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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 time activities in the United States, yet the potential impacts of climate change on this activity are largely unknown or poorly understood. We estimate the effect of temperature and precipitation on the demand for a significant segment of the outdoor recreation economy – coastal recreational fishing in the Atlantic and Gulf Coast regions – from 2004-2009. Combining our econometric estimates from a structural model of angler behavior with downscaled climate projections, we find declines in participation (up to 15 percent) and welfare (up to $312 million annually) for recreational anglers primarily due to more days with extreme temperatures under predicted climate futures. We find evidence of regional and temporal heterogeneity, with projected losses in warmer regions and months and gains predicted in cooler regions and months. We then explore inter- and intra-temporal substitution as potential adaptation strategies to extreme heat. While our results show no significant evidence of angler substituting their recreation decisions across times of the year, we do find that anglers might shift their activities to nighttime as temperatures increase rather than fish less frequently.

JEL Codes: Q22, Q26, Q51, Q54, Q57

Keywords: climate change, recreation demand, temporal adaptation, fishing, coastal economy

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In recent years, the incorporation of weather data into econometric models of firm and individual behavior has emerged as an avenue for exploring the potential impacts of climate change. Exogenous variation in temperature and precipitation across time and space have been used to identify the short run impacts of weather on economic variables of interest (Auffhammer et al. 2013; Hsiang 2016) and, in turn, the potential long run impacts of climate change. To date, this general approach has been used to forecast the effects of climate change on, for example, agriculture (Deschênes and Greenstone 2007; Schlenker and Roberts 2009), labor productivity (Graff Zivin and Neidell 2014), income (Deryugina and Hsiang 2014), mortality (Barreca et al. 2016; Heutel et al. 2017), electricity demand (Auffhammer and Aroonruengsawat 2011) and the quality of life (Albouy et al. 2016).[1]

In this article, we investigate how weather affects participation in outdoor recreation, an activity that contributes $373.7 billion (2016 dollars), or roughly two percent, to U.S. gross domestic product (GDP) (BEA 2018). The outdoor recreation economy is growing faster than the economy as a whole and its contribution to GDP is more than double that of agriculture (BEA 2018), a sector that has been extensively studied in the climate economics literature. Since outdoor recreational activities are highly dependent on the natural environment, participation may be sensitive to potential shifts in the distribution of weather that are predicted over both the near and long terms.

Our focus is on how weather impacts local outdoor recreation decisions, which is an important conduit through which climate change may affect the quality of life and associated nonmarket amenities. Better quantification of these impacts has been noted as a needed research direction in the refinement of social cost of carbon estimates by Burke et al. (2016). Our research also helps fill a significant gap in the literature on the nonmarket economic impacts of climate noted by Shaw and Loomis (2008).[2] The potential impacts of weather on recreation operate through multiple channels. First, the demand for a given activity may be directly affected by observed weather. That is, individuals may choose to not participate in local recreation activities if temperatures are too hot or too cold on any given day. It is this direct, demand-side mechanism that we investigate here, as we hypothesize that the decision to participate in recreation activities is sensitive to an individual's comfort outdoors in observed weather

[1] See Dell, Jones, & Olken (2014) for an extensive review of research at the interface of economics, weather, and climate.
[2] "… much of the existing economic literature related to climate change neglects to mention the losses or gains in benefits from non-market goods such as recreation outings" (Shaw and Loomis 2008, p. 260).

conditions. It is then plausible to posit that the direction and magnitude of changes in long-run weather conditions (i.e., climate shifts) may also impact those decisions. Perhaps more difficult to quantify, changes in climate may also have indirect, or supply-side, effects through impacts on the quality of the ecosystem services related to the recreation visit.[3]

There are a number of econometric strategies to identify the impacts of weather and climate on economic activity, including cross-sectional and panel approaches (Hsiang 2016; Massetti and Mendelsohn 2018). A cross-sectional approach examines a single time period and assumes different populations across space have similar preferences. Then, by comparing populations in different climates, differences in observed behavior can be attributed to differences in climate. The major drawback of this approach is that weather in a particular year may not be representative of climate, which can create difficulty in differentiating the effect of climate from weather and other correlated variables. In contrast, panel methods compare the same population at different points in time, utilizing intertemporal variation in weather to causally identify the effects. This approach lessens concerns of omitted variable bias by systematically controlling for time-invariant unobservables. Identification in these models relies on the assumption that the estimated effect of a small change in realized weather is the same as the effect of similar small adjustment in climate (Hsiang 2016). Panel models help overcome identification issues but estimate only short-run responses to weather. This may introduce bias 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).

Using cross-sectional approaches and highly aggregated data, the modest existing literature on outdoor recreation and climate has generated predictions that suggest climate change will have a positive effect on outdoor recreation. Mendelsohn and Markowski (1999) and Loomis and Crespi (1999) offer single-year national assessments by U.S. state of climate change on outdoor recreation, and both predict a net increase in annual welfare of $2.8 billion (1991 and 1992 dollars, respectively). The impacts vary in both papers by activity type, with gains predicted for warm-weather activities (i.e., boating, fishing, and golfing) and losses for cold-weather activities (i.e., skiing). The studies differ in that Mendelsohn and Markowski (1999) account for direct effects of weather on recreation demand only while Loomis and Crespi (1999) also account for

[3] For example, Loomis and Crespi (1999) model climate-induced changes in the hydrology of streamflow to estimate the impact of climate on freshwater fishing.

indirect effects related to climate-induced alterations in ecosystem services. More recently, Whitehead and Willard (2016) used a similar approach and predicted large increases in marine recreational fishing days (27 percent) and welfare gains ($2.5 billion annually, 2010 dollars) attributable to climate change.[4,5] The results of these studies are susceptible to potential bias as they all contain very few spatially-varying controls that may be correlated with local climate (Massetti and Mendelsohn 2018). Lastly, Chan and Wichman (2018) examine high frequency bike-share data within a reduced form modeling approach that exploits spatial and temporal variation in weather for identification. The authors estimate large potential benefits ($900 million annually, 2016 dollars) to cyclists because of climate change. Taken as whole, this literature generally suggests that welfare gains are expected because climate change will extend the recreation season by shifting more cold weather days into preferred temperature ranges.

Our empirical analysis concentrates on marine recreational fishing, which represents a sizeable share (~ 16 percent) of the outdoor recreation economy.[6] Given our focus on the direct demand response to weather and the nature of our data, we adopt a panel approach for our analysis.[7] Our study follows current empirical practice in the climate literature by combining high-resolution weather data with rich behavioral data over space (Maine to Louisiana) and time (2004-2009) to identify the effects of weather on coastal recreational fishing participation. A repeated discrete choice, random utility maximization (RUM) framework is used to sequentially model both participation and site choice using a pseudo-panel of recreation data. Our structural approach allows us to identify the impacts of weather on recreation in similar observable units across time and to forecast welfare changes as a result of changes in the number trips taken and trips still taken but with different value in a given climate future. The application exploits data obtained from two separate and independent surveys administered by the National Oceanic and

[4] Three other studies focus of freshwater systems. Pendleton and Mendelsohn (1998) model the indirect ecological effects on catch rate in freshwater sport fishing in the northeastern U.S and find a range of welfare implications from a $4.6 million loss to $20.5 million gain. Ahn et al. (2000) estimate a 2 to 20 percent loss in angler consumer surplus due to loss of trout habitat in North Carolina. Jones et al. (2013) conduct a national accounting of freshwater fishing in the U.S. and show a remarkable range of potential indirect annual losses driven by habitat loss from $81 million to $6.4 billion.

[5] In a related context, Whitehead et al. (2009) predict a 39 percent welfare loss to shoreline anglers in North Carolina as a result of sea level rise due to lost beach width (an indirect effect).

[6] NOAA estimates that this activity produced $63.4 billion in spending and accounted for 61 million recreational trips in 2015 (NMFS 2015). They also estimate that the recreation activities of approximately 8.9 million saltwater anglers in the U.S supported 439,000 jobs and generated more than $23 billion in income impacts and $36 billion in value-added impacts. (NMFS 2015, p. 11).

[7] We also estimate cross-section models (see online-only appendix) across different climates in our data. However, these models suffer from the same omitted variable bias problem as previous studies as we do not have a full set of spatially-varying controls to adequately overcome this issue.

Atmospheric Administration's (NOAA) Marine Recreational Information Program (MRIP) – a point-of-access intercept survey and a random-digit-dial phone survey of coastal counties. Weather in the local coastal area closest to each angler origin observation enters into the participation model as we construct temperature and precipitation bins in order to estimate a nonlinear relationship between these variables and recreation decisions along the Atlantic and Gulf Coasts of the U.S. The spatial extent of our study area includes a large majority of the estimated marine recreational fishing trips taken in 2015 (NMFS 2015).

Our primary results suggest that overall angler participation declines at extreme temperatures. We identify the nonlinearity in impacts of extreme heat (>=95° F) and cold (<= 40° F) on the participation margin, implying an inverted U-shape for our temperature-response function. 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. We then use these estimated functions to predict demand-side impacts of climate change using 1/8 degree downscaled daily predictions from 132 unique general circulation models (GCMs) corresponding to one of four climate future scenarios (Representative Concentration Pathways or RCPs) and three time horizons (2020-2049, 2050-2079, and 2080-2099).[8]

Our simulations suggest that an increase in the number of days with extreme heat (>= 95° F) will lead to welfare losses for recreational anglers in the future – an important finding that previous work has not detected. We estimate participation declining between 1.1 to 15.1 percent across all RCPs. Second, welfare losses are predicted for all emissions scenarios over all time horizons, and these results are robust to uncertainty in the climate projections as changes in temperature and precipitation forecast by each of the 132 GCM predictions all imply losses. In the short-run, the losses in RCP 8.5 (business-as-usual) are $54 million annually and increase to $312 million per year in the long term. Furthermore, estimation of additional model specifications indicate that temperature is the primary weather factor driving our simulation results. The scope of our data allow us to also identify seasonal and regional heterogeneity in the effect of weather on participation. Hotter baseline regions (Gulf and Southeast) and months

[8] 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. 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.

(March through October) experience losses under climate change. With a colder baseline climate, anglers in New England and those who recreate during cooler months of the year (November through February) experience welfare gains from climate change. Importantly, our results are for a water-based, warm weather activity and are not uniform across regions and months of the year. This finding suggests that, in addition to extreme temperatures, recreation type and variation across space and time are critical factors to consider when estimating climate impacts on recreation behavior. Furthermore, 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. and fills one of the many "missing sectors" of the economy noted by Hsiang et al. (2017).

Given our findings on the importance of extreme temperatures on recreation demand, we conduct additional analyses exploring both inter- and intra-temporal substitution as adaptation strategies for recreational anglers. The temporal heterogeneity in our main results suggest inter-temporal substitution is a plausible adaptation strategy as anglers could respond to extreme heat by shifting the time of year they recreate. Although the pseudo-panel structure of our data is not ideally suited for such an analysis (i.e., for a given spatial unit, we observe person A choosing to recreate in July and person B in September), we estimate models with one-period weather lags and do not find significant evidence of inter-temporal substitution patterns. Since we observe the self-reported timing of each recreation visit, we can explore the potential for intra-temporal substitution in response to temperature. A reduced-form model of night fishing using participation data in the warmer months (May through October) and regions (Gulf and Southeast) suggests that coastal fishermen are likely already adapting to rising temperatures, as the probability of an angler choosing to recreate at night increases as the number of days with extreme heat (>=95° F) increase. Simulations that eliminate observations utilizing this adaptation channel result in significant increases in welfare losses compared to our baseline estimates, suggesting that these latter estimates are inclusive of at least one adaptive behavior and help mitigate concerns of an upward bias in our welfare damage predictions.

This article proceeds as follows. The next two sections describe our modeling approach and data. In section 3, we discuss results from the site choice and participation models as well as the climate simulations and predicted demand and welfare changes. Section 4 discusses the potential of temporal substitution as an adaptation to weather and the final section concludes.

1. MODELING APPROACH

We use a structural approach to modeling recreation choices with a pseudo-panel of observed data to exploit marginal changes in the distribution of weather as our identification strategy.[9] We compare recreation participation decisions in the same spatial unit at different points in time with different realizations of weather. Furthermore, our model allows us to estimate welfare changes in future climates from both a reduction (increase) in the number of recreation trips and losses (gains) from trips still taken but at diminished (increased) level of utility compared to the baseline. This has advantages over common back-of-the-envelope welfare estimation that would likely either over- or under-estimate this measure by not accounting for recreation activity where the participation decision remains unchanged, but the utility derived from infra-marginal trips is affected by weather (i.e., an angler still goes fishing but it is less enjoyable in hotter weather). In addition to these advantages, we choose this strategy over a cross-sectional approach due to concern of omitted variable bias – our data (described in Section 2) lack information on variables related to recreational trip quality that may be correlated with climate.

Our modeling approach utilizes the RUM discrete choice framework introduced by McFadden (1974) and first applied to recreation demand models by Hanemann (1978). The RUM model is the dominant method for recreation demand analysis due to its ability to yield consistent welfare measures and allow for meaningful substitution among recreation sites.[10] To address participation, i.e., the possibility that different individuals take different quantities of trips, we employ a *repeated* discrete choice framework (Morey et al. 1993), whereby individuals repeatedly make discrete choice participation and site choice decisions across a series of choice occasions, with the sum of these choices representing their demand over a fixed time horizon.

The key assumption with RUM models is that individuals choose the alternative that maximizes their utility. Not all factors that influence utility are observed by the analyst, so utility and choice can be interpreted as random from her perspective. A representative angler *i*'s conditional indirect utility from choosing site *j* on choice occasion *t* can be specified in general terms as:

[9]Our pseudo-panel is constructed from independent surveys collected on the same reference population over time. However, we do not observe a true panel of choices from each individual, but a panel of choices from individuals in the same spatial unit, and the resulting data structure precludes modeling unobserved preference heterogeneity and state dependence (i.e. Smith 2005).

[10] For examples, see Hausman et al. (1995), Parsons and Hauber (1998), Parsons and Needleman (1992), Hauber and Parsons (2000), Parsons et al. (2000), Whitehead and Haab (2000), Murdock (2006), and Carson et al. (2009).

