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RESOURCES FOR THE FUTURE

The Effects of Climate on Leisure Demand: Evidence from North America*

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Abstract

There is extensive research documenting the economic consequences of climate change, yet our understanding of climate impacts on nonmarket activities remains incomplete. Here, we investigate the effect of weather on leisure demand. Using data from 27 million bicycle trips in 16 North American cities, we estimate how outdoor recreation responds to daily weather fluctuations. Combining these estimates with time-use survey data and climate projections, we project annual surplus gains of $894 million from climate-induced cycling by mid-century. Extrapolating to a broad measure of outdoor recreation, our back-of-the-envelope calculations suggest climate-induced benefits of $20.7 billion per year.

Key Words: leisure demand, outdoor recreation, climate change, nonmarket damages, time allocation
JEL codes: J22, Q54, R49

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1 Introduction

Climate change will affect economic conditions globally, with wide-ranging implications for economic growth, productivity, public health, and ecological function. Recent work has shown that local climate affects the growth rate of national economies (e.g., Burke et al., 2015b; Dell et al., 2012), labor supply (e.g., Graff Zivin and Neidell, 2014), agricultural production (e.g., Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Burke and Emerick, 2016), and natural systems (e.g., Walther et al., 2002; Tol, 2009). There is evidence that extreme temperatures cause dramatic health consequences (Barreca et al., 2016) and can even affect traffic and driving risks (Leard and Roth, 2017).

Despite extensive research detailing the effects of climate change on economic production, human health, and natural capital, we have relatively few causal estimates of climate change effects in other realms, especially for nonmarket activities. In this paper, we help fill this gap by quantifying impacts for leisure. We estimate outdoor recreation demand as a function of weather anomalies, and we use these estimates to predict future impacts from climate change. Our analysis highlights both short- and long-run implications and sheds light on the role of adaptation.

Although much of the extant literature finds that climate change will have deleterious effects on economic productivity, the implications for recreation demand are theoretically ambiguous. Global warming entails a rightward shift of the temperature distribution. Therefore, for most outdoor activities, we anticipate diminished recreation demand on the warmer end of the distribution, where increases in temperature will make hot days and regions more inhospitable for outdoor activity, holding rainfall constant. However, on the cold end of the distribution, climate change will beget milder conditions, potentially stimulating greater recreation demand. Identifying the net effect is an empirical question that depends on the distribution of weather and its interaction with preferences, population, and wealth across the geography in question. Prior research has found positive aggregate impacts on outdoor recreation due to a reduction in the number of cold days (Mendelsohn and Markowski, 1999; Loomis and Crespi, 1999), but lacks a causal foundation.

In this paper, we estimate the net impact of weather on leisure demand by analyzing a representative mode of outdoor recreation: riding bicycles.[1] Cycling is attractive to study for two primary reasons: (1) it is prevalent throughout the world, undertaken in a wide range of climatological zones and by people from vastly different socioeconomic backgrounds, and (2) there are high-quality data sets on bicycle usage available from bicycle-sharing (bikeshare) programs at fine spatial and temporal resolutions. These programs exist in hundreds of cities worldwide, with tens of millions of trips recorded annually. We analyze temporally

[1]Here and throughout the paper, we use the term “leisure” interchangeably with warm-weather “outdoor recreation.” Our primary outcome of interest is nonworking, nonproductive time that is complemented by pleasant weather, including exercise and sightseeing.

disaggregated data over multiple years for 16 similar bikeshare programs throughout North America, from Mexico City to San Francisco to Montreal. We use high-frequency data that are recorded in real time, an advantage over traditional leisure studies that rely upon survey data. Our diverse set of programs and the fine data resolution provide distinct advantages, as we are able to compare, apples-to-apples, a leisure activity in climatologically distinct settings, something that is not possible for more geographically specific activities such as fishing, boating, or swimming.

Of course, not all bicycle trips constitute leisure activity. Individuals may use bikeshare programs for work commutes, as well. To focus on recreation demand, we restrict our analysis to weekend trips. Although weekend trips do not perfectly correspond to leisure rides, we demonstrate that this is a very strong proxy using four additional pieces of evidence. First, we show striking similarities between the weather responses in our sample and weather responses for recreational cycling demand from time use surveys; however, we note that our estimates are much more precise due to the unique nature of our data set and our estimand is more economically meaningful for projecting future leisure demand under climate change. Second, we find a virtually identical demand response to weather for a subsample of "casual" weekend cyclists—those who have short term bikeshare memberships—that make up 27% of our sample. Third, we observe similar behavior in our weekend sample and a separate sample of federal holidays, both of which differ from weekday cycling demand. Fourth, the patterns of intraday substitution that we observe are consistent with discretionary leisure activity, as individuals shift their rides to morning and evening on hot days, presumably to avoid the intense heat of the midday hours; no such substitution patterns are observed on weekdays, when obligatory work commutes constitute a larger portion of rides.

Altogether, we observe more than 27 million weekend bicycle trips totaling more than 9 million hours of cycling time, one of the largest compilations of recreational trips used in the economics literature. We couple these highly detailed bikeshare data with disaggregated climatic variables, which allows us to parameterize the leisure-weather dose-response function for cycling. In particular, we exploit within-city deviations in weather each month to estimate a causal, nonlinear relationship between temperature and precipitation and resultant leisure demand.

After establishing this relationship, we overlay an ensemble of climate projections from coupled atmosphere-ocean general circulation models onto our weather-response functions. From this, we project spatially explicit changes in leisure demand attributable to climate change, and we derive economic values for these changes. Importantly, the weather variation in our data subsumes the most likely range of temperatures and precipitation in mid-century climate projections, so that our final results do not rely upon large out-of-sample extrapolations. By analyzing recreation data from time use surveys, we are able to scale our cycling-specific estimates into overall estimates for outdoor leisure. Our results suggest that climate change will generate net benefits from induced cycling demand around \$894 million per year (2016 USD) by 2060. Extrapolating this value to outdoor recreation more generally, our back-of-the-envelope calculations suggest climate-induced outdoor recreation benefits on the order of \$20.7 billion per year. This value exceeds the negative impact of climate change on US corn yields by a factor of 3 by midcentury (Burke and Emerick, 2016), but has received comparatively little attention in the economics literature.

