with the estimated dissimilarity coefficient.[11] We use a calibration procedure to address this issue with the simulations applying

[11] Moreover, the fact that the ASCs that feed into the inclusive values are calibrated with fishing pressure data in the site registry and not precisely estimated with choice data may introduce additional measurement error.

the climate scenarios, following Dundas et al. (2018). Here, however, it is important to note that the key parameters of interest from the participation model – the coefficients on the temperature and precipitation bins – are unlikely to be contaminated because weather is not as spatially sensitive to measurement error in the origin. Stated differently, weather variables are likely to be highly correlated across sites in an angler's choice set, so their parameter estimates are likely to be only modestly affected.

We conduct a number of robustness checks. First, we run precipitation-only and temperature-only versions of our preferred model and the coefficients are relatively similar across the model variants. Results from these models are displayed in table A.2 in the online appendix. Second, we aggregate our pseudo-panel data into cross-sections and regress trips on average weather across different regions. We also run year-specific cross-sectional models for 2004 to 2009. Generally, these results show similar negative impacts on participation at extreme temperatures although the coefficients likely contain some bias because these specifications lack controls for spatially-varying omitted variables. Full model results for the cross-sectional models are included in the online appendix (table A.3). Lastly, we re-estimate our participation model (eq. 11) with region-specific models. The full table of results from the region-specific models and the temperature response functions by region are provided as table A.4 and figure A.2 in the online appendix. We observe similar negative effects at extreme temperatures compared to the preferred model, but differences in magnitude and significance that varies across regions. These differences are likely due to data limitations when we focus on regions only – the MRIP only samples Louisiana, Mississippi, Alabama, Florida and North Carolina during January and February (wave 1), and Maine and New Hampshire do not sample during March and April (wave 2). This fact reinforces our preference for using the pooled model across time and space for our simulations.

3.1 Simulations Applying Climate Scenarios

Simulations of economic behavior in future climate scenarios are important undertakings but contain multiple dimensions of uncertainty that require some discussion. In addition to our implicit assumption of no indirect changes to the ecological system, a further caveat is that we assume the weather-participation margin we find remains constant over time. In other words, we implicitly assume a static counterfactual baseline for recreational behavior that may change as climate changes in unknown ways. For example, there may be tipping points where avid recreators in southern latitudes will re-locate poleward to move away from conditions not suitable for outdoor recreation (and for other quality-of-life factors). This is a common limitation of this type of analysis but it does allow us to describe a reasonable starting point for assessing the magnitude and sign of climate impacts on recreation and our framework could be easily adapted to incorporate new information in this area. Second, adaptation of recreational anglers to climate change is also a potential area of concern that may bias our estimates. To explore this issue, we analyze temporal substitution as an adaptation strategy in detail in Section 4. Third, we address uncertainty of climate predictions by utilizing output from 132 unique GCMs to bound the demand and welfare projections in our analysis.

To begin our simulation exercise, we establish a baseline measure of climate by taking the average daily distribution of historical weather variables for each combination of wave and origin location. The predicted changes in the distributions of daily maximum temperature and precipitation bins for each wave are estimated for all 132 runs of the 20 GCMs at nearly 750 unique 1/8 degree grid cells in our coastal study area. Each grid cell is geocoded to match coastal areas nearest to each origin location in our participation data. Importantly, our climate predictions are specific to each spatial unit of the analysis (six-digit phone exchange) whereas previous recreation climate studies tend to use uniform values across space for their projection exercises. In general, all model/scenario combinations predict temperature increases in all areas while precipitation change predictions vary in sign depending on location. Predictions from the GCMs are daily and aggregated into our 15 temperature and 10 precipitation bins by wave to match the baseline data.

We then simulate the compensating variation for a representative household *i* in each wave using the following equation (Haab and McConnell 2002):

$$CV_i = -\frac{1}{\eta}\left(E(V_{it}^1) - E(V_{it}^0)\right) \times C, \tag{12}$$

where $E(V_{it}^k)$ equals $\ln\left(e^{-v_{i0t}^k} + \left[\exp(IV_i)\right]^{\lambda}\right)$ with our nested logit specification and corresponds to the individual's expected utility on choice occasion *t* in the baseline scenario (*k*=0) and the predicted climate change scenario (*k*=1), respectively. The baseline scenario is constructed by averaging the binned weather variables across our six years of data separately by wave, and the predicted climate change scenario is constructed separately by wave for each of the 132 GCMs. In words, CV_i is estimated by multiplying the choice occasion-specific expected change in utility resulting from climate change $\left(E(V_{it}^1) - E(V_{it}^0)\right)$ by the inverse of the marginal utility of income

$(-\eta)$ and the total number of choice occasions (C) in a given wave. To construct annual welfare measures, we then sum CV_i across waves.

As noted earlier, the dissimilarity coefficient, λ, is likely estimated with bias due to measurement error in our travel cost variable. We follow Dundas et al. (2018) to correct for this in the simulations and calibrate the dissimilarity coefficient and constant term predicted by the participation model to maintain consistent in-sample predictions under the assumption that the value of a lost trip is \$30 ($1/\eta$ in eq. 12). This value is chosen as it best approximates the value of a coastal shoreline fishing trip as shown by two recent meta-analyses of numerous valuation studies (Moeltner and Rosenberger 2014; Johnston and Moeltner 2014).[12] Since neither meta-analysis contains a directly equivalent value for this research (i.e., all shoreline fishing from New England to Louisiana), the average of the meta-analysis WTP/day means from the two studies (~\$30) is used here as the value of a lost trip. This assumption is critical since our simulation results are proportional to the value of a lost trip. This implies that if we employed a different value of a trip that was X% higher (lower), our welfare results reported below would also be X% higher (lower). Simulations are run for each separate ensemble forecast to generate a distribution of predicted recreational trip counts and welfare outcomes accounting for the uncertainty in the GCM predictions (Burke et al. 2015). Standard errors for these estimates are generated with a parametric bootstrap (Krinsky and Robb 1986) and 200 draws from the asymptotic variance-covariance matrix.[13] The annual compensating variation estimates are multiplied by the population in the coastal areas (as defined by MRIP phone survey) to arrive at the aggregate measures presented. Population estimates are adjusted in future time horizons by U.S. Census Bureau predictions of population growth.

Our preferred econometric model predicts 46.1 million annual shoreline recreational fishing trips originating from coastal counties of the Atlantic and Gulf coast regions of the U.S.[14] As shown in table 3, the predicted trips decline on average about 2.7 percent across RCP scenarios in the short term (2020-2049) and up to 7.6 percent in the long-run (2080-2099). Panel B displays

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[12] Moeltner and Rosenberger (2014) report the average WTP/day for a saltwater fishing trip in the Northeast is \$39.39 (2010 dollars). In Johnston and Moeltner (2014), the authors find mean Hicksian WTP/day for saltwater fishing of big-game species is approximately \$33.06 and small-game is \$21.33.

[13] The complexity of the simulations and available computing resources limited the reasonable number of draws for the parametric bootstrap to 200. Running the simulations with 2000 draws would require > 100 hours of computing time.