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

where m_{it} is income, c_{ij} is travel cost, $\mathbf{X}_j$ is a vector of site characteristics, and ε_{ijt} captures idiosyncratic, random factors. A rational, utility-maximizing individual selects the site that generates the highest utility, i.e., site j is chosen if $V_{ijt} > V_{ikt}, \forall k \neq j$. Assuming a continuous probability density function for ε_{ijt} [11], the probability of selecting site j at time t is given as:

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

A distinctive characteristic of our data is that information about recreation participation and site choice are collected separately with independent samples. Therefore, when choosing an econometric model, we require a specification that allows for decomposition and separate estimation of these two dimensions of choice. We therefore employ a two-level nested logit model (Morey 1999) and estimate the site choice and participation decisions sequentially (Dundas et al. 2018). The two-level nested logit model generalizes the traditional logit model by allowing for a common random factor to enter the site-specific errors, thus inducing a correlation among site utilities and more reasonable substitution patterns. Sequential estimation allows us to leverage and integrate all of our data into a consistent behavior model. Although there is 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 function as consisting of both a systematic, observable component, v_{ijt}, and a random component, ε_{ijt}. Assuming that utility is linear and additive in ε_{ijt} (i.e., $V_{ijt} = v_{ijt} + \varepsilon_{ijt}$), the probability of choosing site j on choice occasion t is:

$$P_{ijt} = P_{it}(j \mid trip) \times P_{it}(trip) = \frac{e^{(v_{ijt}/\lambda)}}{\sum_{j=1}^{J} e^{v_{ijt}/\lambda}} \frac{\left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda}}{e^{v_{i0t}} + \left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda}} = \frac{e^{(v_{ijt}/\lambda)} \left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda-1}}{e^{v_{i0t}} + \left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right]^{\lambda}} \tag{3}$$

where λ is the dissimilarity coefficient and bounded by theory between 0 and 1 (Herriges and Kling 1997). The probability of not taking a trip is then:

[11] The continuous distribution assumption rules out any ties and implies that equation (2) should be strict inequality.

$$P_{i0t} = \frac{e^{v_{i0t}}}{e^{v_{i0t}} + \left[\sum_{j=1}^{J} e^{v_{ijt}/\lambda} \right]^{\lambda}} \tag{4}$$

Using the properties of a nested logit model that easily partition the model into a product of different logit models (e.g., Ben-Akiva and Lerman 1985, pp. 295-299), all parameters can be estimated by first estimating the site choice model and then conditionally estimating the participation model using standard logit estimation techniques.

First, we assume the conditional indirect utility from visiting site *j* can be specified as follows:

$$V_{ijt} = \eta c_{ij} + \delta_j + \varepsilon_{ijt} \tag{5}$$

where η is the coefficient on travel cost and δ_j is an alternative specific constant (ASC) for site *j*. We estimate a conditional logit site choice model with a full set of ASCs separately for every year of data. Regional heterogeneity in travel costs is accommodated by allowing the travel cost coefficient to vary across four regions of origin (i.e., New England, Mid-Atlantic, Southeast and Gulf).[12] Although this first step generates consistent estimates for the travel cost coefficient, it does not generate consistent estimates for the ASCs because the MRIP only samples a fraction of shoreline fishing sites in every year/wave and we essentially have a choice-based sampling design (Ben-Akiva and Lerman 1985). For unsampled sites, the ASCs are not identified. We therefore follow Dundas et al. (2018) and use auxiliary fishing pressure data to recover calibrated ASC estimates with Berry's (1994) contraction mapping for all sites in the second step and construct the following inclusive value index:

$$IV_i = \ln\left(\sum_{k=1}^{J} e^{\left(\eta/\lambda c_{ik} + \delta_k\right)} \right) \tag{6}$$

where η / λ 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 where we estimate participation.

[12] The Gulf region is defined as all site choices and phone responses in Louisiana, Alabama, Mississippi, Florida, and Georgia while the Southeast includes Virginia, North Carolina, and South Carolina. The Mid-Atlantic includes New York, New Jersey, Delaware, and Maryland and New England is defined as Connecticut, Rhode Island, Massachusetts, New Hampshire, and Maine.

To model participation during each bimonthly wave[13] and capture the response to weather, we specify the indirect utility function associated with not taking a trip (alternative 0) in the following way:

$$V_{i0t} = \delta_0 + \beta^k \boldsymbol{T}_{iwy}^k + \mu^j \boldsymbol{P}_{iwy}^j + \lambda IV_i + \psi_y + \tau_{wr} + \chi_s + \varepsilon_{i0t}\,, \tag{7}$$

where δ_0 is the ASC for the no-trip alternative, ψ_y is a year fixed effect to account for common annual shocks, τ_{wr} is a wave-by-region fixed effect to control for seasonal trends common to each region (e.g., an annual autumn run of a fish species, season- and region-specific alternative recreation opportunities), χ_s is a spatial fixed effect to control for time-invariant unobservables that may differ across trip origins, and the coefficient on IV_i is the dissimilarity coefficient (λ).[14] Our weather data is assigned to each trip origin as the average conditions in the local coastal area proximate to the origin (see section 2.3 for more details). $\boldsymbol{T}_{iwy}^k$ is a vector that includes k temperature bins and each bin contains a count of the number of days in wave w and year y where the daily maximum temperature in the local coastal area is in each bin. In other words, we calculate the count of days in each bin as $\boldsymbol{T}_{iwy}^k = \sum_{m=1}^{12} 1(m \in w) \sum_{d=1}^{D_m} 1(\max temp_d^k)$, where $1(m \in w)$ is an indicator function equal to 1 if the month falls in a particular wave and $1(\max temp_d^k)$ is an indicator function equal to 1 if the maximum temperature recorded for a given day (d) in month m falls in the k^{th} bin. We use 15 temperature bins, ranging from <= 30° F (k=1) to >= 95° F (k=15) in 5° F increments. We omit the 70° - 75° F bin (k=10) in estimation. The coefficients on these bins (β^k) are the focus of our estimation as they capture the marginal effect of an additional day per wave in that bin (relative to the omitted category) on the participation decision. We define precipitation bins ($\boldsymbol{P}_{iwy}^j$) in a manner similar to our temperature bins using daily precipitation (in inches) with 10 bins ranging from no precipitation (j=1) to > 2 inches (j=10) in ¼ inch increments, with bin j=1 as the omitted bin in estimation. Our specification includes weather as influencing the participation decision (eq. 7) rather than the site choice

[13] Waves: 1 = Jan/Feb, 2 =Mar/Apr, 3=May/Jun, 4 = Jul/Aug, 5 = Sep/Aug, & 6 = Nov/Dec.

[14] The inclusive value links the site choice and participation models by bringing information from the site choice model into the participation model. The coefficient on this term reflects the relationship between unobserved portions of utility for alternatives in a given nest (i.e., the dissimilarity coefficient). These terms together enter the participation model and represent the additional expected utility from an individual's site choice relative to the expected utility from other sites in their choice set. The reader is referred to Train (2009, pp. 83-84) for more detailed discussion.

decision. Our maintained assumption is that temporal day-to-day variation in weather is a significant driver of the participation decision, and our focus on local single-day trips implies the spatial variation in weather across sites in an individual's choice set aggregated over a two-month period is likely small, if not negligible. Lastly, the model is estimated with robust standard errors clustered spatially to account for correlation across individuals within similar geographic areas.[15]

Following Deryugina and Hsiang (2014) and Hsiang (2016), Figure 1 displays two examples of our strategy to identify the effect of weather on participation in coastal recreational fishing. Since we observe the number of trips taken per wave by each household, we then use the random realizations of weather at the proximate local coastal area for each household in each given 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. For example, in Panel A of Figure 1, our coefficient for wave 4 in 2008 on $T^{11}_{i,4,2008}$ (80° – 85° F) is identified in Asbury Park, NJ off the additional 5 days observed in that wave in that temperature bin compared to the baseline.

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 and the same six years of phone data to estimate participation.[16] The data are restricted to

[15] We use six-digit phone exchanges as our spatial unit of analysis as this is the scale of data collection for the NOAA phone survey data. The North American Numbering Plan dictates that each phone number in the U.S. has ten digits, including a three-digit area code followed by a three-digit exchange (together, our six-digit phone exchange). An area code identifies a broad geographic area that typically contain multiple towns or a portion of large cities. The exchange provides a more specific location of a telephone number, such as a single town or a section of a city. To give the reader a sense of scale, our data contain observations from 12,075 six-digit phone exchanges across 328 counties, implying an average of 37 six-digit phone exchanges per county.

[16] 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. Because this information is collected on-site, it suffers from both truncation and endogenous stratification (Hindsley et al. 2011), and although several authors have developed methods to account for these data features, the methods require strong parametric distribution assumptions. Moreover, 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.

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 a zip code of residence identifier for each survey respondent. There are 2,473 intercept sites 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 more recently 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; Lovell and Carter 2014). Moreover, using these weights in estimation allows us to recover consistent estimates of the 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 (see figure 2, panel A) 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 idea 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.[17] 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 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.[18] Costs that can be shared by all persons on a given trip (e.g. tolls, 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 number 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 2, panel A).

Given that we have six years of MRIP data from 2004-2009, our final estimation data set consists of 372,657 observations corresponding to phone exchange/year/wave combination where sampling occurred.[19] We have data for 1,558,635 interviewed 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 recreating 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.

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[17] Similar assumptions are typical in recreation demand analysis (e.g. Parson and Hauber 1998; Dundas et al. 2018). Moreover, most non-local trips involve significant expenditures and advanced planning, and thus unanticipated fluctuations in weather are not likely to generate significant behavioral response.

[18] The scale of variable construction for our travel cost estimate is not likely to significantly influence our results as more localized variation in gas prices or state-level variation in fuel economy or operation costs are likely to have a negligible effect. Our results are sensitive to our assumption about the opportunity cost of time. Our assumption has been standard practice in this literature for many years, and despite recent research suggesting otherwise (e.g. Fezzi et al. 2014), we feel our assumption is a defensible conservative estimate of these costs.

[19] Sampling did not occur in all combinations of phone exchanges, years and waves due to low expected shoreline fishing activity during winter months. In particular, only Louisiana, Mississippi, Alabama, Florida and North Carolina sample during January and February (wave 1), and Maine and New Hampshire do not sample during March and April (wave 2).

(2018). Since the survey is conducted using RDD within counties, each six-digit phone exchange is assigned a population-weighted proportion of the count of non-anglers in the county where the exchange is located. For example, assume a county has three phone exchanges, each with a population of 10,000 people. If the survey contacted 300 non-anglers in the county, randomization implies that we can assign 100 non-anglers to each phone exchange in that given two-month period. 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 zip code (covering ~ 62.5 mi^2) to represent weather conditions along the shoreline at the time of the participation decision. Panel B of figure 2 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 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 of the conditional site choice model yields results that conform to prior expectations for travel cost. As shown in table 1, the coefficients are negative and robust across all years and regions. 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 6) 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 could be 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 recreation participation. We estimate a pooled model using data across all regions and waves, with few exceptions due to MRIP sampling constraints.[20] 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 3 and 4 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

[20] In particular, gaps in our data arise because MRIP only samples in NC, FL, MS, AL, and LA during wave 1 and does not sample in NH and ME during waves 2 and 6. These gaps therefore imply that our pseudo-panel is unbalanced.

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). Previously, 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.

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.[21] We use a calibration procedure to address this issue with the simulations applying 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,

[21] 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.

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 (tables A.3 and A.4). Lastly, we re-estimate our participation model (eq.7) 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.5 and Figure A.1 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 – MRIP only samples in wave 1 (Jan./Feb.) for NC, FL, MS, AL, and LA, and also does not sample in waves 2 (Mar./Apr.) and 6 (Nov./Dec.) data in NH and ME. 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 below. 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 average the weather variables in the PRISM data across space and wave to establish a baseline measure of climate. The predicted changes in composition of the daily maximum temperature and precipitation bins 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 each observation in our participation data. 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 agent from origin *i* in wave *w* using the following equation (Haab and McConnell 2002):

$$CV_{iw} = -\frac{1}{\beta}\left(\ln\left(e^{-v_{iw0}^{1}} + \left[\exp(IV_i)\right]^{\lambda}\right) - \ln\left(e^{-v_{iw0}^{0}} + \left[\exp(IV_i)\right]^{\lambda}\right)\right) \text{ x } CO_{iw} \qquad (8)$$

where v_{iw0}^{1} represents indirect utility in future time horizons, v_{iw0}^{0} is indirect utility in the baseline period 2004-2009, and CO_{iw} is choice occasions in wave *w*. To construct annual welfare measures, we then sum CV_{iw} across waves, which correspond to the time horizon of choice in our model. In equation (8), the differences in indirect utility from the baseline to each climate scenario are driven by predicted variation in daily maximum temperature and precipitation bins. Importantly, our welfare estimates are specific to each spatial unit of the analysis (six-digit phone exchange) whereas previous recreation climate studies tend to use uniform values for their projection exercises (e.g. Chan and Wichman 2018).

As noted earlier, the dissimilarity coefficient is likely estimated with bias due to measurement error in travel costs. 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 trip is $30. 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).[22] 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 trip. This assumption is critical since our simulation results are proportional to the value of a 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.[23] 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.[24]

Our preferred econometric model predicts 46.1 million annual shoreline recreational fishing trips originating from coastal counties of the Eastern and Gulf coast regions of the U.S.[25] As shown in Table 3, the predicted trips decline on average about 2.7 percent across RCP scenarios in the short term (2020-2050) and up to 7.6 percent in the long-run (2080-2099).[26] Panel B displays regional estimates, suggesting that the demand response to rising temperatures are 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

[22] Moeltner and Rosenberger (2014) report the average WTP/day for a saltwater fishing trip in the Northeast is $39.39 (2010 dollars) from five relevant valuation studies. In Johnston and Moeltner (2014), the authors show that the mean Hicksian WTP/day from 14 different studies for saltwater fishing of big-game species is approximately $33.06. They also report the average WTP/day for small-game saltwater fishing across 13 studies as $21.33.