Our work contributes to a growing body of literature that projects climate impacts on various economic activities. We take a reduced-form approach, exploiting weather fluctuations to identify the effect of climate variables on leisure demand, and we couple these empirical estimates with climate model projections to predict how future leisure activity will be influenced by a changing climate. Similar approaches have been used to predict climate change consequences for economic growth, labor supply, human health, agricultural production, and ecological systems (Walther et al., 2002; Deschênes and Greenstone, 2007; Tol, 2009; Dell et al., 2012; Graff Zivin and Neidell, 2014; Burke et al., 2015a; Burke and Emerick, 2016).

However, relatively little work has studied the causal relationship between climate and nonmarket recreation activity.[2] Mendelsohn and Markowski (1999) conducted some early work in this vein, using cross-sectional variation in weather patterns across the 48 contiguous states to estimate how demand for six summer recreation activities (boating, camping, fishing, golfing, hunting, and wildlife viewing) vary with weather. They then use this empirical model to predict how the number of recreation days for each activity will change under nine hypothetical climate scenarios. In particular, they consider temperature increases of 1.5, 2.5, and 5.0 degrees Celsius and precipitation increases of 0, 7, and 15 percent, and they multiply demand changes by values from the literature for (average) consumer surplus per day. Their central estimates indicate net gains in the neighborhood of \$3–\$4 billion by the year 2060 (in 1991 USD).

Loomis and Crespi (1999) take a similar approach by estimating how visitation rates for various recreation activities vary with weather conditions. Coupling these estimates with Intergovernmental Panel on Climate Change climate projections and average consumer surplus values from the literature, they estimate overall benefits of \$3 billion (in 1992 USD). They predict gains for golf and water-based activities such as swimming, fishing, and boating and losses for skiing, hiking, and camping. However, the studies by Loomis and Crespi (1999) and Mendelsohn and Markowski (1999) use aggregate (e.g., state or regional) measures of

[2] In complementary research, Leard and Roth (2017) estimate the welfare impact from fatal traffic accidents induced by climate change. They find large costs associated with traffic fatalities by the end of the century. Further, they posit that "voluntary exposure benefits" from more pedestrians, cyclists, and motorcyclists on the roads with higher temperatures offset the costs of fatalities, thus mitigating the consequences of climate change on traffic accidents. This latter finding is in line with our estimates for cycling, although our data permit us to estimate the benefits from climate-induced recreational activities. We find that annual welfare benefits for climate-induced recreation by midcentury constitute more than half of Leard and Roth's discounted stream of costs from climate-induced traffic fatalities from 2015-2099.

participation, relying on cross-sectional variation across jurisdictions to pin down weather effects. The reliance on cross-sectional variation in both cases creates challenges for causal identification if local climates are correlated with recreational opportunities.

Further, Graff Zivin and Neidell (2014) use short term temperature shocks to study how temperatures affect individuals' allocation of time between labor and leisure, using data from the American Time Use Survey. They report that additional warming at high temperatures reduces labor hours, but that these impacts are primarily concentrated in industries exposed to climate. They also find that such warming encourages individuals to take part in indoor leisure activities in lieu of outdoor leisure. The leisure substitution works in the opposite direction when there is warming at the low end of the temperature distribution, as expected, and they find no appreciable response in labor time in such cases. They also provide evidence that individuals may acclimatize to higher temperatures or adapt through temporal substitution of activities.

Like our paper, Obradovich and Fowler (2017) also examine how climate change will influence physical activity patterns. They use data from 1.9 million respondents to the the Behavioral Risk Factor Surveillance Survey (BRFSS) and examine dose-responses to short term weather variation. They find large, pronounced effects at low temperatures and more modest effects at high temperatures, which is consistent with our findings; however, the magnitudes of their responses are more muted. We posit that this discrepancy arises because the BRFSS questions elicit binary responses about general physical activity for the 30-day window prior to the interview ("During the past month, other than your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?"), providing a coarse measure of the outcome variable of interest. Moreover, given the temporal scale of their survey data, they use month-long averages of explanatory variables like temperature and precipitation, which likely attenuate the estimated responses.

We are not the first researchers to consider the responsiveness of cycling to weather. Using automatic bicycle-traffic receptors, Nosal and Miranda-Moreno (2014) explore a similar dose-response relationship between weather and cycling along 14 routes in Montreal, Ottawa, Vancouver, and Portland, and Quebec over a span of 1-to-3 years. They segment their data into utilitarian and recreational routes on weekdays and weekends. They model the temperature relationship as quadratic and their results suggest an inverted U-shape, which is amplified when considering weekend, recreational trips. These results are consistent with what we find, although we model our dose-response function more flexibly and include a wider variety of cities, over a longer timespan, with a broader set of controls and fixed effects, thus extending the validity of the results estimated by Nosal and Miranda-Moreno (2014). Going several steps further, we combine our estimates with climate projections and an economic welfare framework to predict climate change impacts on a national scale.

In this paper, we add to the small but growing literature studying the future impacts of climate change on leisure. The basic arc of our research is similar to those discussed above, as we use short-run variation in weather in conjunction with climate projections to predict future outcomes. However, we distinguish our work from others in several key dimensions. First, this study takes advantage of a unique, high resolution data set. By their nature, many recreational activities are infrequent, leaving researchers with relatively coarse data aggregated over large jurisdictions (e.g., state level), long temporal scales (e.g., months or seasons), or both. Such data limitations make it challenging to estimate precise effects and to identify causal relationships cleanly, especially because weather data must often be averaged over long time periods or large regions to mesh with the available recreation data. The bikeshare data that we use, on the other hand, are extremely rich, with bike usage information discernible at timescales finer than a minute. As a virtue of these detailed data, we can control for a battery of fixed effects to remove confounding variation from location- or time-specific unobservables, thus giving us confidence in the causal interpretation of our estimates. Moreover, we can analyze the effects of climate change at the daily or intradaily level to infer substitution and adaptation behavior.