[14] For reference, NMFS (2018) estimated 63.6 million coastal recreational trips in 2015, with around 89 percent of those trips occurring in our study area. Our model predictions match well to these estimates.

regional estimates under RCP 8.5 (business-as-usual) that suggest the demand response to rising temperatures is likely negative in the Gulf (-26 percent) and Southeast (-15 percent), regions that are relatively hotter in the baseline, and positive in the cooler region of New England (+7.3 percent). Panel C suggests substantial declines in predicted trips in warmer months (May through October; waves 3-5) and trip increases in cooler months (November through April; waves 1, 2 and 6). These findings are consistent with our estimated temperature-response function as warmer baseline months are likely to have more days shift from "ideal" (70° - 75° F) to hotter temperatures in the future, with the opposite effect arising for cooler baseline months. These results are also consistent with previous findings suggesting warm weather recreation may shift northward and to cooler seasons in the future (Massetti and Mendelsohn 2018) and that the economic impacts of climate are region-specific (Hsiang et al. 2017).

A simple back-of-the-envelope calculation of welfare impacts would be to multiply lost trips by our assumed trip value of $30. Calculating this as an average across RCP scenarios in each time period, we find that annual welfare losses would be $37 million in the short term, $80 million by mid-century, and $210 million per in the long run. Using our preferred method of estimating welfare change using eq. (12), we find losses 15 percent larger in the short term (2020-2049) and 49 percent larger in the long term (2080-2099). These differences stem from the fact that our preferred method captures the value of both lost trips and inframarginal trips that are diminished in quality from climate change, while the back-of-the-envelope approach only captures the former. These welfare results are displayed in table 4 in the aggregate (panel A), regionally for RCP 8.5 (panel B), and by wave for RCP 8.5 (panel C). [15] We focus our discussion on RCP 8.5, where the predicted welfare losses in the pooled model range from $54 million (2020 – 2049) to $312 million (2080 – 2099) annually. Figure 4 depicts the potential climate uncertainty around the welfare predictions, with the mean of all GCM scenario predictions shown as the dotted line with the shaded area representing the entire range of welfare outcomes predicted under the full suite of GCMs for each RCP. The results strongly suggest that climate change is likely to negatively impact coastal recreational fishing and variation in climate model outputs are not likely to alter this finding. Additionally, simulations run with temperature-only and precipitation-only econometric estimates confirm that temperature is the primary driver of the welfare and demand shifts predicted in this exercise.

[15] Results by region and wave for RCP 2.6 and 4.5 are including in the online appendix (Tables A.5 – A.8; Figures A.3 - A.6).

The spatial and temporal heterogeneity in our results are shown in panels B and C of table 4 and figures 5 and 6 (for RCP 8.5). Across the different regions of our analysis, the Gulf and Southeast experience annual losses ranging from $62 million to $265 million and $8 million to $50 million, respectively. The Mid-Atlantic does not appear to be significantly impacted by climate change and New England is predicted to have modest annual welfare gains ranging from $15 million to $19 million. Looking at the potential impacts at different times of the year, we find annual losses from May to October (-$470 million by 2080) and gains in cooler months (+$159 million by 2080).

Relatively speaking, our worst-case welfare loss estimates ($312 million annually) across multiple regions of the U.S. for a specific recreation activity are small compared to other known climate impacts. That said, existing studies tend to forecast national or multi-national impacts aggregated to a sector of the economy so the scales are not necessarily comparable. For example, estimated impacts to U.S. agriculture can range from a $1.3 billion gain (Deschenes and Greenstone 2007) to a $6.7 billion loss (Burke and Emerick 2016). The spatial pattern of our results (i.e., damages in the Gulf, modest gain in New England) are similar to previous findings related to quality-of-life amenities (Albouy et al. 2016) and total economic impacts (Hsiang et al. 2017). Our results are both qualitatively and quantitatively different when compared to previous work on the climate impacts on outdoor recreation. These studies estimate large gains nationally ranging from $2.7 billion to $25 billion annually inclusive of many types of recreation (Loomis and Crespi 1999; Mendelsohn and Markowski 1999). Our focus on a single type of outdoor recreation but with a much larger dataset and approach that explicitly models recreation behavior allows us to identify the impact of extreme heat on recreation behavior. If we could include impacts to other forms of recreation, the effects could be substantially larger. Anecdotally, extreme heat may raise the risk of heat-related illness (e.g., heat stroke), force alterations to recreation events (e.g., the Iditarod Trail Sled Dog Race shifting its route by 40 miles in 2016) including cancelations (e.g., the Invercharron Highland Games in Scotland in 2018). Given the likely shift of future weather distributions to include more days with extreme heat, this is an important finding that is consistent with negative effects of extreme heat on agricultural production found by Schlenker and Roberts (2009) and Burke and Emerick (2016) and has direct implications for estimating impacts of climate change on recreation.

4. TEMPORAL SUBSITUTION AS ADAPTATION

The results above suggest that climate change will affect demand for and welfare related to shoreline marine recreational fishing activities. One of the primary caveats to our findings is the adaptation of recreators in response to changes in temperature may mitigate some future losses. Adaptation could be substituting recreation activities to more amenable time of year (inter-temporal substitution), which has potential to bias our reported results upward. Conversely, short-run responses to extreme temperature (intra-temporal substitution) are likely captured by our panel data and would only bias our results if these adaptive actions were no longer available in future time periods. We explore these two dimensions of temporal substitution as potential adaptation mechanisms.

First, we investigate the potential for substitution across waves in response to extreme temperature. The structure of our dependent variable (aggregate number of trips taken in a two-month period) prevents analysis of inter-day substitution within a two-month wave. However, we can look at the potential for substitution across waves (e.g. shifting an August trip to September). The concern is that by not allowing for such a substitution pattern, we could be over-estimating our damage estimates from the previous section. We run an additional participation model with one-period lagged weather variables. Coefficients for the contemporaneous variables are quantitatively similar and nearly all coefficients on the lagged variables are insignificant, indicating that previous period weather is unlikely to impact current period recreational participation decisions (table A.9). Furthermore, simulations run with coefficients from the model with lags produce marginally larger welfare and trip losses. This suggests substitution across waves may not be a confounding factor that significantly impacts our simulation results. It is possible that there was not enough heat extremes across our observed data (e.g., we do not observe heat waves exceeding 2 months in duration) to generate this type of substitution across waves. In other words, inter-temporal substitution remains as a potential long-run option to mitigate welfare losses in the future that current data constraints did not allow us to explore fully.

The focus on individuals participating in localized recreation in this research and elements of our data do allow for the potential to identify a mechanism for an intensive margin adaptation – *intraday* substitution (i.e. shifting coastal fishing activities from day to night). Consider an individual taking a local angling trip to a specific site on a particularly hot day (> 95°F). The ability to substitute to a different site within the individual's choice set with significantly more amenable weather conditions is unlikely. However, the individual has the ability to make an intraday temporal substitution of the timing of the activity to avoid the extreme daytime heat. To test if this type of activity is occurring in our observed data, we use the MRIP phone survey to estimate the probability of an individual choosing to fish during nighttime hours. An observation is designated as night fishing if the self-reported time that fishing activities were completed for individual *i* on trip *f* occurs between sunset and sunrise in that particular wave (e.g., wave 3 = 9 PM to 6 AM). A logit model is estimated based on the following equation:

Individual *i* fishes at night on trip *f iff:*

$$\beta \boldsymbol{T}_i + \mu \boldsymbol{P}_i + \omega_{if} + \psi_y + \tau_{w \times r} + \chi_i + \kappa_{if} > 0, \tag{13}$$

where the temperature and precipitation variables as well as the year, wave-by-region, and spatial fixed effects are defined following eq. (11), and a dummy (ω_{if}) is added to control for mode of fishing (pier, jetty, bridge, beach, or other), and κ_{if} is a logistically distributed random variable. Recognizing the ambiguity in the definition of a night trip, we conduct sensitivity analyses varying the definition of nighttime fishing. Although not reported here, our main results are robust to these perturbations.