[23] 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.

[24] http://www.census.gov/population/projections/files/summary/NP2014-T1.csv

[25] For reference, NMFS (2015) estimated 61 million coastal recreational trips in 2015, with around 88 percent of those trips occurring in our study area. Our model predictions match well to these estimates.

[26] The changes in participation may potentially have impacts on fish stocks that, in turn, may influence catch rates. For instance, a decrease in participation may result in an increase in catch rates, potentially offsetting some of the losses from climate change identified here. Assessing this potential feedback loop is an area for future research and is not addressed in this paper.

likely to have more days shift from "ideal" (70° - 75° F) to warmer 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 equation (8), 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 infra-marginal trips that are diminished from climate change, while the back-of-the-envelope approach only captures the value of lost trips. 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). [27] We focus our discussion on RCP 8.5 (business-as-usual), where the predicted welfare losses in the pooled model range from $54 million (2020 – 2049) to $312 million (2080 – 2099) annually. Figure 5 depicts the potential climate uncertainty around the welfare predictions, with the mean GCM prediction shown as the dotted line and 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 show that temperature is the primary driver of the welfare and demand shifts predicted in this exercise.

The spatial and temporal heterogeneity in our results are shown in panels B and C of table 4 and figures 6 and 7 (for RCP 8.5).[28] 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

[27] Tables A.6 – A.9 in the online appendix provide these results by region and wave for RCP 2.6 and 4.5.
[28] Figures A.2 - A.5 in the online appendix display these results for RCP 2.6 and 4.5

$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 between $900 million annually (Chan and Wichman 2018) and $2.8 billion annually (Loomis and Crespi 1999; Mendelsohn and Markowski 1999). This divergence is due to our panel approach that allows us to identify the impact of extreme heat on recreation behavior. 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 coastal shoreline recreational fishing activities. One of the primary caveats to that analysis is the potential for adaptation of recreators in response to changes in temperature. 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 (e.g., 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. Here we look at night fishing, a potential adaptive behavior that would still be available to anglers in future time periods. We explore these two dimensions of temporal substitution as potential adaptation mechanisms.

First, we investigate the potential for substitution across days and 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 a July 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 model with one-period lagged weather variables and results are reported in table A.10 in the online appendix. Nearly all coefficients on the lagged variables are insignificant, indicating that previous period weather is unlikely to impact current period recreation participation decisions. Furthermore, simulations run with coefficients from the model with lags produce marginally larger welfare and trip losses. Although our data is not ideally suited to investigate this adaptation pathway, these results suggest substitution across waves may not be a confounding factor that significantly impacts our simulation results.

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 trip to a specific site on a particularly hot day (i.e. > 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 night fishing ($Night_{it}$ =1) if the self-reported time that fishing activities for individual *i* on choice occasion *t* were completed occurs between sunset and sunrise in that particular wave.[29] A logit model is estimated as follows:

$$Night_{it} = \begin{cases} 1, \ \alpha + \beta^k T_{it}^k + \mu^j P_{it}^j + \eta_{it} + \psi_t + \tau_{wr} + \chi_s + \varepsilon_{it} \\ 0, \ otherwise \end{cases}, \quad (9)$$

[29] For example, night fishing in wave 3 (May/June) is defined using the interval 9 PM to 6 AM.

where the temperature and precipitation bins, and year, wave, and spatial fixed effects are defined following equation (7) and a dummy (η_{it}) is added to control for mode of fishing (pier, jetty, bridge, beach, or other). Recognizing the ambiguity in the definition of a night trip, we conducted sensitivity analyses where we vary the definition of nighttime fishing to gauge the sensitivity of our results. Although not reported here, our main results reported in panel A of table 5 and discussed below are robust to these perturbations.

We estimate equation (9) with data from the Gulf and Southeast regions across warmer months of the year (May to October) since these are the areas and times of year with observed extreme heat in our data. Results (see panel A table 5) 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 % for each day per wave above 95°F. Given this suggestive evidence, we stratify our data by our hypothesized adaptation mechanism (Hsiang 2016) and estimate our participation model with day fishing observations only, eliminating the 25,849 night fishing trips.[30] 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 annually in the short run to a $17.8 million increase by 2080. This suggests that our main simulation results are inclusive of this adaptation behavior and anglers are already adapting at the margin to extreme heat when making their participation decisions.

5. CONCLUSION

In this article, we extend the literature on quantifying the potential economic impacts of weather and climate to a nonmarket good – recreational fishing. We estimate non-linear temperature- and precipitation-response functions that suggests significant changes in participation in coastal shoreline recreational fishing in response to observed weather conditions. The key results from our econometric model is that extreme temperatures are likely the primary driver of recreation behavior changes and extreme heat (>=95°F) is likely to reduce 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

[30] Model results included in the online appendix in table A.11.

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), Whitehead and Willard (2016) and Chan and Wichman (2018) 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 long-run response to climate. 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 (Ahn et al. 2000; Jones et al. 2013) 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).[31] 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 (ITQ) 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.

[31] Other work on fish stock response to climate change has been conducted in the East China Sea (Chueng et al. 2008), Canada (Chueng et al. 2009), the Baltic Sea (Nieminen et al. 2012) and Greenland/Iceland (Arnasen 2007).

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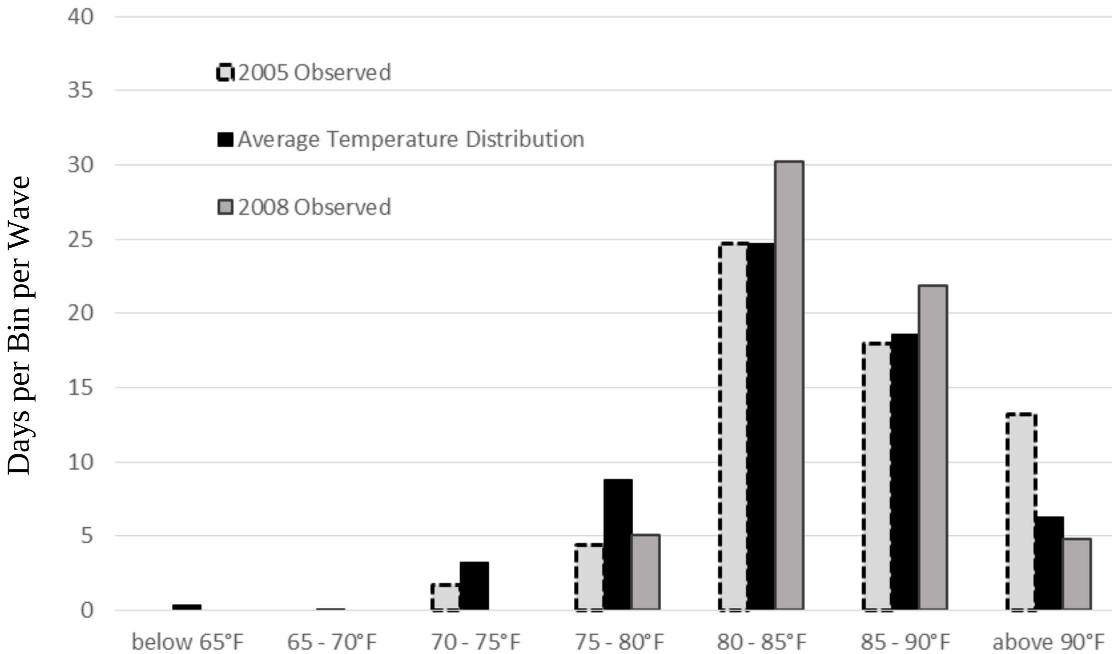
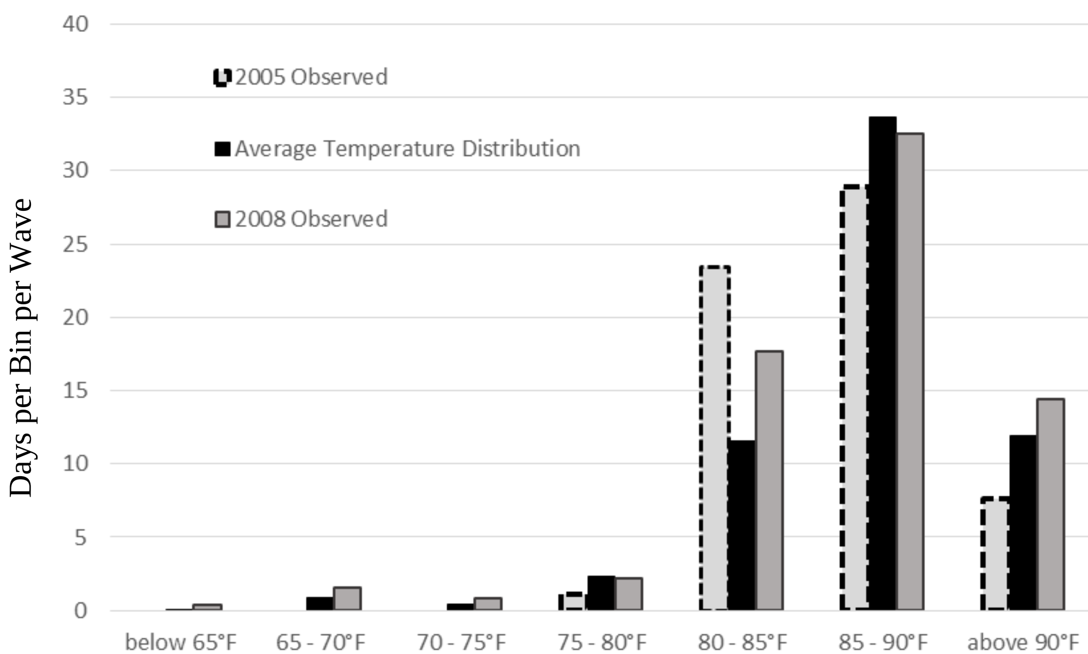
Figure 1. Identification of Temperature Effects

Panel A: Asbury Park, NJ during July and August (Wave 4)



Panel B: Melbourne, FL during September & October (Wave 5)



Note: Panels A and B provide two examples for our identification strategy. We utilize random realizations of weather at each location in a given wave to identify the impact of temperature on participation. The black bars indicate the average temperature distribution that is absorbed by spatial fixed effects and inference is gleaned from the deviations in actual observed weather (2005 and 2008 realizations of actual weather shaded in gray).

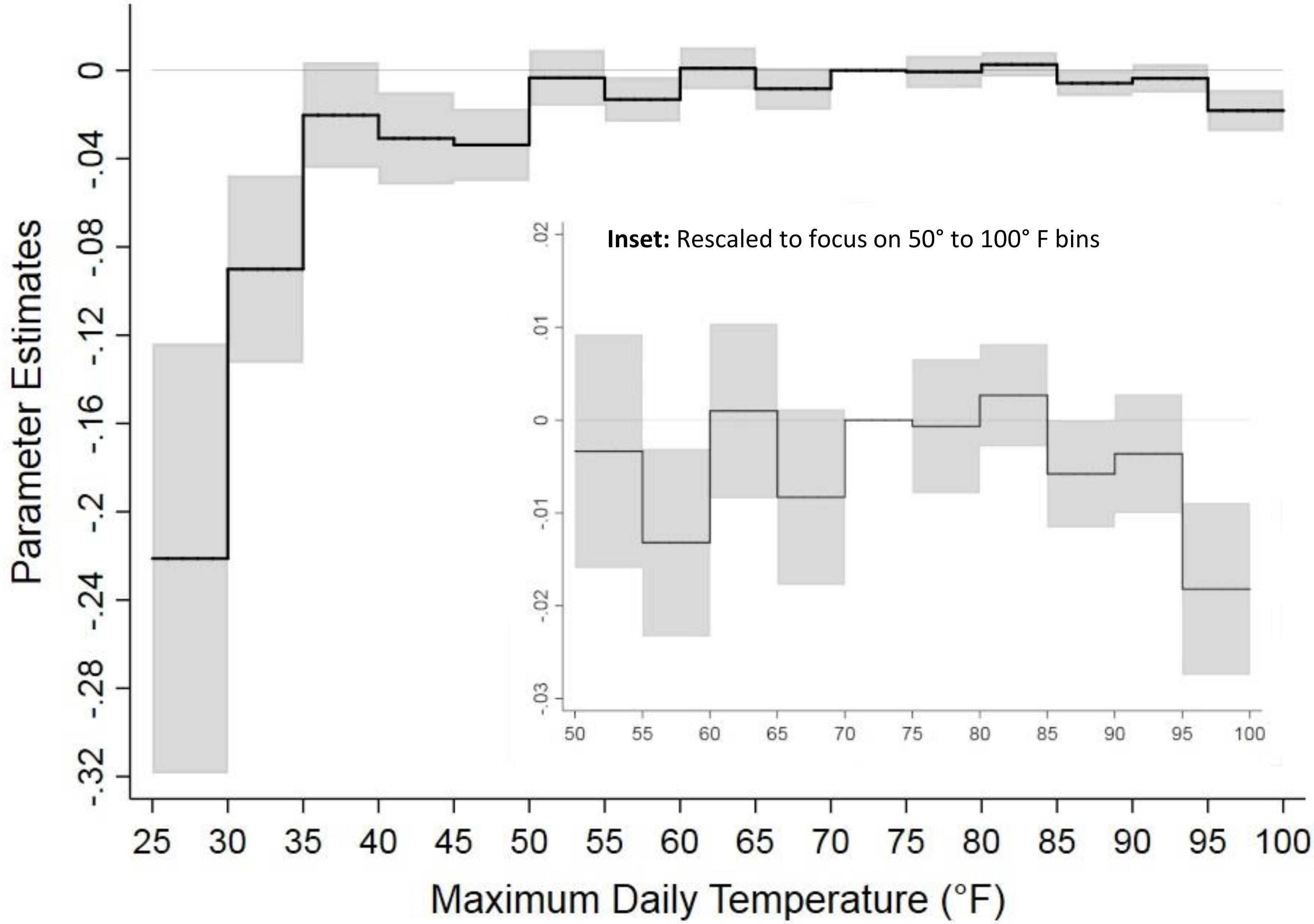
Figure 2. Maps Representing the Study Area