Second, our application is unique, as we study short cycling trips made in bikeshare programs. Not only is this particular focal area unexplored, but it also differs in nature from the activities typically studied in the recreation demand literature. That is, more standard analyses examine activities such as boating, fishing, or camping—activities that often entail significant fixed costs and investments of time to undertake. Bikeshare trips, by contrast, constitute an everyday activity that individuals can engage in on a whim and that may take as little time as a few minutes. Such everyday activities have typically been overlooked by the recreation literature; this represents an important oversight because the value of cycling and other quotidian pursuits can be significant and large, as we show. Although these activities may seem insignificant, their sheer participation rates and revealed demand lead to substantial welfare impacts that should not be ignored.[3]

This research has immediate policy implications and fills an important gap in the existing literature. This is the first study, to our knowledge, to generate causal estimates of weather on recreation demand to provide insight on notoriously difficult-to-measure nonmarket climate damages. In doing so, our analysis complements existing work that examines market impacts, making it possible to construct a more comprehensive measure of climate damages.

2 Analytical and empirical framework

We begin with a model of consumer behavior to motivate our empirical analysis. Consider a representative consumer who derives utility from a numeraire x and leisure Y. She has

[3] We observe more than 3,500 years of cumulative time spent on bicycles in our full 8-year sample.

utility $u(x, Y; W, Z)$, where W captures a vector of weather variables that influence the value of leisure and Z is a vector of shifters such as demographic characteristics. Her budget constraint is $x + pY = I$, where p is the price of leisure. She optimizes

$$\max u(x, Y; W, Z) \text{ subject to } x + pY = I \tag{1}$$

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

Our empirical goal is to relate leisure demand Y to weather W, and by doing so, we can quantify the welfare impact of weather changes. Specifically, we seek to establish a causal relationship between weather outcomes and usage of the bikeshare system. For each city, c, in our sample, we aggregate bicycle trip statistics to the daily level, t. We focus on two outcomes, $Y_{ct} \in \{\text{Trips}_{ct}, \text{Duration}_{ct}\}$, that capture both the aggregate number of trips taken in a given day and the aggregate number of minutes spent by all bikeshare users within the day for each city. We specify the following baseline equation to link demand and weather:

$$\ln Y_{ct} = f(W_{ct}|\Theta) + \alpha_c + \lambda_t + \delta_{cm} + \kappa_1 t_c + \kappa_2 t_c^2 + \varepsilon_{ct}. \tag{2}$$

The city fixed effect is captured by α_c, while λ_t is a set of common time fixed effects (in our primary specification, these are day-of-week and month-of-sample indicator variables). δ_{cm} is a city-by-month-of-sample fixed effect. t_c is a (quadratic) city-specific time trend, which is important to capture the effect of different start dates, growth rates, and other time trends across sites. ε_{ct} is the residual error, with serial correlation present within a city over time. And, finally, $f(W_{ct}|\Theta)$ is a flexible function of prevailing weather conditions, parameterized by Θ.

To capture the relationship between weather and our dependent variable of interest, we specify the partially nonparametric functional form to $f(\cdot|\Theta)$ in Equation 2,

$$f(\cdot|\Theta) = \sum_{s \in S} \gamma_s \mathbb{1}[\text{T}_{ct} = s] + \sum_{r \in R} \beta_r \mathbb{1}[\text{P}_{ct} = r] + \eta \text{Snow}_{ct} \tag{3}$$

where the first term in the summation s indicates a set of 10°F temperature bins that equal one if the observed daily average temperature T_{ct} falls within that range, and zero otherwise. The second term is a set of $\frac{1}{4}$-inch precipitation bins that equal one if observed daily precipitation P_{ct} falls within that range.[4] Snow_{ct} is an indicator equal to one if any snowfall is observed that day.

The relationship captured empirically by the set of coefficients in $f(\cdot|\Theta)$ provides a foundation to understand how bicycle users respond to deviations in weather outcomes in the

[4]Formally, the temperature bins, in degrees Fahrenheit, are $(-\infty, 30]$, $(30, 40]$, $(40, 50]$, $(50, 60]$, $(70, 80]$, and $(80, \infty)$, with the $(60, 70]$ bin omitted. The precipitation bins, in inches per day, are $(0, 0.25]$, $(0.25, 0.50]$, $(0.50, 0.75]$, $(0.75, 1]$, and $(1, \infty)$, with days with no precipitation omitted.

short run. In our primary specifications, we control for (1) global day-of-week effects (e.g., Saturday), (2) global month-of-sample effects (e.g., February 2012), and (3) idiosyncratic city-by-month-of-sample effects (e.g., June 2014 in Chicago), so the identifying power in our sample is driven by day-of-week-specific variation within each month-city combination in our sample. That is, identification arises by comparing an unusually warm Saturday in Chicago in June 2014 with a relatively more temperate Saturday in Chicago in June 2014.

Our two outcome variables, Trips and Duration, provide insight into both the extensive and intensive margin of choice for cyclists. That is, how does weather affect the likelihood of cycling, and conditional on choosing to bicycle, how much time is spent cycling in response to weather? By estimating the change in quantity of minutes demanded by cyclists in response to weather and employing existing estimates of consumer surplus per unit of time from prior work, we can directly estimate welfare changes in response to deviations in weather.

2.1 Weather vs. climate?

We follow recent empirical work that uses weather fluctuations to identify relationships between climate and economic outcomes (e.g., Schlenker and Roberts, 2009; Dell et al., 2012, 2014; Burke et al., 2015b; Barreca et al., 2016; Hsiang et al., 2017).[5] Specifically, consider two stylized climate distributions presented in the top panel of Figure 1. These two distributions could represent geographic differences at a single point in time (e.g., comparing Boston with San Francisco) or these could represent hypothetical climates for one geography at different points in time (e.g., Washington, DC, in 2015 and Washington, DC, in 2050).

Now, consider realizations of temperature holding precipitation fixed. In our quasi-experimental setting, we seek to identify the relationship between leisure demand and temperature, represented in the lower panel by $Y(T)$. By allowing nature to take random draws from the distributions C_0 and C_1, which we observe as fluctuations in temperature, we are able to identify points along the dose-response function, $Y(T)$. Our approach, then, derives an empirical relationship between leisure demand and weather conditional on climate.