We estimate eq. (13) with data from the areas (Gulf and Southeast) and times of year (May to October) with observed extreme heat. Results show evidence of this adaptation behavior, as the marginal effect of an additional day of extreme heat increases the probability of night fishing by 0.8 percent for each day per wave above 95°F (table 5 panel A). Given this suggestive evidence, we stratify our data by our hypothesized adaptation mechanism (Hsiang 2016) and estimate a counterfactual simulation based on the idea that if this adaptation margin was eliminated, these trips would no longer take place. We estimate our participation model with day trips only, turning the 25,849 observed night fishing trips into non-participation observations and run our simulation exercise based on the coefficients from this new model.[16] The welfare results and the difference relative to our full model simulation are presented in panel B of table 5. Across all time periods and RCPs, the welfare damages predicted in the model that eliminated the night fishing observations are significantly higher, ranging from an increase of \$7.2 million (18.3 percent) annually in the short run to a \$17.8 million increase (8.6 percent) by 2080. Although this exercise is exploratory in nature and should be interpreted cautiously, it does suggest the importance and

[16] Model results included in the online appendix in table A.10.

value of this adaptation channel.[17] Furthermore, the decline in percent of damage mitigated as time progresses is suggestive that as climate becomes hotter, the efficacy of this option as an adaptation pathway may decline.

5. CONCLUSION

In this article, we extend the literature on quantifying the potential economic impacts of weather and climate to a non-market good – shoreline recreational fishing. We estimate non-linear temperature- and precipitation-response functions that suggest significant changes in participation in coastal shoreline recreational fishing in response to observed weather conditions. The key results from our econometric model is temperature is likely a significant driver of recreation behavior changes and extreme heat (>=95°F) reduces participation. We simulate 132 unique counterfactual climate scenarios that suggest significant reductions in recreation demand and negative welfare impacts from climate change as a result of an increase in the number of days with extreme heat. These impacts are precisely estimated, and accounting for climate model uncertainty does not appear to change the direction or significance of these results. Our finding of a negative effect of climate on recreation is counter to research by Mendelsohn and Markowski (1999), Loomis and Crespi (1999), and Whitehead and Willard (2016) that find large, positive effects associated with climate change. We also show that our estimates include adaptive behavior as we find suggestive evidence of intraday temporal substitution to night fishing as temperatures increase and omitting these observations likely increases welfare losses.

Our results are subject to a few important caveats. First, the MRIP data structure imposed several limitations on our analysis. The fact that participation and site choice information are collected with independent surveys, the phone survey samples only coastal counties, and the intercept and phone surveys collect information on the location of respondents' residences at different spatial scales significantly limited our statistical analysis. Although we believe our modeling decisions are defensible given these data constraints, they are certainly restrictive and should be considered when interpreting our results. Second, our panel approach helps us identify the effects of weather on recreation behavior without potential confounds associated with cross-section approaches but relies on the assumption that short-run responses to weather are similar to

[17] Two concerns, in particular, warrant caution when interpreting these results: 1) we assume that day and night trips are each worth $30, which may not hold empirically; and 2) it is possible that anglers whose first choice is a night trip might substitute to a day trip over no trip if night trips were unavailable.

long-run response to climate (Hsiang 2016). Third, we are limited by assuming no changes in indirect ecosystem effects as the climate changes. The implications of this assumption are unclear. Mendelsohn and Markowski (1999) and Loomis and Crespi (1999) find nearly identical welfare effects in their national accounts of climate impacts despite the former only estimating direct effects. Evidence from freshwater fishing studies (e.g. Ahn et al. 2000) suggests negative indirect welfare implications from climate-induced ecosystem changes. It is plausible that climate effects on fish stocks and their resulting impacts on behavior through changes in catch rates may be significant. For instance, if an ecological shift from climate change leads to a reduction in catch rates, welfare losses are likely to be higher than our predictions. However, the magnitude and sign of the indirect effects remains an open empirical question.

Despite these limitations, our modeling approach estimating the direct impacts of weather provide a starting point to provide more refined estimates of the overall impacts of climate change on outdoor recreation. For example, scientific understanding of the impacts on marine fish stocks in response to climate change is evolving, with recent work predicting shifts in geographic distribution (Morley et al. 2018) and identifying potential mechanisms for such shifts (Pinsky et al. 2013; Deutsch et al. 2015). This suggest credible forecasting of future marine fish stocks in response to climate change may be on the horizon. In addition to directly incorporating ecological impacts, policy matters as well – policy reforms such as individual transferable quota systems or the establishment of marine reserves could significantly impact future marine fish stocks. Furthermore, sea level rise could impact shoreline recreational fishing indirectly through reduction in beach width (Whitehead et al. 2009) or destruction of built infrastructure, which may further increase welfare losses. Lastly, we do not model potential feedbacks that may result from model predictions. For instance, the reduction in predicted trips may allow fish stocks to increase in certain areas, leading to higher catch rates that could offset some of the predicted losses (but also induce participation increases). As such, a full accounting of both direct and indirect effects of climate change and potential cascading sets of behavioral responses remains important avenues for future research. Given the potential for increased knowledge in these areas, future work may incorporate dynamic bio-economic models of fish stocks, policy impacts, and feedback loops into the assessment of the direct effects modeled here that could provide a more complete understanding of the effects of climate change on shoreline recreational fishing and a blueprint for interdisciplinary collaboration needed to tackle future climate impact assessment challenges.