Panel A: Coastal Counties Sampled in MRIP Phone Survey

Panel B: Example of Weather Assignment to Origin Zip Codes

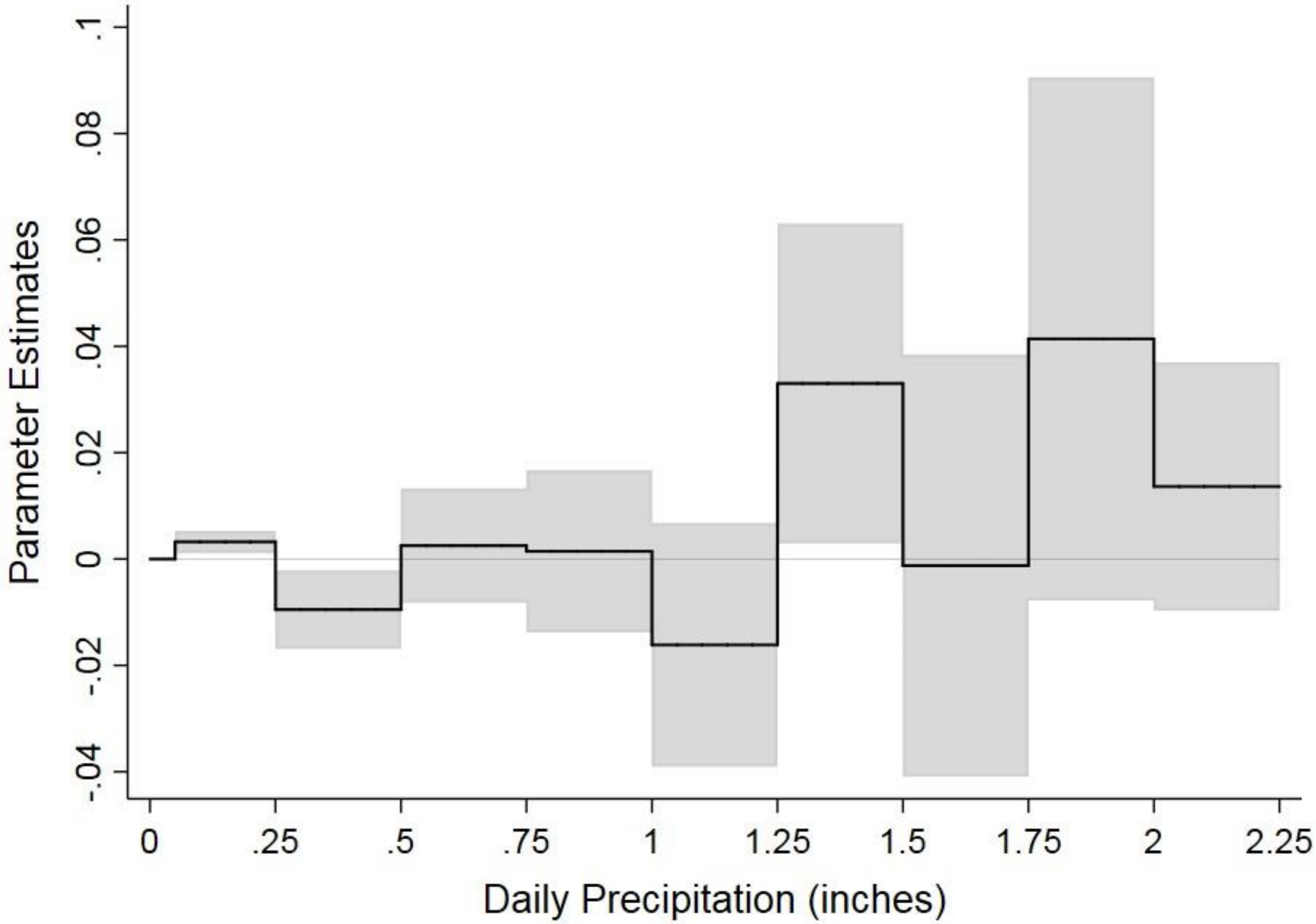
Note: In panel A, gray areas represent the coastal counties that are in the sampling frame for the MRIP participation phone survey. In panel B, dots indicate locations of PRISM weather data and the gray areas represent zip codes of origin in our participation data that are assigned data from the PRISM locations.

Figure 3. 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.

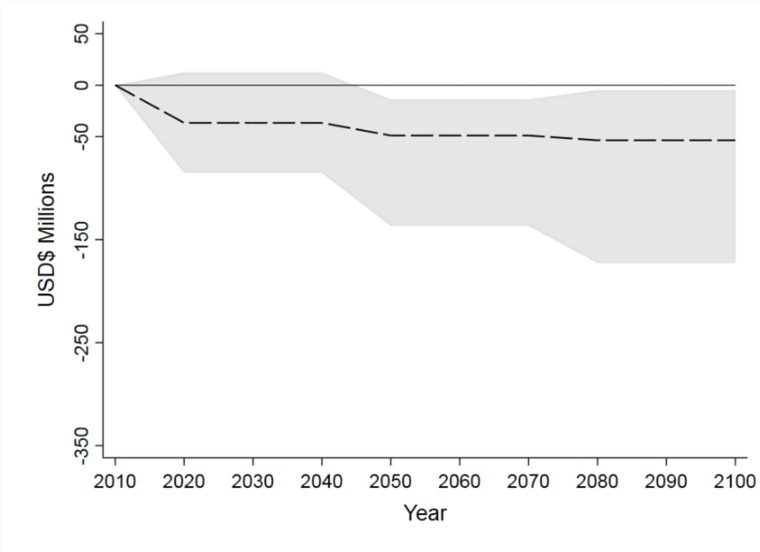
Figure 4. The Effect of Precipitation on Participation in Marine Recreational Fishing



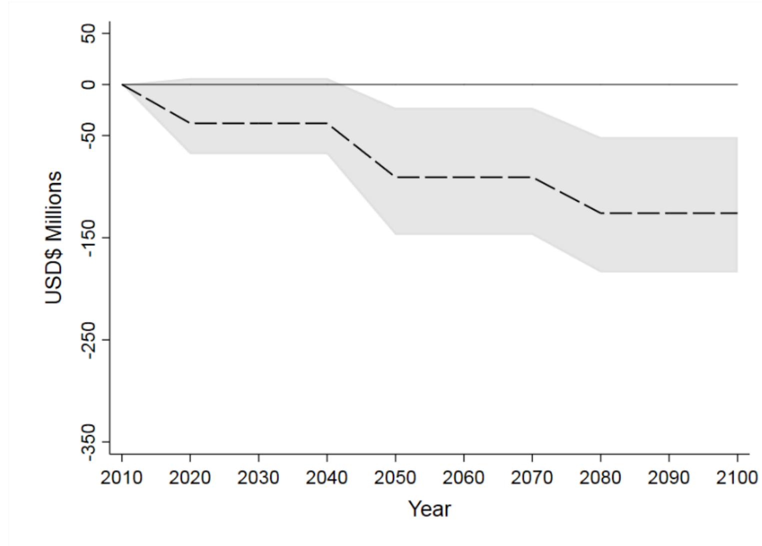
Note: Solid line indicates point estimates at each quarter-inch precipitation bin. Shaded area indicates the 95% confidence interval.