An immediate conclusion from the hypothetical construction in Figure 1 is that it is ambiguous whether a positive mean shift (e.g., moving from T_0 to T_1) will stimulate or diminish leisure demand. Assuming that there is some optimal temperature T^* associated with leisure demand (holding precipitation and other factors fixed), any rightward shift in local mean temperatures for $T_0 < T^*$ will result in positive welfare benefits denoted by the region A, whereas rightward shifts for $T_0 > T^*$ will negatively affect welfare derived from leisure, the region B. It stands to reason that there may be winners and losers with respect to climate-induced changes in leisure demand. The net value of this effect will be determined by geographically explicit climate effects and their interaction with the distribution of preferences, population,

[5]See Dell et al. (2014) and Carleton and Hsiang (2016) for broad reviews of this literature.

and wealth across the area considered.

Of course, this conclusion is complicated by the fact that climate is multidimensional and represented by higher-order moments than its mean temperature, and that demand for leisure is potentially correlated with unobservable factors also associated with climate at the local level. Our rich set of weather variables, time controls, and geographic fixed effects, then, plays an important role in interpreting our results as causal.

Another concern is that long-run responses to climate may differ from short-run reactions to weather because of factors such as adaptation or sorting, an important challenge for studies that use dose-response functions to infer climate impacts. For example, a farmer may react differently to year-to-year weather fluctuations than to longer-term changes in climate, so measurements of the former shed little light on the latter. Our focus on bikeshare usage mitigates this concern to an extent. Because our outcome variable has virtually zero fixed cost, especially relative to phenomena like locational sorting or agricultural adaptation, it is easier to claim that our estimated dose-response function for spontaneous bicycle trips may be quite close to that of climate.

2.2 Welfare measurement

Upon estimating demand as a function of weather, we use the following framework for calculating welfare implications stemming from likely changes in weather due to climate change. This approach follows the methodology adopted by Mendelsohn and Markowski (1999) and evaluated by Chan and Wichman (2018). Recall the demand function for leisure, $Y(p, I; W, Z)$. To focus on the variables of interest, let us suppress I and Z and consider an initial set of weather conditions, W_0. Demand can be written as $Y_0(p)$, and we define the choke price $\bar{p}_0$ as the value of p for which $Y_0(\bar{p}_0) = 0$.

For any opportunity cost p^*, we can calculate the consumer surplus as

$$CS_0 = \int_{p^*}^{\bar{p}_0} Y_0(p)dp.$$

Climate change will result in different weather conditions, W_1, and a shift in demand to $Y_1(p)$. A new choke price $\bar{p}_1$ and consumer surplus CS_1 will then arise, with accompanying welfare implications. The change in welfare can be quantified as

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

This conceptual framework provides a guide for empirical investigation into the welfare impacts of climate change. In particular, one needs to estimate a price-quantity relationship and characterize how this demand function shifts based on weather. From this, it is possible to compute consumer surplus by integrating between the estimated curves.

Our dose-response function precisely estimates how weather influences the equilibrium quantity of demand at p^*, but we do not observe necessary price variation to identify the full shifted demand curve. Thus, we will approximate welfare changes by coupling our estimates of weather-induced shifts with CS_0 values available in the literature, a benefits-transfer approach also taken by others such as Mendelsohn and Markowski (1999) and Loomis and Crespi (1999). Specifically, we multiply the estimated change in aggregate cycling duration by the average consumer surplus per hour of cycling.[6]

Formally, we compute

$$\Delta Y \times \overline{CS}_0 \approx \Delta CS \tag{4}$$

where $\Delta Y \equiv Y_1^* - Y_0^*$ and $\overline{CS}_0 \equiv CS_0/Y_0^*$ is the average consumer surplus per unit of activity given the original demand curve $Y_0(p)$. Y_1^* and Y_0^* represent the equilibrium levels of demand under weather conditions W_1 and W_0, respectively. CS_0 is available from prior work, while Y_1^* and Y_0^* can be calculated from our analysis.

Although imperfect, this approximation will have a predictable bias, as shown by Chan and Wichman (2018). In particular, Expression 4 will underestimate the magnitude of welfare changes for common specifications of demand, such as linear demand models or demand functions that shift linearly in weather, thus yielding conservative estimates. Alternatively, for semi-log specifications, such as the commonly-used Poisson and negative binomial forms, Expression 4 will give an exact measure of consumer surplus changes. Figure 2 explains the intuition for this welfare calculation, while more detailed analysis is available in Chan and Wichman (2018).

3 Data

3.1 Bikeshare data

Bikesharing is an urban transit system in which members can use bicycles from stations in public places and return them to other stations when their ride is complete. Modern systems require members to purchase a membership for a specified time (e.g., 24 hours or one year). A member uses a key to unlock a bicycle at any station and can return it to an empty dock at a station near the end destination. Generally, the marginal cost of a trip completed within a given amount of time (typically 30 minutes) is zero; trips that last longer than that are priced

[6] Note that CS_0 is revealed from travel cost studies, yielding a measure that is net of opportunity costs. Therefore, when calculating the value of additional cycling activity, we do not need to explicitly account for forgone wages or reductions in other leisure activities. Opportunity costs are already embedded in the ΔCS calculation via CS_0.

according to an increasing tiered schedule.[7]

We compiled data from each bicycle-sharing program in the United States, Canada, and Mexico, and obtained publicly available trip history records for each program online. Our sample contains all publicly available bikesharing data for programs in North America in the spring of 2017. Overall, we use data from 16 independent programs across North America as shown in Figure 3. Each data set contains the start and end time and location of each bicycle trip. From this, we can calculate each trip's elapsed duration. We aggregate individual trips to the daily level (i.e., the calendar date on which the trip began). Our primary outcomes of interest are (1) the total number of trips in a given day for a given city, and (2) the total duration (in minutes) of all trips taken during a given day in a given city. To isolate leisure demand (as opposed to commuting behavior), we analyze trips on Saturdays and Sundays. Wichman and Cunningham (2017) find cycling behavior on weekends commensurate with lower values of time that are likely more representative of leisurely rides than weekday commutes. In subsequent discussion, we provide several additional pieces of evidence to corroborate our claim that these are leisure trips.