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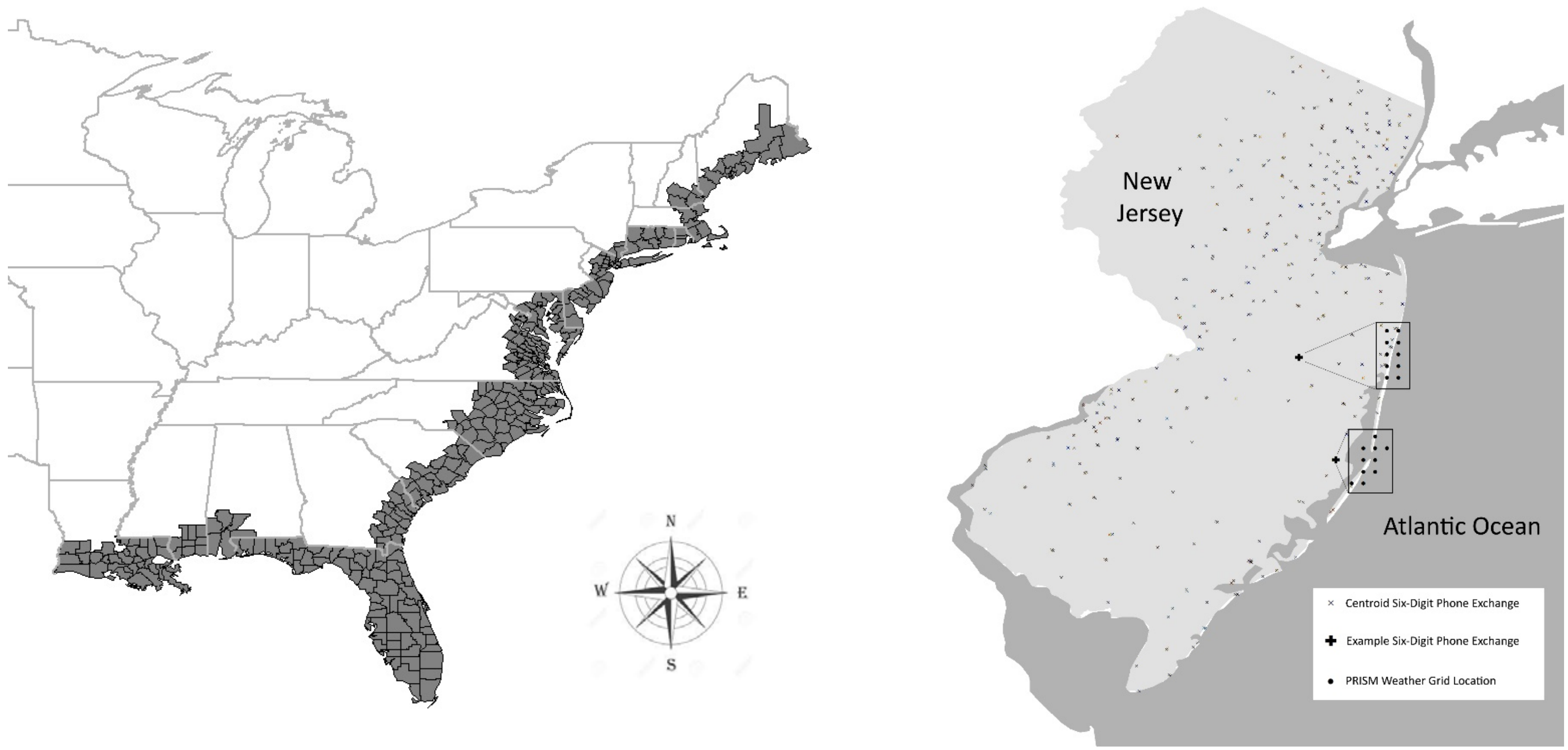
Figure 1. Study Area Maps

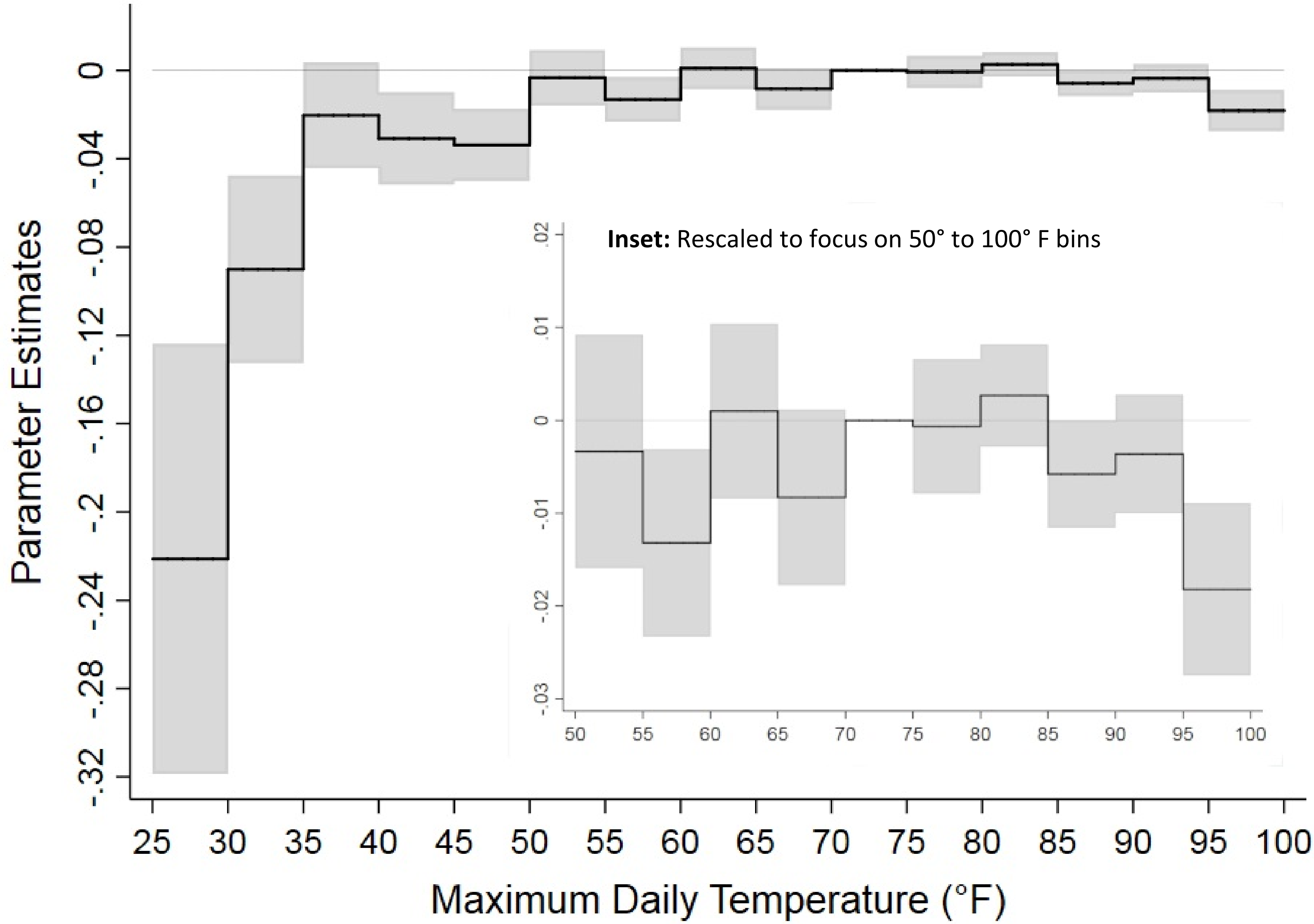
(a) Coastal Counties Sampled in MRIP Phone Survey