Figure 5. Welfare Effects under Different Climate Change Scenarios

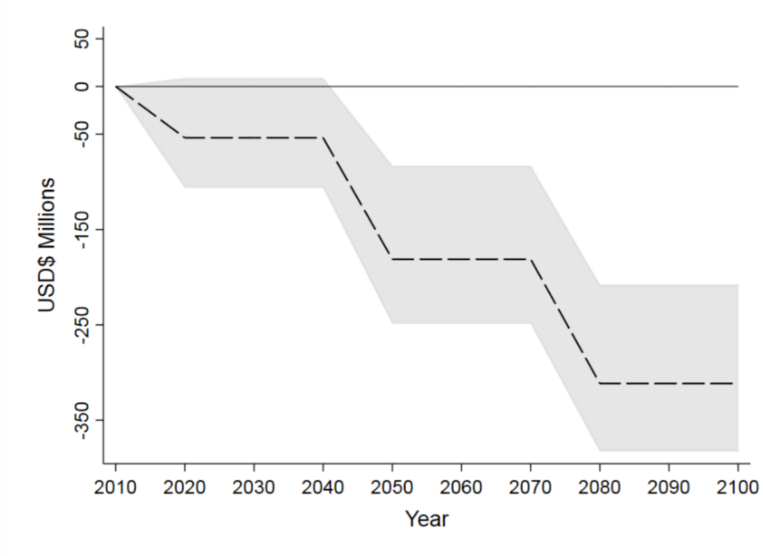
Panel A: RCP 2.6



Panel B: RCP 4.5

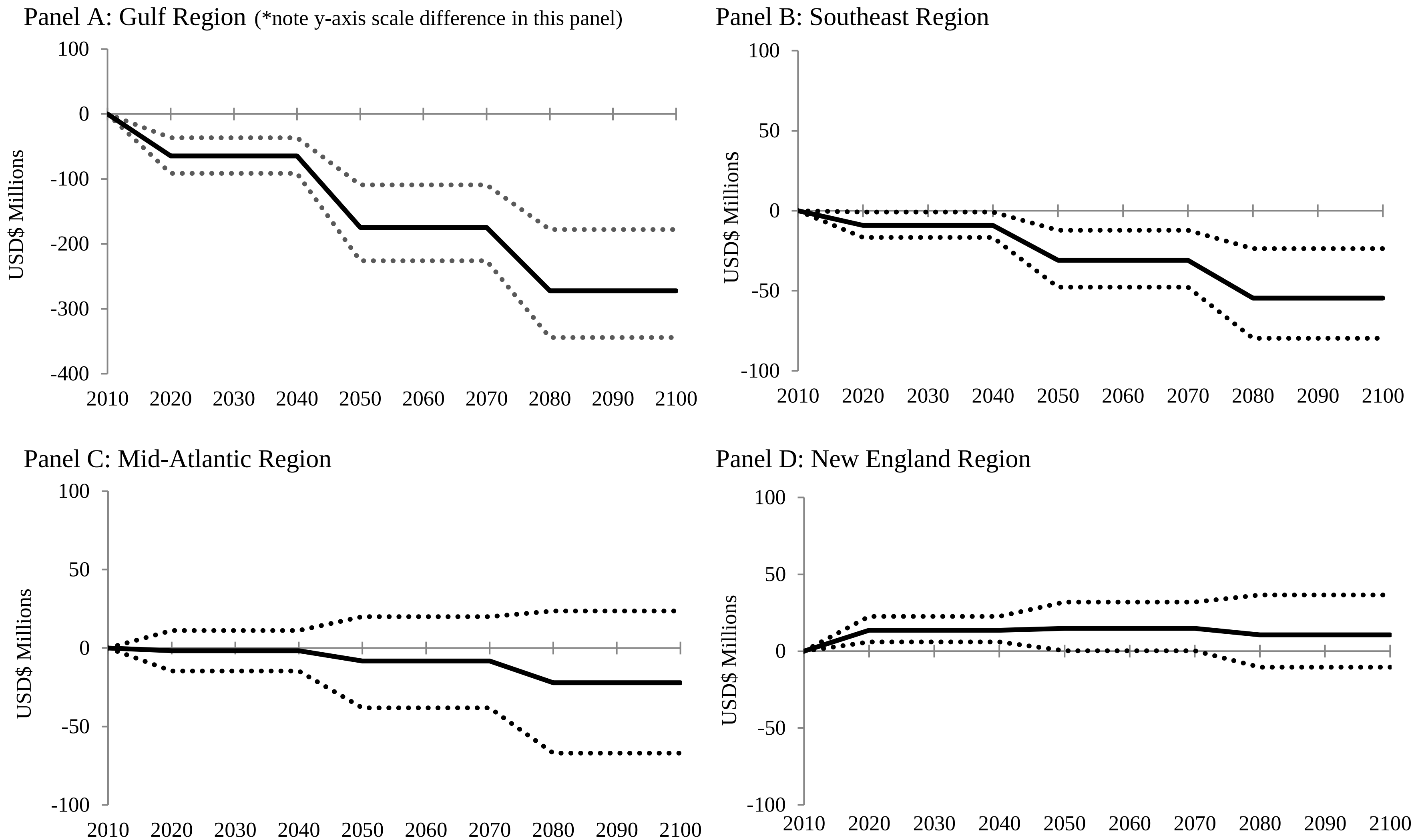


Panel C: RCP 8.5



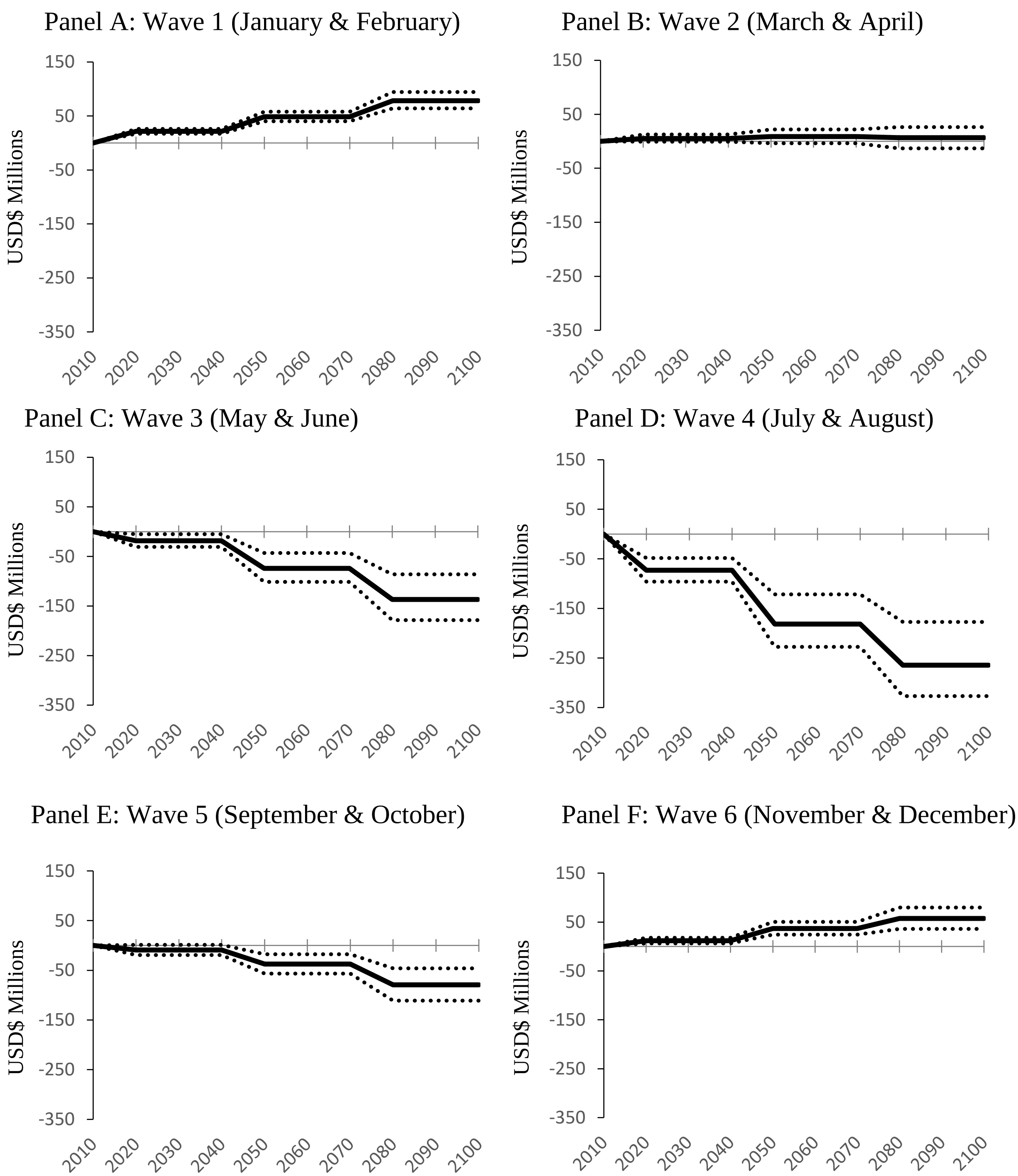
Note: For RCP 2.6 (4.5, 8.5), we used 36 (42, 41) different GCMs. The dashed line shows the average of those models and the gray area represents the full range (i.e., highest and lowest welfare estimates) from all tested GCMs for each RCP scenario.

Figure 6: Regional Welfare Effects under RCP 8.5



Note: To better visualize the estimated impacts for Panes B, C, and D, please note that we used a different scale for the y-axis than Panel A (Gulf). The solid lines represents the average of all 41 RCP 8.5 predictions for each region and the dotted lines indicate the 95% confidence intervals estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

Figure 7: Temporal Welfare Effects under RCP 8.5



Note: The sold lines represents the average of all 41 RCP 8.5 predictions for each wave and the dotted lines 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		**Mid-Atlantic Region**		**New England Region**		**Southeast Region**	
Year	*Coeff.*	*T-stat*	*Coeff.*	*T-stat*	*Coeff.*	*T-stat*	*Coeff.*	*t-stat*
2004	-0.172***	-30.87	-0.092***	-15.81	-0.110***	-5.73	-0.072***	-19.99
2005	-0.161***	-26.76	-0.079***	-16.53	-0.085***	-12.87	-0.070***	-16.99
2006	-0.170***	-32.20	-0.082***	-15.85	-0.085***	-14.06	-0.067***	-19.03
2007	-0.157***	-31.36	-0.087***	-15.96	-0.094***	-10.87	-0.081***	-24.52
2008	-0.136***	-29.39	-0.084***	-16.55	-0.092***	-11.20	-0.069***	-19.51
2009	-0.160***	-30.41	-0.069***	-11.40	-0.086***	-9.99	-0.070***	-18.88

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.	Model 1 Std. Err.	Model 2 Coeff.	Model 2 Std. Err.	Model 3# Coeff.	Model 3# 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	2020 – 2049		2050 – 2079		2080 – 2099	
	Estimated Trips	Percent Change		Percent Change		Percent Change	
	(in Millions)	*Estimate*	*95% CI*	*Estimate*	*95% CI*	*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	7.43	-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	(4.0, 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	5.5	3.6	(0.3, 7.5)	5.4	(-0.6, 11.6)	4.5	(-4.3, 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 estimated change (Δ) reported is predicted trips for each scenario minus the baseline estimate. 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)	10.3	(-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	67,725	
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 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.

Supplemental Material for: Steven J. Dundas, Roger H. von Haefen. 2018. "The Effects of Weather on Recreational Fishing Demand and Adaptation: Implications for a Changing Climate."

APPENDIX (For On-line Publication)

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

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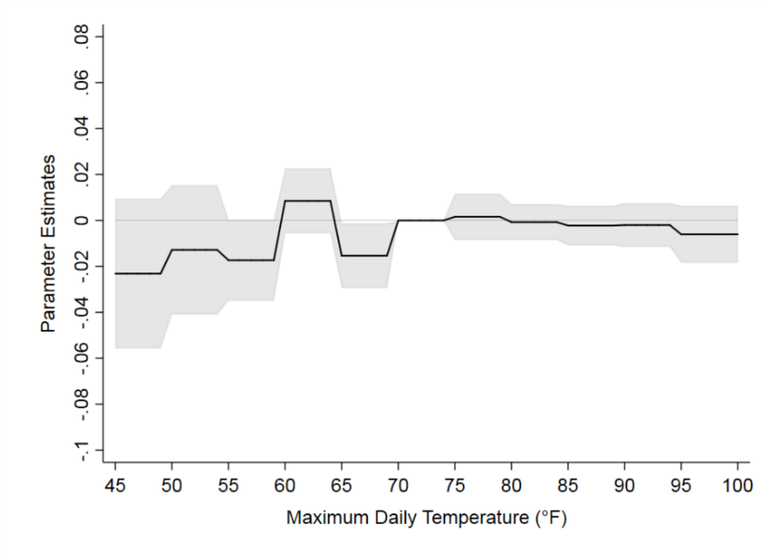
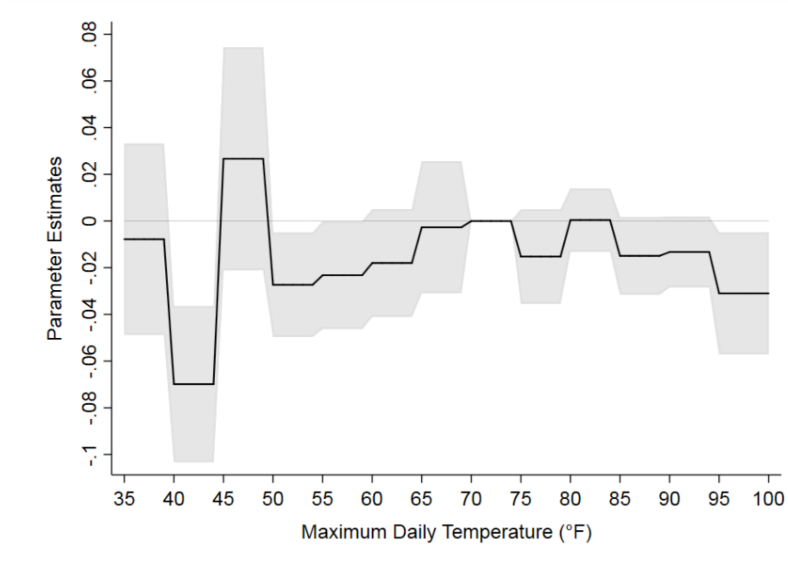
Appendix A: Additional Figures and Tables

Figure A.1. The Effect of Temperature on Participation in Marine Recreational Fishing – Regional Models

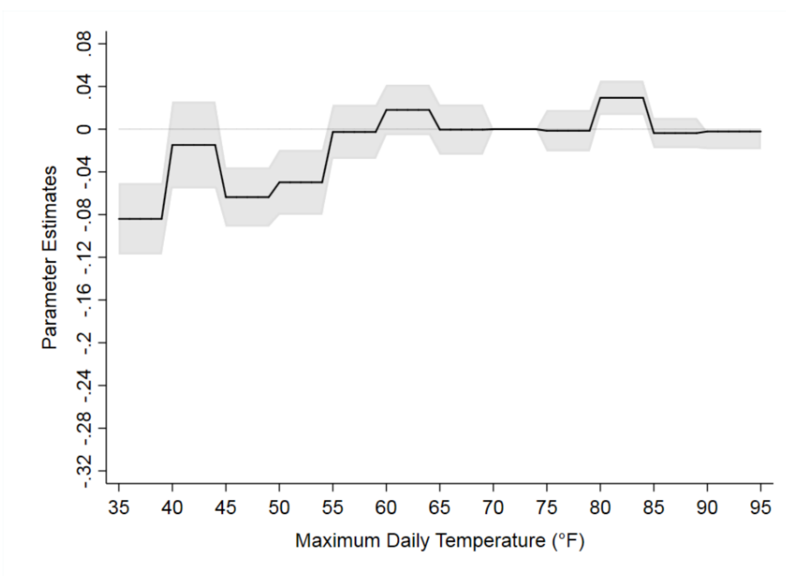
Panel A: Gulf Region



Panel B: Southeast Region



Panel C: Mid-Atlantic Region (*note y-axis scale difference)



Panel D: New England Region

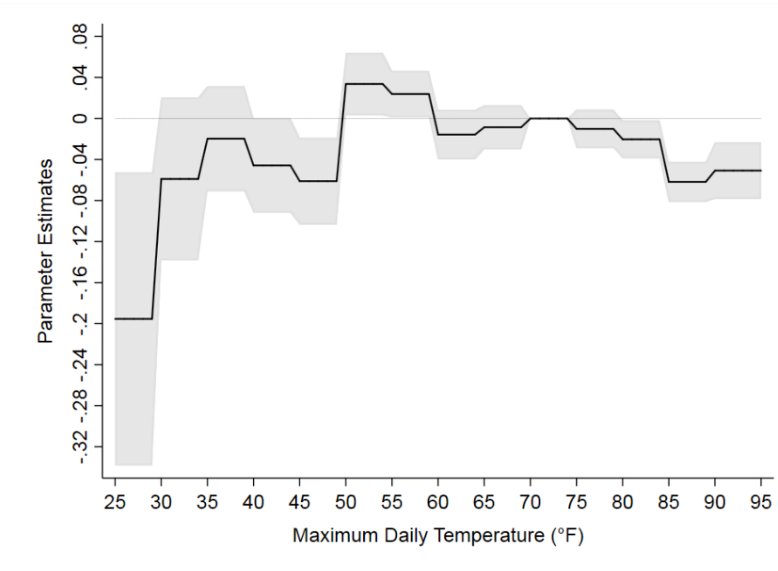
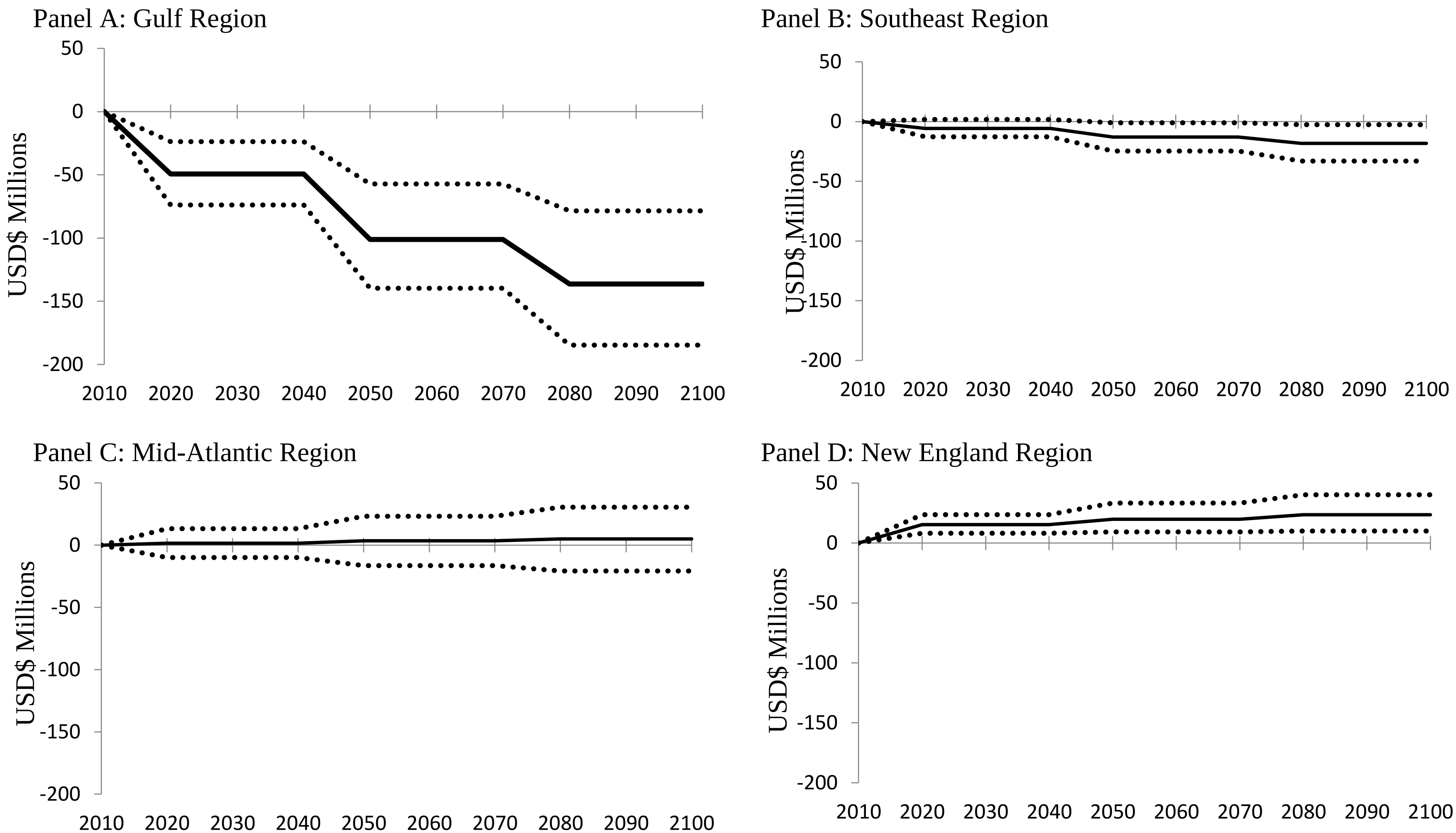