We summarize the bikeshare data in Table 1. Our sample spans from February 2010 through May 2017, although the time periods differ by data availability in each city's bikeshare program. In our full sample, we observe more than 120 million bicycle trips totaling more than 32 million hours in elapsed duration. When restricting the sample to weekend observations, we observe 27 million trips totaling more than 9 million hours of recreation. The number and duration of trips scale with the size of the program and the length of its operation. New York has the largest program, averaging more than 24,000 trips per weekend day. Los Angeles has the smallest program primarily because it has been in operation only since the summer of 2016. We have the longest panel of data in Washington, DC, spanning 654 daily weekend observations.

3.2 Weather data

We use daily weather data from the Global Historical Climate Network (GHCN-Daily). For each city in our sample, we gather four weather measurements from each weather station within 100km of the city's centroid: maximum and minimum daily temperatures, precipitation, and snowfall. We remove any weather station that has all values missing for any of these four measures.[8] We weight observations by the station's inverse distance squared from the city centroid. We also take a simple geographic average, giving each weather station within 100km equal weight, as a sensitivity check.

[7] For more details on bikesharing programs, see Hamilton and Wichman (2018) and Wichman and Cunningham (2017).

[8] Further, we interpolate seven observations total in Montreal, San Francisco, and Seattle for missing snowfall.

Our final weather data set is a balanced panel of daily observations for each city in our sample spanning the time period in which we observe bikeshare trips. We take a simple average of maximum and minimum daily temperatures to construct a daily average temperature. Our primary weather variables are this average daily temperature (degrees F) along with rainfall (inches) and snowfall (inches).

As shown in Figure 4, our sample includes a wide variety of climatological conditions, including hot cities such as Austin, colder cities such as Minneapolis and Montreal, and temperate cities such as San Francisco. This figure illustrates the variation we use to trace out leisure demand across a diverse set of climates.

We also use a supplementary weather data set to test the robustness of our findings. We hand-select weather stations (one station for each city) from the Local Climatological Data (LCD) Daily Summary. These data allow for daily observations of an additional suite of weather metrics for our US cities, including wind speed and direction, wet-bulb temperature, and pressure, among others. Because we use a parsimonious measure of daily temperature in our primary specification, we utilize these observations to assess whether alternative measures of weather influence our results.[9]

3.3 Climate projection data

Together, the bikeshare data and weather data allow us to identify how leisure demand is influenced by weather. We seek to project this relationship into the future to quantify climate impacts, which requires highly detailed weather projections. We obtain daily average temperature predictions and daily precipitation fluxes from models in the CMIP3 archive (Phase 3 of the Coupled Model Intercomparison Project). We select models that ran the A1B ("business-as-usual") climate scenario and had projections for 2055 through 2060, giving us 15 climate models in total. For this set of climate model outputs, we assign observations from each model's grid point nearest to the city centroid in our sample.

For each of the 15 climate models, we calculate the percentage change in temperature and level change for precipitation between 2055-2060 and 1995-2000, the baseline climate period for this CMIP3 experiment, for each day in that period. That is, we compare weather projections for January 1, 1995, with those for January 1, 2055. We truncate precipitation changes from below at zero. We assume that temperature and preciptiation changes trend linearly and remove the fraction of the change prior to our 2011-2016 sample. Finally, for each climate model, we add these predicted changes in temperature and precipitation to our observed local weather from the GHCN-Daily data set to account for any location-specific biases (Auffhammer et al., 2013). By retaining a large suite of climate models, we allow

[9]Because the primary purpose of this exercise is to establish robustness, we do not correct or impute missing values.

the disagreement across models to capture uncertainty in climate predictions (Burke et al., 2015a). A more detailed exposition of this procedure is provided in the next section.

3.4 Leisure demand data

Using the 2016 American Time Use Survey (ATUS), we construct a nationally representative data set of time spent cycling and engaging in other outdoor recreational activities. We calculate the average number of minutes spent cycling and recreating outdoors per day per ATUS respondent, averaged at the state level. For each state, we multiply this average recreation demand by its 2016 population (obtained from the US Census), which provides an approximation of the total time spent recreating outdoors per day for state residents. The ATUS data provide a means for extrapolating our bikeshare results to inform effects on cycling and recreation more generally.

4 Results

4.1 A precursory note on standard errors

The identifying variation in our data arises from comparing outcomes within a city-month, which serves as an appropriate level to cluster standard errors (Bertrand et al., 2004). In our primary results, we take a more conservative approach and cluster standard errors at the city level, which provides generally wider confidence bands. This conservatism comes at the price of biased standard errors with few cluster groups. In our case, a sample of 16 cities is too few to trust asymptotic results from common adjustments for clustered standard errors (Cameron et al., 2008). In the appendix (see Figure A.3), we present our primary city-level results alongside alternative standard error formulations with clustering at the city-season level, clustering at the city-month level, and using wild-cluster bootstrap standard errors (Cameron et al., 2008; Cameron and Miller, 2015). Importantly, inference based on any of these clustering variations is similar: coefficients that are significant in our primary results remain so under the three alternative formulations, and coefficients that are insignificant are consistently so across all variations. In what follows, we use larger but potentially biased standard errors clustered at the city level for our primary results rather than clustering at the city-month level to avoid creating a sense of false precision in our estimated effects.

4.2 Dose-response function

In Tables 2 and 3 we present marginal coefficients from our initial model specifications that regress the log quantity of trips and the log duration of trips on binned weather variables. Moving from left to right in both tables, we estimate the same model while adding a progressively richer set of controls. In column (1), the only included fixed effects are for day-of-week and month-of-year. In column (2), we add city fixed effects, which absorbs any time-invariant factors that may affect the propensity to use the bikeshare system (e.g., the bicycle-friendliness of an urban area) and increases the precision of our estimates substantially. The coefficient on the $> 80°$F temperature bin in Table 3 column (2) is -0.21, which can be interpreted as the marginal effect of exchanging one day in the $60° - 70°$ bin for one additional day in the $> 80°$ bin conditional on day-of-week, month-of-year, and city fixed effects. That is, one additional $> 80°$ day results in a 0.21 reduction in the log duration of trips.