(b) Weather Assignment to Origin Phone Exchange



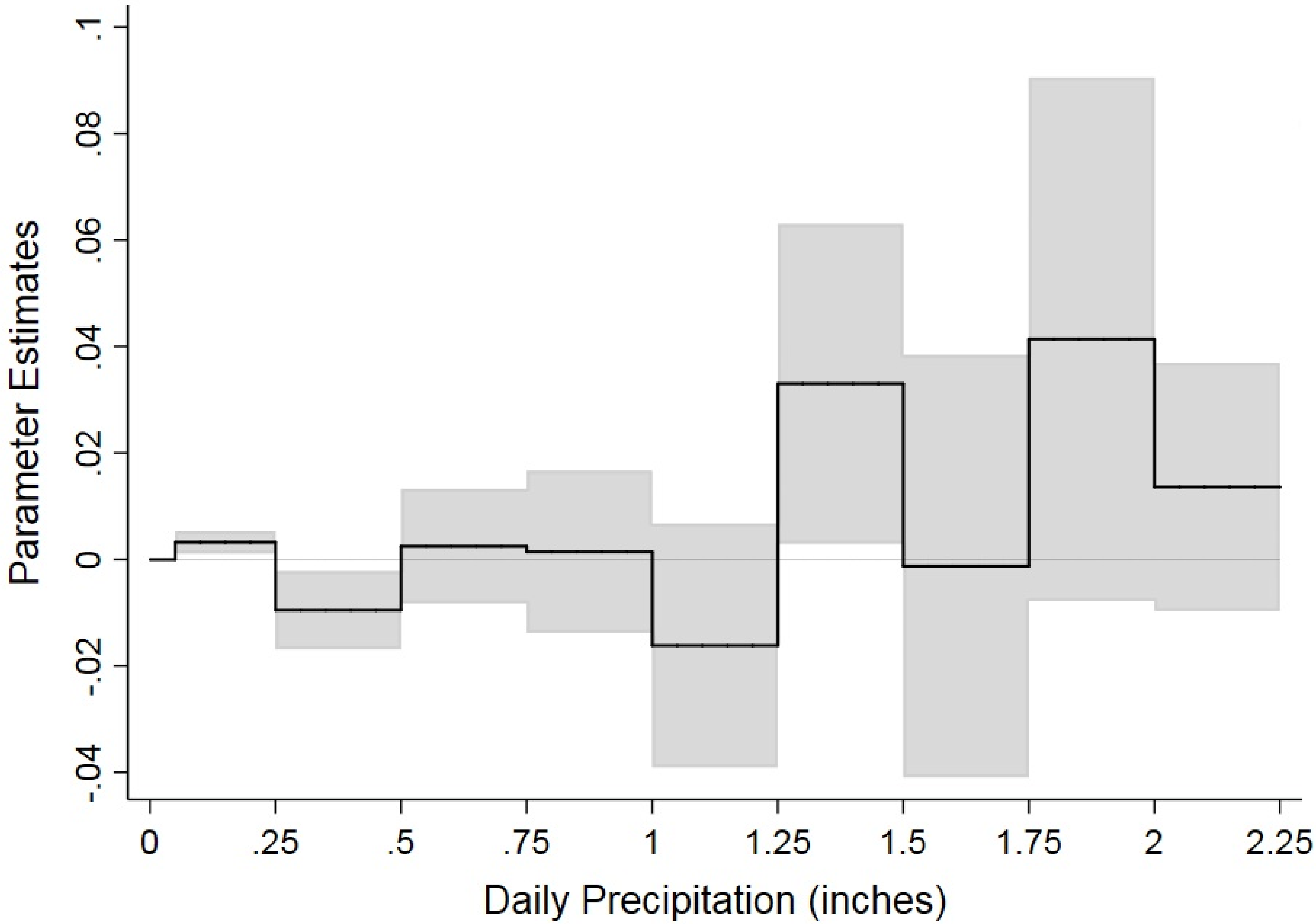
Note: In (a), dark gray areas represent the coastal counties that are in the sampling frame for the MRIP participation phone survey. In (b), dots indicate locations of PRISM weather data and the small black x's represent origin six-digit phone exchanges in our participation data. The two black crosses illustrate two examples of origins connected to the PRISM locations.

Figure 2. The Effect of Temperature on Participation in Marine Recreational Fishing



Note: Solid line indicates point estimates at each 5° F temperature bin. Shaded area indicates the 95% confidence interval.

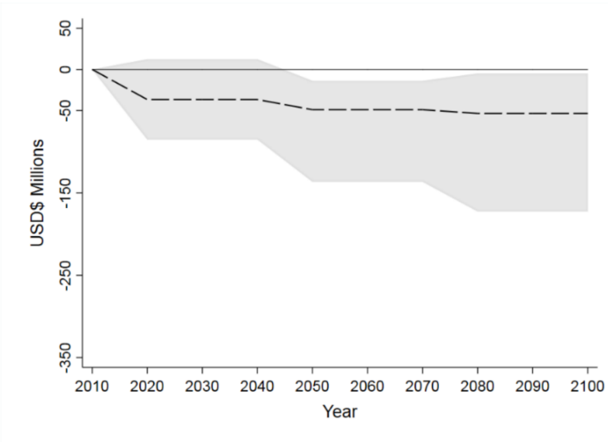
Figure 3. The Effect of Precipitation on Participation in Marine Recreational Fishing



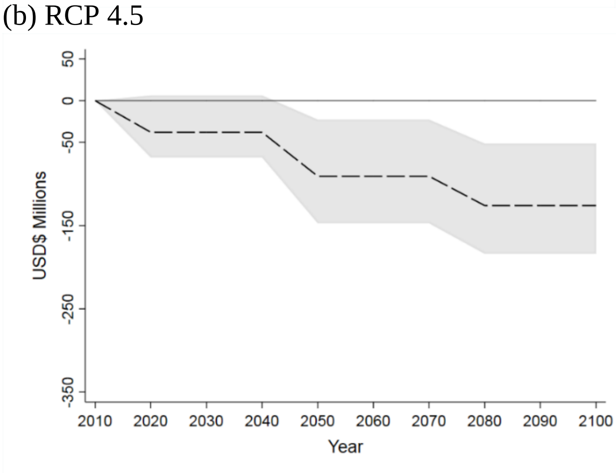
Note: Solid line indicates point estimates at each quarter-inch precipitation bin. Shaded area indicates the 95% confidence interval.