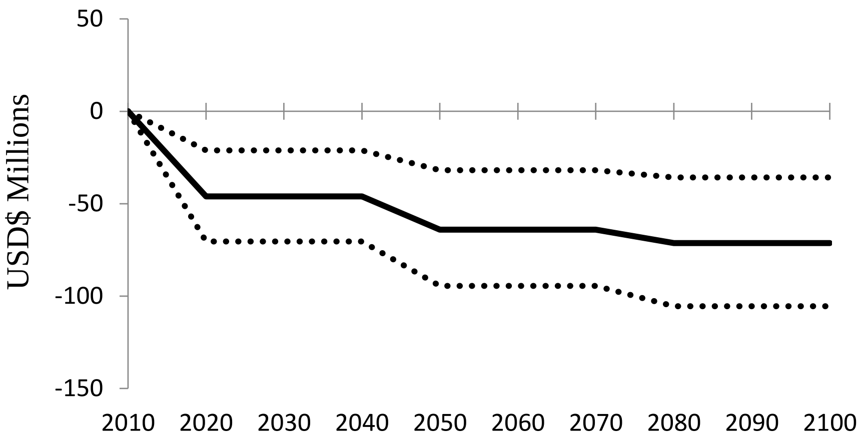
Figure A.2. Regional Welfare Effects under RCP 4.5



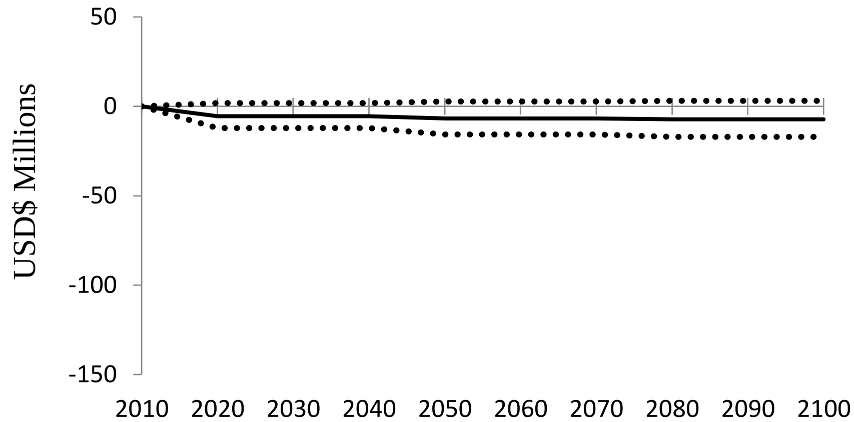
Note: The solid lines represents the average of all 41 RCP 8.5 predictions for each region and the dotted lines indicate the 95% confidence intervals estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

Figure A.3: Regional Welfare Effects under RCP 2.6

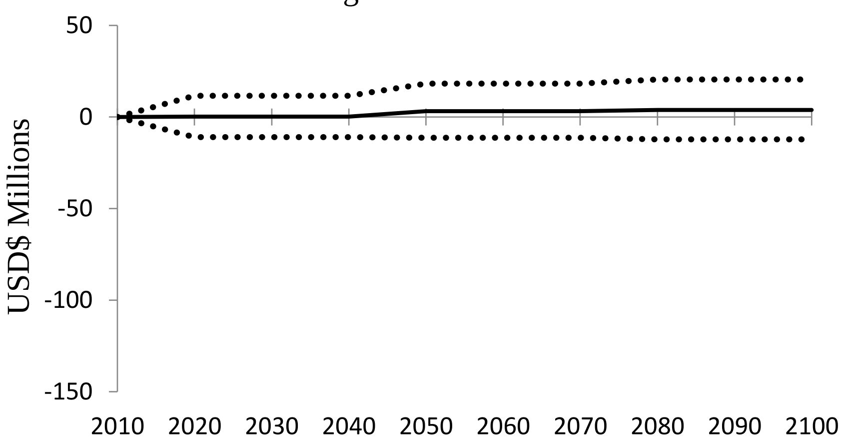
Panel A: Gulf Region



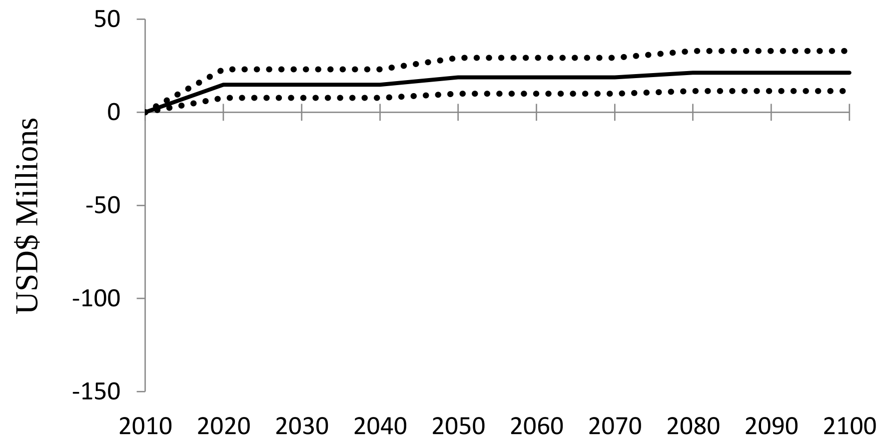
Panel B: Southeast Region



Panel C: Mid-Atlantic Region

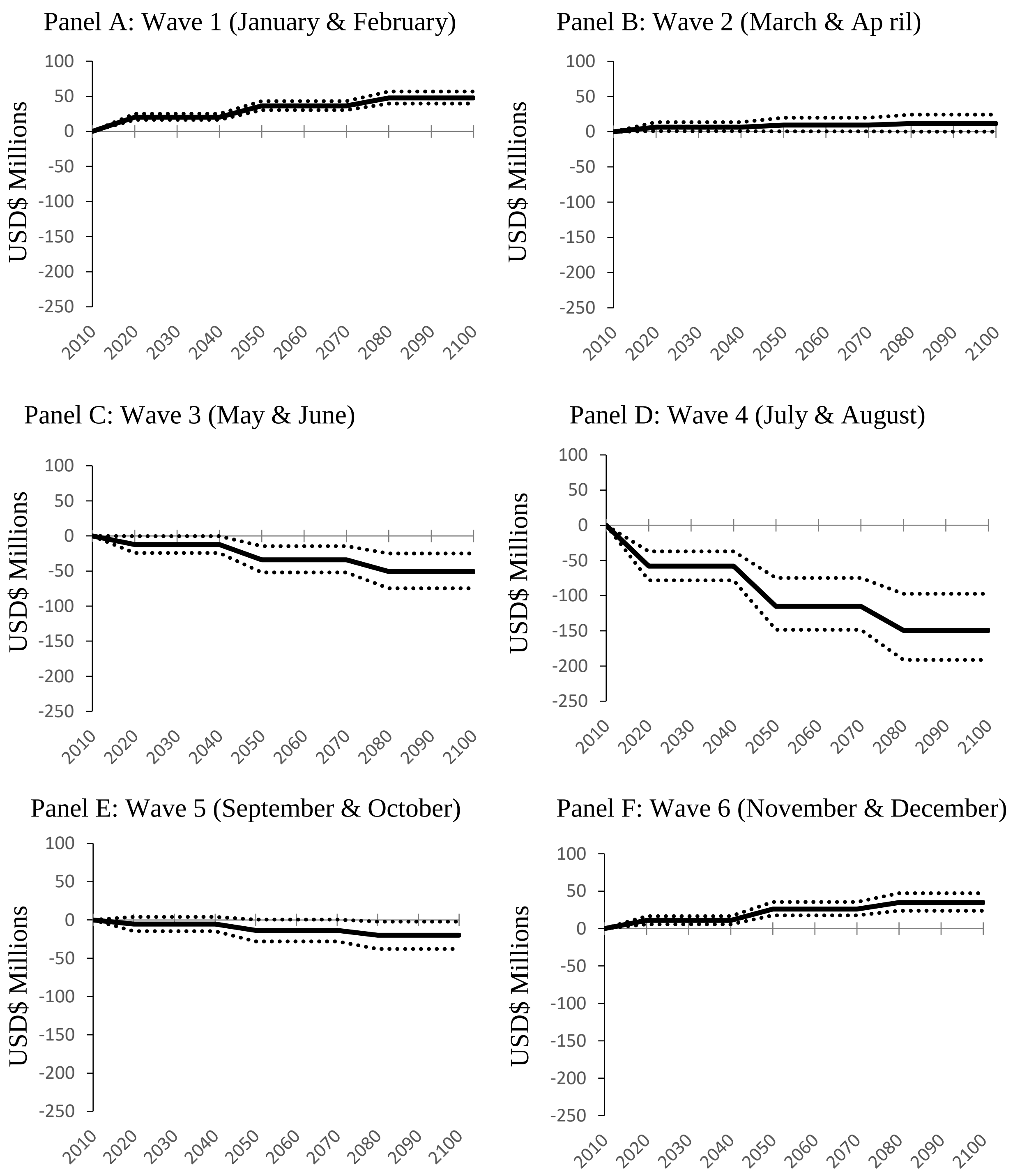


Panel D: New England Region



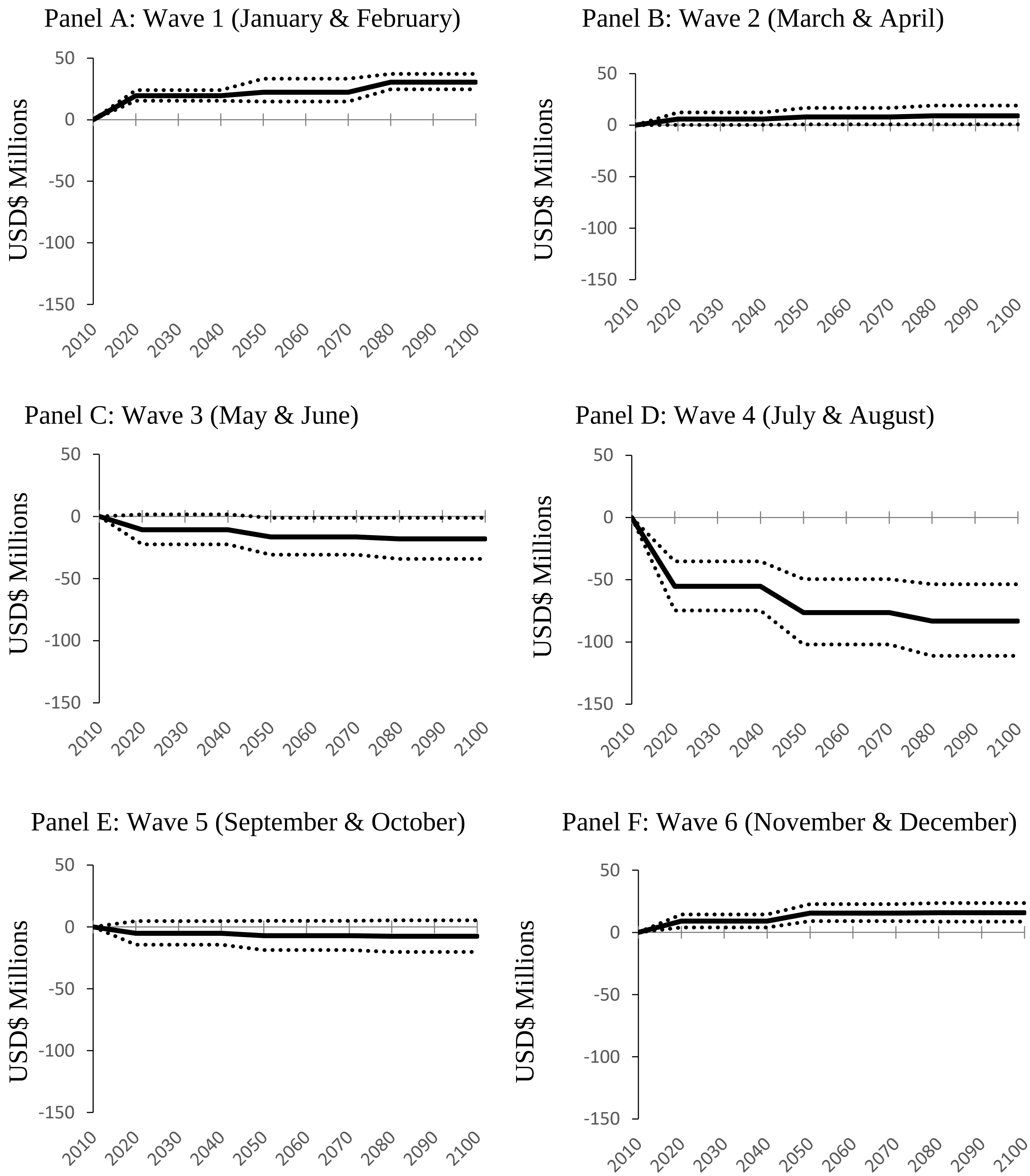
Note: The solid lines represents the average of all 41 RCP 8.5 predictions for each region and the dotted lines indicate the 95% confidence intervals estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

Figure A.4: Temporal Welfare Effects under RCP 4.5



Note: The sold lines represents the average of all 41 RCP 8.5 predictions for each wave and the dotted lines indicate the 95% confidence intervals estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