With the exception of our most naïve model excluding city fixed effects, the results within and across Tables 2 and 3 are in relatively strong agreement. Additional days below 60° reduce the quantity and duration of bicycle trips, with colder days being incrementally more detrimental, relative to the omitted temperature bin ($60° - 70°$). Days above 80° have a marginal effect on demand that is statistically similar to zero in our richest specification (column (6)). Coefficients on precipitation bins and snowfall are also consistent: all results suggest that the quantity and duration of bicycle trips decrease with additional rain and snowfall.

To illustrate these effects, we present in Figure 5 the percentage change in the quantity (in panel (a)) and duration (in panel (b)) of trips as a function of temperature and precipitation bins. The quantities shown are transformed marginal effects from the final column of Tables 2 and 3.[10] These figures highlight our primary results. Demand for bicycle trips increases as temperature increases, but this trend flattens out beyond average temperatures of 70°. Exchanging one $60° - 70°$ day with a $< 30°$ day within a given month-city combination would reduce demand for and duration of bicycle trips by roughly 75 percent. Our failure to find a statistically significant reduction on the upper end of the temperature distribution suggests that bicyclists in North America dislike recreating in cold temperatures but are not averse to riding in warm temperatures. Rainfall reduces demand monotonically, with higher levels of precipitation displaying a more pronounced effect. In Figure A.3, we show that inference on these primary effects is unchanged when considering alternative methods of clustering to construct confidence intervals.

We also consider the interaction between temperature and rainfall. To do this, we interact

[10]Because our outcome variables are natural logarithms and our variables of interest are dummy variables, we transform all marginal coefficients, as summarized by Wichman (2017), prior to interpreting our results as percentage effects. Specifically, percentage effects are calculated as

$$\hat{g} = \exp\left(\hat{\beta} - 0.5\hat{V}(\hat{\beta})\right) - 1$$

where $\hat{\beta}$ is our estimated marginal effect and $\hat{V}(\hat{\beta})$ is an estimate of its variance. Similarly, our measure of variance around percentage effects is calculated as

$$\tilde{V}(\hat{g}) = \exp(2\hat{g})\left[\exp\left(-\hat{V}(\hat{\beta})\right) - \exp\left(-2\hat{V}(\hat{\beta})\right)\right].$$

We present our primary results in log scale for comparison in Figure A.1, and in levels in Figure A.2.

each temperature bin with a dummy variable indicating whether there was any rainfall that day. We present trends for each response function in Figure 6. As shown, days with rainfall reduce demand for bicycle trips relative to days without rainfall across temperature bins. For the $60° - 70°$ bin, the magnitude of the additional effect of rainfall is roughly -20 percent. This effect is less pronounced in the tails of the temperature distribution, where the effects with and without precipitation are statistically similar. This observation could perhaps be explained by a selection effect between "committed" riders who are relatively insensitive to weather and "fair-weather" riders who are sensitive to extreme temperatures and precipitation. At moderate temperatures, fair-weather riders may be deterred by precipitation, leading to the drop in demand observed in the middle of the distribution. However, at the tails, only committed riders participate and fair-weather riders have already opted out because of inhospitable temperatures; thus, conditional on extreme temperature, precipitation does little to change overall demand.

Having established average effects across our study sites, we now consider the question of heterogeneity. How do results vary across climatic zones? We segment our cities into climatic zones according to the classifications specified by the United States Department of Agriculture (USDA, 2012). In Figure 7, we plot zone-specific response functions for temperature and precipitation moving from coldest (Zone 4) to warmest (Zone 10).[11] Although there is more variation in the estimated parameters, the overall trend for each zone reflects that of the pooled model. For temperature, colder days reduce demand for every zone. An additional $< 30°$F day for warm southern cities (Zone 8) reduces duration of trips by roughly 85 percent. A similar metric for cold northern cities (Zone 4) is noticeably smaller, at roughly 50 percent for the same temperature bin. This effect, however, is much less pronounced when we analyze the log quantity of trips as our dependent variable. This variation across cities suggests that acclimatization may take place to some extent, as those living in colder climates are less deterred by bouts of cold temperatures.

On the warm end of the temperature distribution, the duration of trips is reduced in hotter cities much more than in cooler cities. At first glance, this result seems to undermine the notion of acclimatization. However, this regional heterogeneity is likely driven by the fact that the $> 80°$ bin pools a wide variety of heat conditions, including moderate heat near the $80°$ threshold as well as extreme heat exceeding $100°$. We suspect that the estimated effects for the $> 80°$ bin include a larger preponderance of extreme-heat days in warm-weather cities than in cooler cities, leading to divergence in the estimates. In this light, the strong negative response for hotter cities makes sense, as they will experience an increasing number of extremely hot days that dampen outdoor activity. At more moderate temperatures, there is little dispersion across cities. For the precipitation response, results are relatively consistent

[11] We present these same figures with confidence intervals in Figure A.4. We omit confidence intervals in the main text for clarity.

across zones, with precipitation reducing demand at all levels for all cities.[12]

Overall, although there are different responses to extreme temperature across cities, our results paint a consistent picture. Colder, wetter days are much less pleasant for outdoor recreation than are hot days. All regions in our sample will benefit from a reduction in the number of cold days, while an increase in hot days will have spatially distinct effects. Still, on average, the negative effects from extreme hot temperatures are small.

Acclimatization is not the only form of adaptation that could be present in our data. Individuals may shift recreational trips away from the hottest times of day in favor of being outside during cooler mornings and nights. We exploit the temporal granularity of our data and estimate time-of-day effects, and we present results in Figure 8. In panel (a), our results correspond with intraday substitution toward mornings (5AM–10AM) and nights (8PM–12AM), as hypothesized, for warmer temperatures.[13] This result likely explains why we do not observe a drop in cycling demand on hot days in our prior estimates pooled across climate regions. On average, cyclists respond to hot days by altering the timing of their trips (morning and night instead of afternoon and evening) rather than reducing the number or duration of their trips. For colder temperatures, there is little variation in effects across time of day. The effect of precipitation also appears rather homogeneous across time of day, which is a sensible result for rain that falls at exogenous times throughout the day.