Figure 4. Welfare Effects under Different Climate Change Scenarios

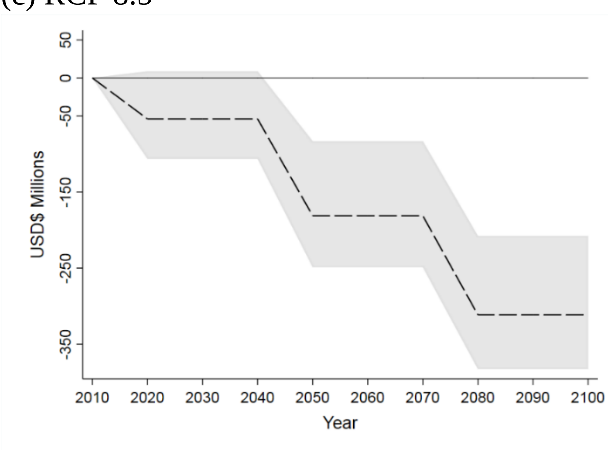
(a) RCP 2.6



(b) RCP 4.5



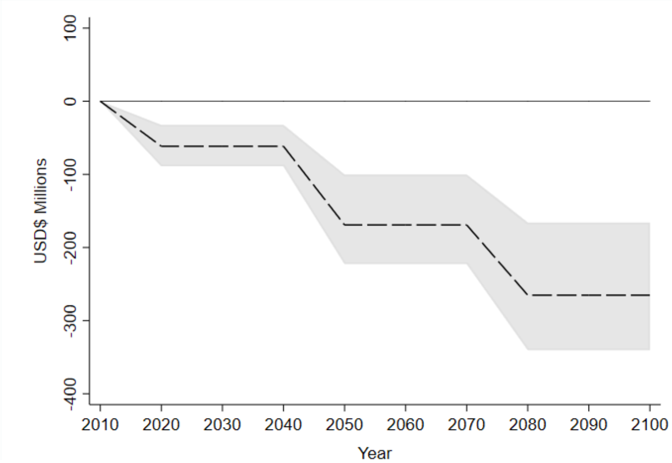
(c) RCP 8.5



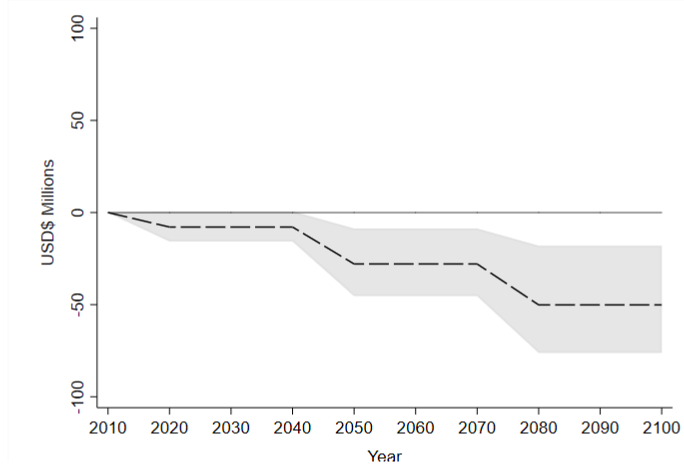
Note: For RCP 2.6 (4.5, 8.5), we used 36 (42, 41) different GCMs. The dashed line shows the average of those models and the gray area represents the full range (i.e., highest and lowest welfare estimates) from all tested GCMs for each RCP scenario.

Figure 5: Regional Welfare Effects under RCP 8.5

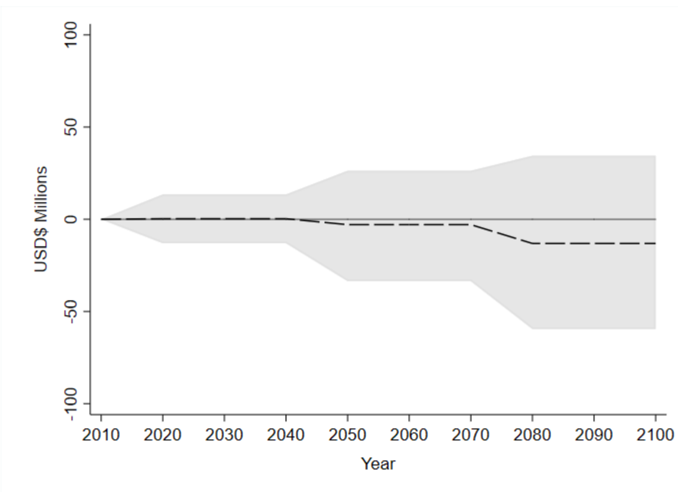
(a) Gulf Region*



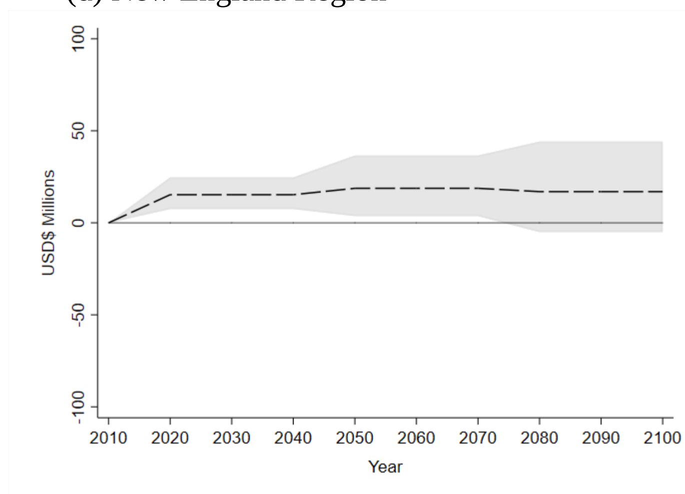
(b) Southeast Region



(c) Mid-Atlantic Region



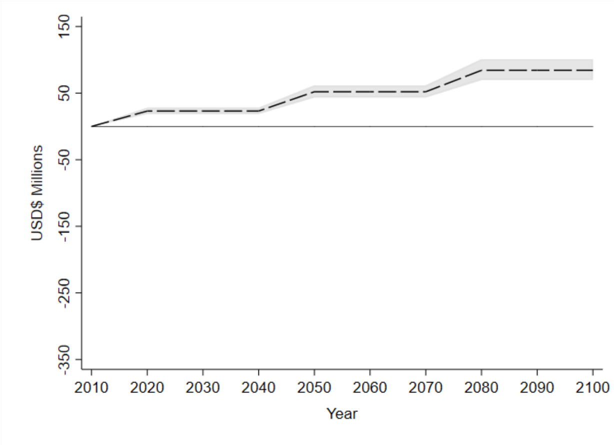
(d) New England Region



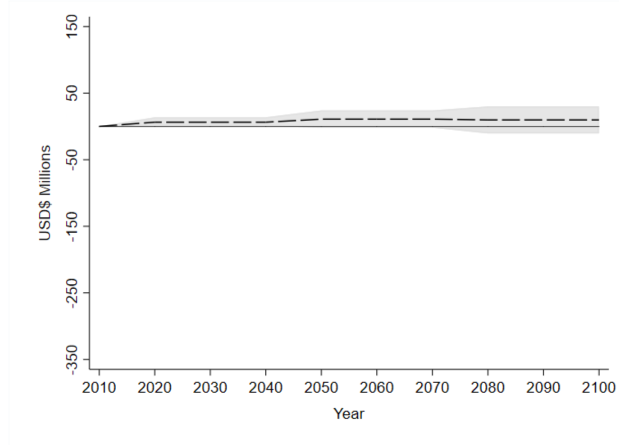
Note: *Please note that we used a different scale for the y-axis in (a) to better visualize results in (b), (c), and (d). The dashed lines are the average of all 41 RCP 8.5 predictions and the gray areas indicate the 95% confidence intervals estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

Figure 6: Temporal Welfare Effects under RCP 8.5

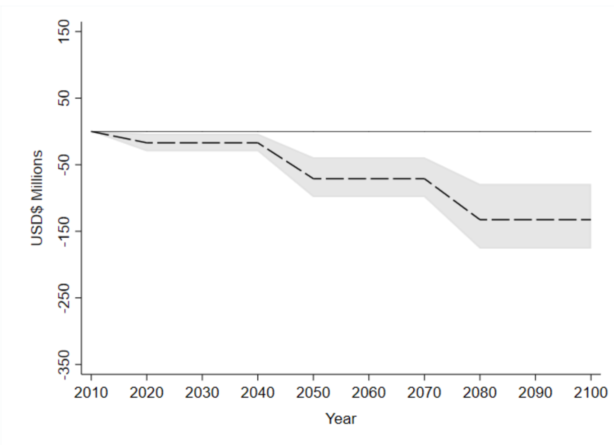
(a) Wave 1 (January & February)