Figure A.5: Temporal Welfare Effects under RCP 2.6

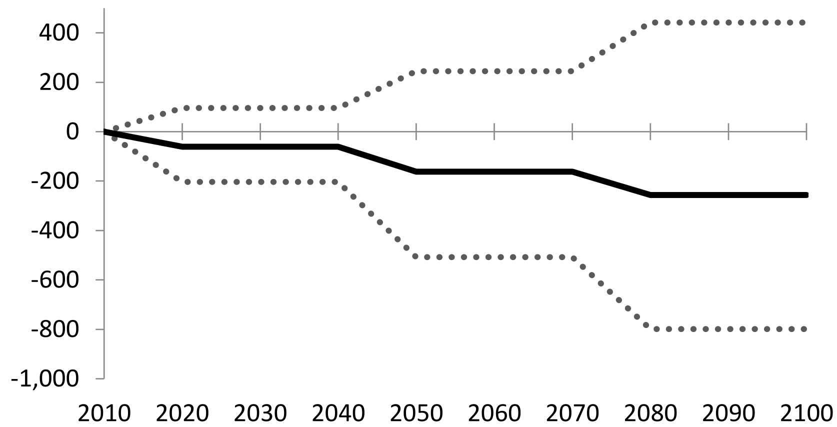


Note: The sold lines represents the average of all 41 RCP 8.5 predictions for each wave and the dotted lines indicate the 95% confidence intervals estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

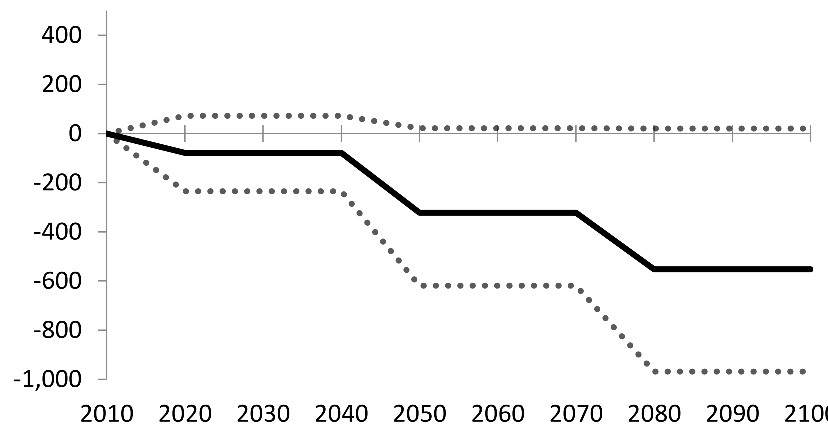
Supplemental Material for: Steven J. Dundas, Roger H. von Haefen. 2018. "The Effects of Weather on Recreational Fishing Demand and Adaptation: Implications for a Changing Climate."

Figure A.6. Welfare Effects under RCP 8.5 with region-specific models

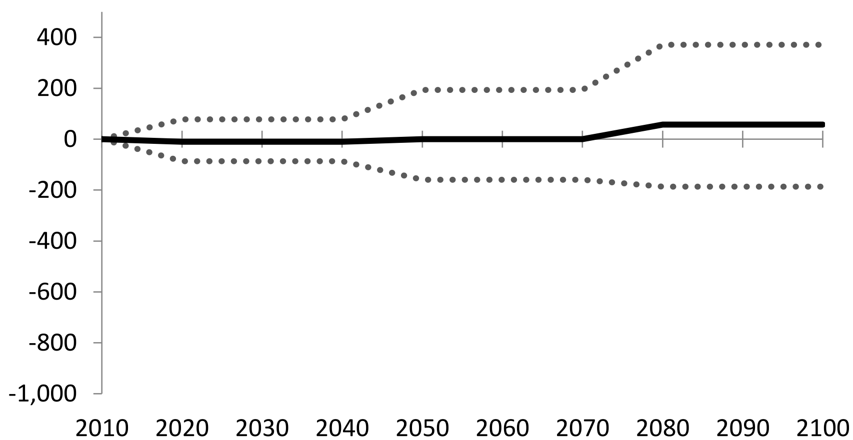
Panel A: Gulf Region



Panel B: Southeast Region



Panel C: Mid-Atlantic Region



Note: The sold lines represents the average of all GCMs for each region and the dashed lines indicate the 95% confidence intervals estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws. Welfare effects for New England are not reported as sampling is not conducted in waves 1, 2, and 6 in the region.

Table A.1. General Circulation Model Data Used

Modeling Center	Institute ID	Model Name	Number of Model Runs Used			
			RCP 2.6	*RCP 4.5*	*RCP 6.0*	*RCP 8.5*
Commonwealth Scientific & Industrial Research Organization (CSIRO) & Bureau of Meteorology (BOM), Australia	CSIRO-BOM	ACCESS1.0	0	1	0	1
Beijing Climate Center, China Meteorological Administration	BCC	BCC-CSM1.1	1	1	1	1
Canadian Centre for Climate Modelling and Analysis	CCCMA	CanESM2	5	5	0	5
University of Miami - RSMAS	RSMAS	CCSM4	2	2	2	2
Community Earth System Model Contributors	NSF-DOE-NCAR	CESM1(BGC)	0	1	0	1
Centre National de Recherches Météorologiques	CNRM-CERFACS	CNRM-CM5	0	1	0	1
Commonwealth Scientific & Industrial Research Organization	CSIRO-QCCCE	CSIRO-Mk3.6.0	10	0	10	10
NOAA Geophysical Fluid Dynamics Laboratory	NOAA GFDL	GFDL-CM3	1	0	1	1
	NOAA GFDL	GFDL-ESM2G	1	1	1	1
	NOAA GFDL	GFDL-ESM2M	1	1	1	1
Institute for Numerical Mathematics	INM	INM-CM4	0	1	0	1
Institut Pierre-Simon Laplace	IPSL	IPSL-CM5A-LR	3	4	1	4
	IPSL	IPSL-CM5A-MR	1	1	1	1
Japan Agency for Marine-Earth Science & Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), & National Institute for Environmental Studies	MIROC	MIROC-ESM	1	1	1	1
	MIROC	MIROC-ESM-CHEM	1	1	1	1
	MIROC	MIROC5	3	3	1	3
Max Planck Institute for Meteorology	MPI-M	MPI-ESM-LR	3	3	0	3
	MPI-M	MPI-ESM-MR	1	3	0	1
Meteorological Research Institute	MRI	MRI-CGCM3	1	1	1	1
Norwegian Climate Centre	NCC	NorESM1-M	1	1	1	1
Totals	*14 Institutes*	*20 GCMs*	36	32	23	41

Note: We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modeling groups above for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

Table A.2. Precipitation-Only and Temperature-Only Participation Model Results

	Precipitation-Only		**Temperature-Only**		**Main Model**	
Variables	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
Temperature Bins						
< 30° F	-	-	-0.218***	0.050	-0.221***	0.022
30° – 35° F	-	-	-0.095***	0.022	-0.090***	0.011
35° – 40° F	-	-	-0.020	0.012	-0.020*	0.009
40° – 45° F	-	-	-0.031**	0.011	-0.031***	0.006
45° – 50° F	-	-	-0.035***	0.008	-0.034***	0.004
50° – 55° F	-	-	-0.002	0.006	-0.003	0.004
55° – 60° F	-	-	-0.014***	0.005	-0.013**	0.003
60° – 65° F	-	-	0.001	0.005	0.001	0.003
65° – 70° F	-	-	-0.009*	0.005	-0.008*	0.006
75° – 80° F	-	-	-0.000	0.004	-0.001	0.004
80° – 85° F	-	-	0.003	0.003	0.003	0.003
85° – 90° F	-	-	-0.006**	0.003	-0.006**	0.004
90° – 95° F	-	-	-0.004	0.003	-0.004	0.003
> 95° F	-	-	-0.018***	0.005	-0.018***	0.005
Precipitation Bins						
0.01” – 0.25“	0.003***	0.001	-	-	0.003***	0.001
0.25” – 0.5”	-0.013***	0.004	-	-	-0.010**	0.003
0.5” – 0.75”	0.002	0.005	-	-	0.003	0.005
0.75” – 1”	-0.002	0.008	-	-	0.001	0.006
1” – 1.25”	-0.017	0.011	-	-	-0.016	0.009
1.25” – 1.5”	0.033**	0.015	-	-	0.033**	0.012
1.5” – 1.75”	0.000	0.020	-	-	-0.001	0.041
1.75” – 2”	0.038	0.025	-	-	0.041*	0.022
> 2”	0.017	0.012	-	-	0.014	0.009
Fixed Effects						
Year	Y		Y		Y	
Wave	N		N		N	
Area Code	Y		Y		Y	
Wave-Region	Y		Y		Y	
Dissimilarity Coefficient	-0.000	0.000	0.001	0.001	0.000	0.001
Observations	372,657		372,657		372,657	
Model Fit	-1.64e+09		-1.64e+09		-1.64e+09	

Note: 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 A.3. Cross Sectional Model Results

Variables	**Model 1** *Coeff.*	**Model 2** *Coeff.*	**Model 3** *Coeff.*
Temperature Bins			
< 30° F	-0.777***	-0.747***	-0.717***
30° – 35° F	-0.176**	-0.152*	-0.220***
35° – 40° F	0.260***	0.248***	0.274***
40° – 45° F	0.023	0.003	-0.016
45° – 50° F	-0.177***	-0.192***	-0.148***
50° – 55° F	0.051**	0.072***	0.055***
55° – 60° F	0.015	0.025	0.006
60° – 65° F	0.088***	0.058***	0.033**
65° – 70° F	-0.032**	-0.042**	-0.051***
75° – 80° F	0.041***	0.035***	0.005
80° – 85° F	0.014**	0.001	-0.014*
85° – 90° F	0.024***	0.015*	-0.011
90° – 95° F	0.030***	0.019**	-0.013
> 95° F	0.039***	-0.013	-0.033***
Precipitation Bins			
0.01” – 0.25“	-0.004***	-0.003***	-0.003**
0.25” – 0.5”	-0.038***	-0.055***	-0.081***
0.5” – 0.75”	-0.012	-0.044**	-0.049***
0.75” – 1”	0.010	-0.010	-0.012
1” – 1.25”	-0.223***	-0.251***	-0.245***
1.25” – 1.5”	0.381***	0.357***	0.295***
1.5” – 1.75”	-0.002	-0.009	-0.013
1.75” – 2”	-0.246***	-0.306***	-0.207**
> 2”	-0.066*	-0.002	-0.104**
Fixed Effects			
Wave	N	Y	Y
Region	N	N	Y
Dissimilarity Coefficient	0.003***	0.008***	0.005***
Observations	372,657	372,657	372,657
Model Fit	-1.66e+09	-1.66e+09	-1.66e+09

Note: All models regress trips on average weather (i.e., climate). 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 A.4. Yearly Cross Section Model Results

	2004	2005	2006	2007	2008	2009
Variables	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff..*	*Coeff.*	*Coeff.*
Temperature Bins						
< 30° F	-0.909**	-1.028***	-0.049	-0.742**	-0.512	-0.595*
30° – 35° F	-0.295	0.131	-0.463***	-0.292	-0.057	0.288
35° – 40° F	0.302***	0.152**	0.185***	0.313***	0.208***	0.136*
40° – 45° F	0.039	0.038	0.056	0.035	0.002	-0.081
45° – 50° F	-0.247***	-0.238***	-0.020	-0.065*	-0.171***	-0.192***
50° – 55° F	0.060	0.106***	0.042	0.010	0.107***	0.123***
55° – 60° F	0.035	0.064**	0.021	0.0112	0.016	-0.016
60° – 65° F	0.021	0.061*	0.053	0.098***	0.088***	0.040
65° – 70° F	-0.084***	-0.046	-0.004	0.029	-0.028	-0.020
75° – 80° F	0.008	0.049**	0.036*	0.058**	0.054***	0.025
80° – 85° F	-0.021	0.014	0.004	0.029*	0.0181	-0.003
85° – 90° F	-0.014	0.017	0.014	0.035**	0.0276*	0.001
90° – 95° F	-0.009	0.029*	0.008	0.042***	0.0221	0.006
> 95° F	-0.009	0.009	-0.056**	-0.046*	-0.0124	-0.057**
Precipitation Bins						
0.01” – 0.25“	-0.005**	-0.002	-0.002	-0.001	-0.005***	-0.006***
0.25” – 0.5”	-0.047**	-0.043***	-0.034	-0.042**	-0.074***	-0.079***
0.5” – 0.75”	-0.050	-0.111***	-0.040	-0.039	0.003	-0.019
0.75” – 1”	0.007	-0.029	-0.054	-0.033	-0.002	0.008
1” – 1.25”	-0.294***	-0.140*	-0.306***	-0.23***	-0.207***	-0.302***
1.25” – 1.5”	0.568***	0.377***	0.173**	0.269***	0.056	0.446***
1.5” – 1.75”	-0.091	0.052	-0.115	0.100	-0.073	-0.023
1.75” – 2”	-0.338**	-0.353**	-0.152	-0.315*	-0.043	-0.255
> 2”	-0.095	0.082	-0.201***	-0.047	-0.061	-0.122
Fixed Effects						
Wave	Y	Y	Y	Y	Y	Y
Dissimilarity Coefficient	0.013***	0.006**	0.031***	0.023***	0.026***	0.032***
Observations	73.213	72,729	73,696	73,259	73,518	71,894
Model Fit	-2.79e+08	-2.72e+08	-2.82e+08	-2.91e+08	-2.88e+08	-2.43e+08

Note: All models regress trips on average weather (i.e., climate). 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 A.5. Regional Participation Model Results