4.2.1 Bikeshare usage as leisure

Do our observed bike trips actually constitute leisure activity? We have restricted our analysis throughout to trips that take place on weekends, thus excluding commuting trips that take place during the workweek.[14] However, weekend trips may be an imperfect proxy for leisure activity, so we examine this claim further by analyzing a subset of "casual" users. In our primary bikeshare data, we have information on the membership type for each trip.[15] Memberships can be long term, such as annual subscriptions, or short term, such as day-long or week-long subscriptions; some users even purchase single trip passes at the bikeshare kiosk. We define "casual" users as individuals who have a membership of 7 days or less, and we observe 7,293,568 casual, weekend trips, which is approximately 27 percent of our full sample. We believe that bikeshare usage by casual users on weekends almost certainly constitutes leisure. In Figure 9 we present our primary results alongside the same models estimated on the subset of trips taken by casual users. The response function is virtually identical between

[12] See Tables A.1 and A.2 in the appendix for city-specific regression results.

[13] This result is sustained when using log duration of trips as our dependent variable in Figure A.7.

[14] In a model of transportation demand, Cutter and Neidell (2009) categorize trips in an analogous manner. They consider trips during rush hours to be commuting (work-related), while classifying trips at other times of day as discretionary (leisure). They also comment that dividing their data into weekday and weekend samples would help sharpen the distinction between discretionary and commuting trips.

[15] We do not, however, have membership designations for Hoboken, Mexico City, or Pittsburgh.

the two samples, although our coefficients are estimated less precisely for casual users presumably due to a loss of statistical power. We take this as very strong evidence that our primary dose-response function, which uses the full sample of all weekend trips, is reflective of leisure activity.

Our prior analysis of intraday effects also lends further support to the notion that weekend cycling is indeed leisure. Returning to Figure 8, there is a virtually identical pattern of intraday substitution on weekend days (panel (a)) and US federal holidays (panel (b)). In both cases, intraday substitution takes place on hot days, with riders shifting their bike trips away from the afternoon and evening in favor of trips during morning and night. This pattern of behavior is consistent with leisurely, discretionary trips as opposed to commuting trips that must take place during a certain window of time due to scheduling constraints (see, e.g., Bento et al., 2014). By contrast, we see the wedge between cooler times of day and warmer times of day shrink when we apply the same model to weekday observations in our sample (panel (c)); here, the reduction in intraday substitution is consistent with inelastic demand for nondiscretionary, commuting trips. A similar relationship holds when we analyze the duration of trips taken as well (see Figure A.7).

In a final analysis, we match individual-level ATUS data from the 2003–2016 surveys with county-level weather to generate dose-response functions for cycling along with two aggregate measures of outdoor recreation. Our approach is nearly identical to that of Chan and Wichman (2018) and we refer readers to that paper for details on data processing. Overall, we model recreation participation decisions in a logit framework as a function of the same temperature and precipitation bins in Equation 3, including household-demographic controls and climate-region, season, and year fixed effects. We focus on three outcomes: recreational cycling and aggregate recreation with and without winter sports. All ATUS estimates are weighted to account for the nationally representative survey design and standard errors are clustered at the climate-region-by-year level.

We present these results in Figure 10. As shown in panel (a), the temperature response function from our bikeshare outcome is statistically equivalent to the relationship we estimate from nationally representative participation in recreational cycling. For precipitation, the percentage changes are statistically similar as well, except for an anomaly in the ATUS response for 0.5–0.75-inch precipitation bin. These results give us further confidence that the weather-response relationships observed for bikesharing is representative of recreational cycling more broadly.[16] Although the relationships here look similar, our outcome variables are different (number of bikeshare trips vs. propensity to recreate) and comparisons should be made cautiously. Further, the identifying variation in the ATUS data is much coarser and

[16]We also find striking parallels between our cycling dose-response functions and those of Obradovich and Fowler (2017), who use survey data on a wide range of physical activity along with month-average weather observations; discrepancies in magnitude likely arise because of measurement error from their use of coarser survey data.

more likely subject to omitted-variables bias. As such, we place more faith in our bikeshare estimates.

We also present in panel (b) of Figure 10 our bikeshare response relative to nationally representative aggregate recreation (i.e., participation in any recreation activity recorded in the ATUS). The estimated response functions for aggregate recreation (including or excluding winter sports) possess the same general shape as our estimated bikeshare relationship for temperature and precipitation. The aggregate recreation functions are, however, closer to zero relative to our bikesharing estimates. This comparison provides some evidence that the primary relationships estimated in this paper are not unique to cycling but, perhaps, emblematic of preferences for other recreational activities on net.

Lastly, we take additional comfort from the fact that we will tend to *underestimate* climate impacts on cycling if our sample is contaminated by nonleisure rides such as work-related commutes. By their nature, these commutes are obligatory and will be relatively inelastic when compared with discretionary, recreational rides. As such, the presence of such trips in our data set will be attenuative, biasing our estimates toward zero. Thus, if anything, our measure of leisure demand will provide a conservative estimate of the response to weather.

4.2.2 Robustness

Could our results be driven by the functional form of temperature and precipitation? Our binned approach restricts the nonlinear relationship between leisure demand and weather to be constant within each bin. This approach offers flexibility in allowing the data to inform the shape of the weather-response function. We can, however, represent this relationship in other ways. In Tables 4 and 5, we present results from alternative assumptions about the form of the weather-leisure demand function. In the first column, rather than six temperature bins, we present coefficients for two bins: days with average temperatures less than or equal to 60° and days with temperatures greater than 80°. We also include precipitation as a continuous variable. Results suggest a similar shape to the binned approach. For both dependent variables, we estimate a significantly negative coefficient for $> 80°$ temperatures, but its effect is relatively small. Interacting these two temperature bins with precipitation strengthens the negative effect for lower temperatures, while offsetting the negative effect for higher temperatures for log trips. Further, implementing a quadratic or cubic relationship between our weather variables and leisure demand suggests the same functional relationships as the primary specifications in Figure 5. Cycling demand is a positive, concave function of temperature and a negative, convex function of precipitation. These sensitivity tests suggest that our primary results are robust to other functional impositions on the data.

Could our results be affected by alternative measures of relevant weather variables? We have simplified the recreation decision to simple summary statistics of weather—namely the mean of daily maximum and minimum temperatures. However, these instrument readings may provide an imperfect proxy for actual rider comfort; a different measure, such as maximum temperature or humidity-adjusted temperature, may be a more proximate driver of cycling demand. Moreover, our interpolation between weather stations may introduce measurement error.