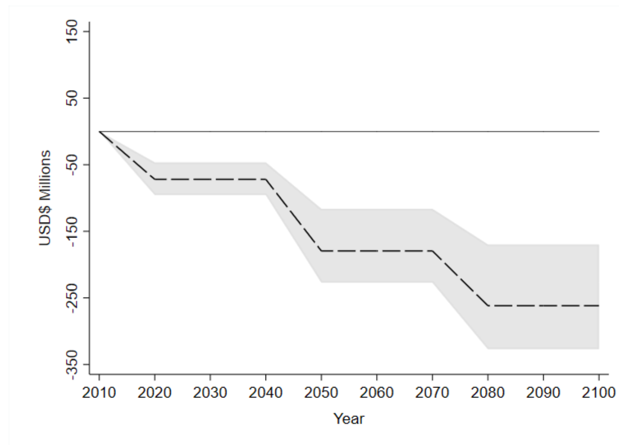
(b) Wave 2 (March & April)



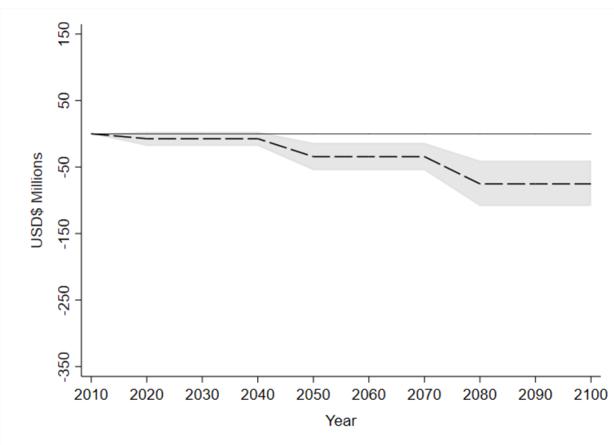
(c) Wave 3 (May & June)



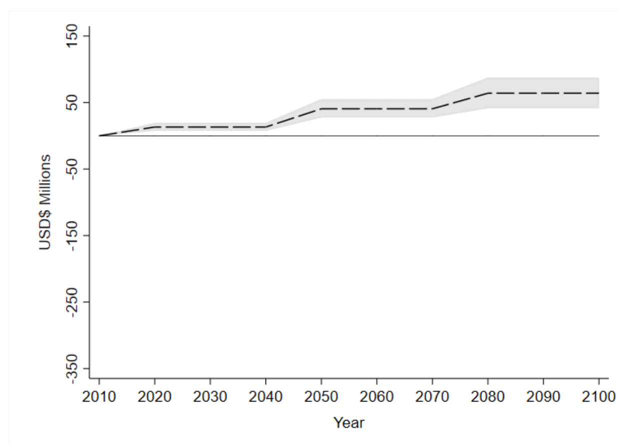
(d) Wave 4 (July & August)



(e) Wave 5 (September & October)



(f) Wave 6 (November & December)



Note: The dashed lines are the average of all 41 RCP 8.5 predictions and the gray areas indicate the 95% confidence intervals estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

Table 1. Site Choice Model Results: Region-by-Year Travel Cost Coefficients

	Gulf Region		**Southeast Region**		**Mid-Atlantic Region**		**New England Region**	
Year	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
2004	-0.172***	-30.87	-0.072***	-19.99	-0.092***	-15.81	-0.110***	-5.73
2005	-0.161***	-26.76	-0.070***	-16.99	-0.079***	-16.53	-0.085***	-12.87
2006	-0.170***	-32.20	-0.067***	-19.03	-0.082***	-15.85	-0.085***	-14.06
2007	-0.157***	-31.36	-0.081***	-24.52	-0.087***	-15.96	-0.094***	-10.87
2008	-0.136***	-29.39	-0.069***	-19.51	-0.084***	-16.55	-0.092***	-11.20
2009	-0.160***	-30.41	-0.070***	-18.88	-0.069***	-11.40	-0.086***	-9.99

Note: Authors' estimates of region-by-year travel cost coefficients from our site choice model run in GAUSS. Models are estimated with robust standard errors clustered by zipcode. *** Significant at the 1 percent level.

Table 2. Participation Model Results

Variables	Model 1 *Coeff.*	*Std. Err.*	Model 2 *Coeff.*	*Std. Err.*	Model 3# *Coeff.*	*Std. Err.*
Temperature Bins						
< 30° F	-0.351***	0.049	-0.298***	0.048	-0.221***	0.050
30° – 35° F	-0.112***	0.020	-0.078***	0.020	-0.090***	0.022
35° – 40° F	0.017	0.011	0.018	0.011	-0.020*	0.012
40° – 45° F	-0.029***	0.010	-0.039***	0.010	-0.031***	0.011
45° – 50° F	-0.051***	0.006	-0.033***	0.006	-0.034***	0.008
50° – 55° F	0.016***	0.006	0.004	0.006	-0.003	0.006
55° – 60° F	-0.012**	0.005	-0.010*	0.005	-0.013**	0.005
60° – 65° F	0.008*	0.005	0.002	0.005	0.001	0.005
65° – 70° F	-0.008*	0.005	-0.011**	0.005	-0.008*	0.005
75° – 80° F	0.009**	0.004	0.003	0.004	-0.001	0.004
80° – 85° F	0.002	0.003	0.006**	0.003	0.003	0.003
85° – 90° F	0.004	0.003	-0.002	0.003	-0.006**	0.003
90° – 95° F	0.003	0.003	-0.004	0.003	-0.004	0.003
> 95° F	-0.003	0.005	-0.013***	0.005	-0.018***	0.005
Precipitation Bins						
0.01” – 0.25“	-0.005***	0.001	0.002*	0.001	0.003***	0.001
0.25” – 0.5”	-0.018***	0.004	-0.016***	0.004	-0.010**	0.004
0.5” – 0.75”	-0.005	0.005	-0.000	0.005	0.003	0.005
0.75” – 1”	-0.002	0.008	0.004	0.008	0.001	0.008
1” – 1.25”	-0.050***	0.012	-0.013	0.012	-0.016	0.012
1.25” – 1.5”	0.087***	0.015	0.035**	0.015	0.033**	0.015
1.5” – 1.75”	-0.010	0.021	0.001	0.020	-0.001	0.020
1.75” – 2”	-0.004	0.026	0.046*	0.025	0.041*	0.025
> 2”	0.005	0.012	0.012	0.012	0.014	0.012
Fixed Effects						
Year	Y		Y		Y	
Wave	Y		Y		N	
Area Code	N		Y		Y	
Wave-Region	N		N		Y	
Dissimilarity Coefficient	0.011***	0.001	0.001	0.001	0.000	0.001
Observations	372,657		372,657		372,657	
Model Fit	-1.66e+09		-1.64e+09		-1.64e+09	