	Gulf		**Southeast**		**Mid-Atlantic**		**New England**	
Variables	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
Temperature Bins								
< 30° F	-	-	-	-	-	-	-0.195***	0.073
30° – 35° F	-	-	-	-	-	-	-0.059	0.041
35° – 40° F	-	-	-0.008	0.021	-0.084***	0.017	-0.020	0.026
40° – 45° F	-	-	-0.070***	0.017	-0.015	0.021	-0.046**	0.024
45° – 50° F	-0.023	0.017	0.027	0.024	-0.064***	0.014	-0.061***	0.022
50° – 55° F	-0.013	0.014	-0.027**	0.011	-0.050***	0.015	0.034**	0.016
55° – 60° F	-0.017*	0.009	-0.023**	0.012	-0.003	0.013	0.024**	0.012
60° – 65° F	0.009	0.007	-0.018	0.012	0.018	0.012	-0.016	0.012
65° – 70° F	-0.015**	0.007	-0.003	0.014	0.000	0.012	-0.009	0.011
75° – 80° F	0.002	0.005	-0.015	0.010	-0.001	0.010	-0.010	0.010
80° – 85° F	-0.001	0.004	0.000	0.007	0.029***	0.008	-0.020**	0.009
85° – 90° F	-0.002	0.004	-0.015*	0.008	-0.004	0.007	-0.062***	0.010
90° – 95° F	-0.002	0.005	-0.013*	0.008	-0.002	0.008	-0.051***	0.014
> 95° F	-0.006	0.006	-0.031**	0.013	-	-	-	-
Precipitation Bins								
0.01” – 0.25“	0.001	0.001	0.012***	0.003	0.006*	0.003	-0.005*	0.003
0.25” – 0.5”	-0.005	0.005	-0.017*	0.010	0.009	0.011	-0.058***	0.013
0.5” – 0.75”	0.002	0.007	0.033**	0.014	0.008	0.013	-0.030	0.020
0.75” – 1”	-0.009	0.010	-0.002	0.020	0.004	0.021	-0.005	0.027
1” – 1.25”	0.010	0.016	-0.035	0.027	-0.054*	0.029	-0.102***	0.037
1.25” – 1.5”	0.020	0.021	0.068*	0.037	0.014	0.037	0.076*	0.045
1.5” – 1.75”	0.083***	0.028	-0.012	0.052	-0.116**	0.047	-0.205***	0.055
1.75” – 2”	0.012	0.035	-0.056	0.055	0.054	0.061	0.058	0.063
> 2”	-0.023	0.016	0.036	0.028	0.073**	0.037	0.138***	0.034
Fixed Effects								
Year	Y		Y		Y		Y	
Wave	Y		Y		Y		Y	
Area Code	Y		Y		Y		Y	
Dissimilarity Coefficient	0.002	0.001	-0.006	0.004	-0.007**	0.003	0.001	0.004
Observations	180,326		64,651		127,123		65,951	
Model Fit	-7.92e+08		-2.36e+08		-4.10e+08		-1.97e+08	

Note: 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 A.6. Annual Demand Responses in Millions of Trips (RCP 4.5)

Time Period	Baseline	2020 – 2049		2050 – 2079		2080 – 2099	
	Estimated Trips	Percent Change		Percent Change		Percent Change	
	(in Millions)	*Estimate*	*95% CI*	*Estimate*	*95% CI*	*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 4.5)							
Gulf	22.5	-6.3	(-9.5, -3.0)	-11.3	(-15.5, -6.2)	-13.5	(-18.2, -7.6)
Southeast	7.43	-2.3	(-5.0, 0.7)	-4.5	(-8.2, -0.3)	-5.6	(-9.9, -0.8)
Mid-Atlantic	10.8	0.5	(-2.7, 3.7)	0.9	(-3.8, 5.6)	1.1	(-4.3, 6.6)
New England	5.4	8.5	(4.5, 13.0)	9.5	(4.5, 15.6)	10.0	(4.3, 16.8)
Panel C: Temporal Results (RCP 4.5)							
Wave 1	3.6	17.1	(13.4, 20.3)	26.3	(20.9, 30.8)	30.8	(24.4, 36.3)
Wave 2	5.5	3.7	(0.6, 7.5)	4.6	(0.4, 9.4)	5.1	(0.3, 10.4)
Wave 3	10.4	-3.5	(-6.8, 0.0)	-8.2	(-12.5, -3.4)	-10.9	(-15.9, -5.3)
Wave 4	12.6	-13.5	(-18.0, -8.6)	-23.2	(-29.9, -15.2)	-26.9	(-34.2, -17.5)
Wave 5	8.4	-1.9	(-5.0, 1.5)	-4.0	(-8.3, 0.3)	-5.3	(-10.1, -0.5)
Wave 6	5.7	5.7	(3.0, 8.8)	11.8	(8.0, 16.1)	14.1	(9.7, 19.1)

Note: The baseline estimate represents the annual number of trips predicted by our model. The estimated change (Δ) reported is predicted trips for each scenario minus the baseline estimate. For RCP 2.6 (4.5, 8.5), we used 36 (42, 41) different GCMs to produce the average estimate. Standard errors are estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

Table A.7. Annual Demand Responses in Millions of Trips (RCP 2.6)

Time Period	Baseline	2020 – 2049		2050 – 2079		2080 – 2099	
	Estimated Trips	Percent Change		Percent Change		Percent Change	
	(in Millions)	*Estimate*	*95% CI*	*Estimate*	*95% CI*	*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 2.6)							
Gulf	22.5	-5.9	(-9.1, -2.7)	-7.1	(-10.5, -3.5)	-7.1	(-10.5, -3.5)
Southeast	7.43	-2.2	(-4.9, 0.8)	-2.3	(-5.3, 0.9)	-2.2	(-5.1, 1.0)
Mid-Atlantic	10.8	0.1	(-3.0, 3.2)	0.8	(-2.7, 4.3)	0.9	(-2.6, 4.3)
New England	5.4	8.2	(4.2, 12.7)	8.9	(4.8, 13.8)	9.0	(4.9, 13.9)
Panel C: Temporal Results (RCP 2.6)							
Wave 1	3.6	16.3	(12.7, 19.5)	19.8	(15.7, 23.5)	19.7	(15.5, 23.4)
Wave 2	5.5	3.3	(0.2, 6.9)	3.9	(0.5, 7.9)	3.9	(0.4, 8.1)
Wave 3	10.4	-3.0	(-6.3, 0.5)	-3.9	(-7.4, 0.2)	-3.9	(-7.3, -0.2)
Wave 4	12.6	-12.9	(-17.2, -8.1)	-15.4	(-20.4, -9.9)	-14.9	(-19.9, -9.6)
Wave 5	8.4	-1.7	(-5.0, 1.7)	-2.6	(-5.6, 1.6)	-2.0	(-28.5, -10.7)
Wave 6	5.7	4.7	(2.1, 7.5)	7.0	(4.1, 10.2)	6.4	(3.5, 9.5)

Note: The baseline estimate represents the annual number of trips predicted by our model. The estimated change (Δ) reported is predicted trips for each scenario minus the baseline estimate. For RCP 2.6 (4.5, 8.5), we used 36 (42, 41) different GCMs to produce the average estimate. Standard errors are estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

Table A.8. Annual Welfare Changes in Millions of 2010 $USD (RCP 4.5)

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	-49.2	(-73.8, -23.6)	-101.2	(-139.8, -57.2)	-136.3	(-184.7, -78.5)
Southeast	-5.7*	(-12.6, 1.8)	-13.0	(-24.7, -0.9)	-18.2	(-33.1, -2.6)
Mid-Atlantic	1.6	(-9.8, 13.2)	3.5	(-16.4, 23.2)	5.0	(-20.7, 30.5)
New England	15.4	(8.2, 23.7)	19.9	(9.3, 33.3)	23.6	(10.0, 40.2)
Panel C: Temporal Average Results (RCP 8.5)						
Wave 1	20.4	(16.4, 25.0)	36.3	(30.2 , 43.4)	47.7	(39.6, 56.8)
Wave 2	6.6	(0.9, 13.6)	9.5	(0.5, 19.8)	11.6	(0.2, 24.3)
Wave 3	-12.4	(-24.4, -0.1)	-33.9	(-52.1, -14.4)	-50.7	(-74.6, -25.0)
Wave 4	-58.1	(-78.2, -37.2)	-115.2	(-148.4, -75.1)	-149.4	(-191.3, -97.4)
Wave 5	-5.4	(-14.7, 4.0)	-13.5	(-28.1, 0.6)	-19.9	(-37.9, -2.2)
Wave 6	11.0	(5.6, 16.7)	26.1	(17.7, 35.7)	34.8	(23.8, 47.2)

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. Confidence intervals are estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

Table A.9. Annual Welfare Changes in Millions of 2010 $USD (RCP 2.6)

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	-46.1	(-70.5, -21.1)	-64.1	(-94.5, -31.9)	-71.3	(-105.5, -35.8)
Southeast	-5.5	(-12.2, 1.9)	-6.8	(-15.7, -2.7)	-7.2	(-17.1, 3.1)
Mid-Atlantic	0.2	(-10.9, 11.6)	3.2	(-11.4, 18.2)	3.8	(-12.2, 20.5)
New England	14.9	(7.7, 23.0)	18.8	(10.0, 29.3)	21.3	(11.4, 32.9)
Panel C: Temporal Average Results (RCP 8.5)						
Wave 1	19.5	(15.4, 24.1)	27.5	(22.2, 33.4)	30.5	(24.7, 37.2)
Wave 2	5.8*	(0.2, 12.5)	8.0	(0.7, 16.8)	9.0	(0.7, 19.0)
Wave 3	-10.7	(-22.5, 1.6)	-16.4	(-30.8, -1.2)	-18.1	(-34.2, -1.1)
Wave 4	-55.2	(-74.6, -35.2)	-76.5	(-101.9, -49.5)	-83.2	(-111.1, -53.6)
Wave 5	-5.1	(-14.4, 4.7)	-7.0	(-18.8, 5.0)	-7.5	(-20.2, 5.3)
Wave 6	9.0	(4.0, 14.4)	15.5	(9.1, 22.6)	15.8	(8.6, 23.6)

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. Confidence intervals are estimated using a parametric bootstrap (Krinsky and Robb 1986) with 200 draws.

Table A.10. Participation Model with Lags Results

	Main Model		Model with Lags			
Variables	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Previous Wave Lag Coeff.*	*Std. Err.*
Temperature Bins						
< 30° F	-0.221***	0.022	-0.198***	0.052	-0.017	0.014
30° – 35° F	-0.090***	0.011	-0.090***	0.022	-0.011	0.010
35° – 40° F	-0.020*	0.009	-0.019	0.012	0.001	0.007
40° – 45° F	-0.031***	0.006	-0.028***	0.011	-0.006	0.006
45° – 50° F	-0.034***	0.004	-0.030***	0.008	0.008	0.006
50° – 55° F	-0.003	0.004	-0.003	0.006	0.012**	0.005
55° – 60° F	-0.013**	0.003	-0.014***	0.005	-0.002	0.004
60° – 65° F	0.001	0.003	0.003	0.005	0.000	0.005
65° – 70° F	-0.008*	0.006	-0.009*	0.005	0.005	0.004
75° – 80° F	-0.001	0.004	-0.001	0.004	-0.001	0.003
80° – 85° F	0.003	0.003	0.003	0.003	-0.005	0.003
85° – 90° F	-0.006**	0.004	-0.005*	0.003	-0.004	0.003
90° – 95° F	-0.004	0.003	-0.003	0.003	-0.005	0.005
> 95° F	-0.018***	0.005	-0.022***	0.005	-0.017	0.014
Precipitation Bins						
0.01” – 0.25“	0.003***	0.001	0.003***	0.001	0.000	0.001
0.25” – 0.5”	-0.010**	0.003	-0.008**	0.004	-0.009**	0.004
0.5” – 0.75”	0.003	0.005	0.002	0.005	-0.021***	0.006
0.75” – 1”	0.001	0.006	0.001	0.008	-0.003	0.008
1” – 1.25”	-0.016	0.009	-0.015	0.012	0.000	0.010
1.25” – 1.5”	0.033**	0.012	0.034**	0.015	-0.005	0.014
1.5” – 1.75”	-0.001	0.041	-0.037	0.042	0.001	0.002
1.75” – 2”	0.041*	0.022	0.046*	0.025	-0.026	0.024
> 2”	0.014	0.009	0.014	0.012	0.001	0.011
Fixed Effects						
Year	Y		Y			
Wave	N		N			
Area Code	Y		Y			
Wave-Region	Y		Y			
Dissimilarity Coefficient	0.000	0.001	0.000	0.001		
Observations	372,657		372,657			
Model Fit	-1.64e+09		-1.64e+09			

Note: 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 A.11. Night Fishing Participation Model Results

	Model without Night Fishing		**Main Model**	
Variables	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
Temperature Bins				
< 30° F	-0.218***	0.051	-0.221***	0.022
30° – 35° F	-0.090***	0.022	-0.090***	0.011
35° – 40° F	-0.016	0.012	-0.020*	0.009
40° – 45° F	-0.030***	0.011	-0.031***	0.006
45° – 50° F	-0.032***	0.008	-0.034***	0.004
50° – 55° F	-0.003	0.006	-0.003	0.004
55° – 60° F	-0.012**	0.005	-0.013**	0.003
60° – 65° F	0.002	0.005	0.001	0.003
65° – 70° F	-0.008*	0.005	-0.008*	0.006
75° – 80° F	0.000	0.004	-0.001	0.004
80° – 85° F	0.002	0.003	0.003	0.003
85° – 90° F	-0.005*	0.003	-0.006**	0.004
90° – 95° F	-0.004	0.003	-0.004	0.003
> 95° F	-0.019***	0.005	-0.018***	0.005
Precipitation Bins				
0.01” – 0.25“	0.003***	0.001	0.003***	0.001
0.25” – 0.5”	-0.010***	0.004	-0.010**	0.003
0.5” – 0.75”	0.002	0.006	0.003	0.005
0.75” – 1”	-0.001	0.008	0.001	0.006
1” – 1.25”	-0.017	0.012	-0.016	0.009
1.25” – 1.5”	0.030*	0.015	0.033**	0.012
1.5” – 1.75”	-0.002	0.020	-0.001	0.041
1.75” – 2”	0.042*	0.025	0.041*	0.022
> 2”	0.016	0.012	0.014	0.009
Fixed Effects				
Year	Y		Y	
Wave	N		N	
Area Code	Y		Y	
Wave-Region	Y		Y	
Dissimilarity Coefficient	-0.000	0.000	0.000	0.001
Observations	372,657		372,657	
Model Fit	-1.64e+09		-1.64e+09	

Note: 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.