Note: # indicates our preferred model. 70° – 75° F and ‘no precipitation’ are the omitted bins in estimation. Models are estimated with robust standard errors clustered by six-digit phone exchange. Model fit is pseudo log-likelihood.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. ***** Significant at the 10 percent level**.**

Table 3. Annual Demand Responses in Millions of Trips

Time Period	Baseline Estimated Trips *(in Millions)*	2020 – 2049 Percent Change *Estimate*	*95% CI*	2050 – 2079 Percent Change *Estimate*	*95% CI*	2080 – 2099 Percent Change *Estimate*	*95% CI*
Panel A: Aggregate Results							
RCP 2.6	46.1	-2.3	(-5.4, 0.8)	-2.6	(-5.6, 0.8)	-2.6	(-5.5, 0.8)
RCP 4.5	46.1	-2.4	(-5.2, 0.8)	-4.9	(-8.8, -0.5)	-6.1	(-10.4, -0.9)
RCP 8.5	46.1	-3.4	(-6.5, 0.2)	-9.9	(-15.5, -3.0)	-15.2	(-22.7, -5.6)
Panel B: Regional Results (RCP 8.5)							
Gulf	22.5	-7.9	(-11.5, -4.1)	-18.8	(-24.6, -11.0)	-26.4	(-33.6, -16.2)
Southeast	7.4	-3.1	(-6.4, 0.3)	-9.6	(-15.2, -3.1)	-15.4	(-23.0, -5.7)
Mid-Atlantic	10.8	0.1	(-3.6, 3.7)	-0.6	(-7.8, 6.3)	-2.8	(-12.6, 7.4)
New England	5.4	8.4	(4.2, 13.4)	9.0	(1.9, 17.0)	7.3	(-2.0, 18.5)
Panel C: Temporal Results (RCP 8.5)							
Wave 1	3.6	19.3	(15.3, 22.8)	37.7	(30.0, 44.5)	54.5	(42.7, 65.1)
Wave 2	5.4	3.6	(0.3, 7.5)	5.4	(-0.6, 11.6)	4.5	(-4.2, 12.9)
Wave 3	10.4	-4.8	(-8.3, -1.0)	-17.1	(-23.6, -9.4)	-28.6	(-37.7, -17.3)
Wave 4	12.6	-16.8	(-22.1, -10.8)	-36.2	(-45.5, -23.6)	-47.2	(-58.6, -30.9)
Wave 5	8.4	-2.5	(-6.3, 1.2)	-10.2	(-16.3, -4.1)	-20.1	(-28.5, -10.7)
Wave 6	5.7	6.9	(4.0, 10.2)	18.4	(12.6, 24.9)	26.0	(16.9, 35.4)

Note: The baseline estimate represents the annual number of trips predicted by our model. The estimates show for future periods show the percent change in estimated trips predicted in each climate scenario. For RCP 2.6 (4.5, 8.5), we used 36 (42, 41) different GCMs to produce the average estimate. 95% confidence intervals are estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

Table 4. Annual Welfare Changes in Millions of 2010 $USD

Time Period	2020 – 2049		2050 – 2079		2080 – 2099	
	Estimate	*95% CI*	*Estimate*	*95% CI*	*Estimate*	*95% CI*
Panel A: Aggregate Average Results						
RCP 2.6	-36.6	(-80.1, 12.0)	-48.9	(-104.1, 13.8)	-53.5	(-114.9, 15.2)
RCP 4.5	-38.0	(-81.9, 11.7)	-90.8	(-162.1, 10.3)	-126.0	(-216.7, -20.7)
RCP 8.5	-53.8	(-103.1, 1.7)	-181.2	(-286.8, -57.1)	-311.5	(-467.8, -117.4)
Panel B: Regional Average Results (RCP 8.5)						
Gulf	-61.5	(-89.0, -32.5)	-169.1	(-222.4, -100.5)	-265.2	(-340.3, -166.1)
Southeast	-7.9	(-15.6, 0.6)	-27.9	(-45.2, -8.8)	-50.1	(-76.1, -18.1)
Mid-Atlantic	0.3	(-13.0, 13.4)	-2.9	(-33.5, 26.3)	-13.1	(-59.5, 34.4)
New England	15.3	(7.5, 24.6)	18.8	(3.7, 36.6)	16.9	(-5.0, 44.1)
Panel C: Temporal Average Results (RCP 8.5)						
Wave 1	23.1	(18.8, 28.1)	52.1	(43.6, 61.6)	84.3	(69.8, 101.0)
Wave 2	6.4	(0.3, 13.8)	10.9	(-1.8, 24.1)	9.9	(-10.6, 30.0)
Wave 3	-17.1	(-29.7, -3.6)	-70.9	(-98.7, -39.1)	-132.5	(-175.9, -79.1)
Wave 4	-72.0	(-95.3, -46.7)	-179.5	(-226.9, -116.4)	-261.8	(-327.0, -170.0)
Wave 5	-7.4	(-18.0, 2.9)	-34.3	(-54.5, -13.9)	-75.3	(-108.5, -40.6)
Wave 6	13.2	(7.6, 19.4)	40.5	(27.6, 55.0)	64.0	(41.5, 87.6)

Note: The estimates represents the mean welfare prediction of all GCMs for each emissions scenario. For RCP 2.6 (4.5, 8.5), we used 36 (42, 41) different GCMs. 95 % confidence intervals are estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

Table 5. Night Fishing / Intraday Substitution Results

Panel A: Logit Model of Night Fishing [a]

Temperature Bins	dy/dx	Std. Err.
Below 50° F	-0.071	0.045
50° – 55° F	-0.018	0.030
55° – 60° F	0.007	0.016
60° – 65° F	-0.011	0.009
65° – 70° F	0.010	0.007
75° – 80° F	0.005	0.004
80° – 85° F	0.006	0.004
85° – 90° F	0.003	0.003
90° – 95° F	0.004	0.004
> 95° F	0.008**	0.004
Observations	67,731	
Log pseudo-likelihood	-23153	

Panel B: Welfare Results and Comparison to Main Model [b]

	2020 – 2049		2050 – 2079		2080 – 2099	
in USD$ millions	Estimate	Difference Relative to Main Model [c]	Estimate	Difference Relative to Main Model	Estimate	Difference Relative to Main Model
RCP 2.6	-43.3	-6.7	-58.2	-9.4	-63.7	-10.3
RCP 4.5	-45.0	-7.0	-103.3	-12.5	-142.2	-16.2
RCP 8.5	-61.8	-8.0	-199.1	-17.9	-338.4	-26.9

Note: [a] In Panel A, the logit model of night fishing is estimated for the regions and times of year predicted to have welfare losses: the Gulf and Southeast regions during the warmer waves 3-5 (May – Oct).The model is estimated with robust standard errors clustered by six-digit phone exchange. Standard errors for marginal effects reported above are calculated by the Delta-Method. ** Significant at the 5 percent level. [b] Panel B shows the welfare predictions (in millions) from the night-fishing exclusion participation model. The estimates represents the mean of all GCM predictions for each emissions scenario. For RCP 2.6 (4.5, 8.5), we used 36 (42, 41) different GCMs. [c] This column reports the size of the decrease in welfare predicted by the night fishing exclusion model compared to our main model results. All differences reported are statistically significant at the 1 percent level.