To explore how sensitive our results are to our temperature measure, we rerun our analysis with 9 alternative temperature specifications. We present these results in Tables A.3 and A.4.[17] Across all models and specifications, there is strong agreement among signs, magnitudes, and statistical significance. For each pair-wise combination, using maximum wet-bulb temperature (column (2)), which accounts for humidity among other factors, returns statistically similar coefficients to the weighted average temperature (column (10)) used in our primary specifications. Using maximum (minimum) temperatures shifts the average response function sensibly rightward (leftward), but preserves its shape. Simple geographic weighting of weather stations has minimal impact on coefficient estimates. This agreement suggests that average temperature provides a sensible, robust, and relevant summary statistic of temperature factors that affect leisure demand.

Is our panel specification too restrictive? Does exploiting cross-sectional variation across cities reveal anything about adaptation to warmer temperatures? In Figure A.5 we show that the cross-sectional response functions for temperature and precipitation possess the same shape as that of the panel model. For all precipitation bins and for all temperature bins except the most extreme hot temperatures, the 95% confidence intervals overlap. The invariance of the response functions to this stratification suggests that there is little adaptation that can be revealed from cross-sectional variation. Although there is a larger negative effect for hot temperatures in the cross-sectional model, we believe this to be an artifact of unobserved city-level heterogeneity, rather than an adaptive effect with economic significance.

4.3 Projections of leisure demand under future climate change

We now proceed to project climate change impacts on cycling demand, and we also speculate on implications for a broader class of recreation activities.

Climate impact projections are fraught with many uncertainties, but we believe our application offers several distinct advantages. The first is that our observed temperature and

[17] Specifically, we construct our binned temperature variables with (1) average daily wet-bulb temperature, (2) maximum daily wet-bulb temperature, (3) average daily dry-bulb temperature, (4) maximum daily dry-bulb temperature, (5) maximum daily temperature in which each weather station within 100km is weighted equally, (6) maximum daily temperature in which each weather station within 100km is weighted by its inverse distance squared, (7) minimum daily temperature in which each weather station within 100km is weighted equally, (8) minimum daily temperature in which each weather station within 100km is weighted by its inverse distance squared, and (9) average daily temperature in which each weather station within 100km is weighted equally. We derive the first four measures from the LCD weather data set, and the last five measures from the GHCN-Daily data set.

precipitation ranges—from Mexico City to Montreal, from Boston to Seattle—cover the potential temperature-precipitation combinations projected by climate models by midcentury. This broad support enables us to have minimal out-of-sample predictions. The second is that our data provide a representative analysis of demand behavior measured on very fine timescales. We measure the precise quantity and duration of trips at the *daily* level, giving us direct insight into demand responses at a frequency that is infeasible for other applications. Whereas other research infers climate exposure from longer-term weather trends at a coarse spatial scale, our work can help elucidate the climate-induced recreation benefits (costs) that affect individuals in their daily lives. The precise, causal estimates that we generate from our bikeshare data form the foundation for broader welfare implications.

4.3.1 Projecting future weather

The projection exercise entails several successive steps. First, we obtain daily average temperature predictions and daily precipitation fluxes from the CMIP3 archive. We select models that ran the A1B ("business-as-usual") climate scenario and had daily projections for 2055 through 2060, giving us a total of 15 climate models to work with.[18] For each of these 15 climate models, we take the temperature and precipitation values for each day during the years 2055-2060, and we assign observations from each model's grid point nearest to the city centroid in our sample. We then calculate the percent change in temperature and level change for precipitation day-by-day relative to 1995-2000, the baseline climate period for this CMIP3 experiment.

Formally, the calculation is as follows. Let $m = 1, ..., 15$ denote the specific model within CMIP3 and $y = 1995, ..., 2060$ denote the year. Then we calculate the percentage change in temperature for $y = 2055, ..., 2060$ for a given location as

$$\%\Delta T_{t,m,y} = \frac{T^{CMIP}_{t,m,y} - T^{CMIP}_{t,m,y-60}}{T^{CMIP}_{t,m,y-60}}. \tag{5}$$

We can calculate $\%\Delta T_{t,m,y}$ for each model $m = 1, ..., 15$, yielding 15 different predictions for

[18] We acknowledge that our climate projections use data from CMIP3, which has been superseded by a larger set of climate models in CMIP5. Further, the SRES scenarios in CMIP3 have been replaced with RCP scenarios in CMIP5. There is relatively strong agreement in midcentury temperature and precipitation projections in the contiguous United States between CMIP3's A1B scenario and CMIP5's RCP4.5 and RCP6.0 scenarios (Sun et al., 2015). Our scenario produces slightly higher mean annual temperatures than RCP6.0 and RCP4.5 and similar mean annual precipitation levels, although confidence intervals overlap substantially. Relative to other sources of uncertainty in our modeling exercise, we do not feel that incorporating CMIP5 projections would change our results in a way that substantially improves the precision of our estimates or better characterizes uncertainty. Further, we use a large set of models spanning the range of temperature-precipitation combinations within CMIP3's A1B scenario (Burke et al., 2015a); this range encompasses the vast majority of projections contained in RCP4.5 and RCP6.0, including their central estimates. Our overall conclusions are based on measures of central tendency that have not changed in a statistically meaningful way between CMIP3 and CMIP5 (Sun et al., 2015).

each day in the 2055-2060 window relative to 1995-2000 levels. To mitigate potential location-specific biases, we then add these predicted changes in temperature and precipitation to our actual observed weather from the GHCN-Daily data set (Auffhammer et al., 2013). Given model m, we project future temperature based on 2011-2016 temperatures as

$$T_{t,m,y}^{proj} = T_{t,m,y-44}^{GHCN} \times \left(1 + \%\Delta T_{t,m,y} \times \frac{44}{60}\right).^{19} \tag{6}$$

By retaining a large suite of climate models, we allow the disagreement across models to capture uncertainty in climate predictions (Burke et al., 2015a). We examine the daily 25th percentile, median, and 75th percentile of $T_{t,m,y}^{proj}$ as summary statistics. We repeat this exercise for precipitation projections, although we calculate changes in precipitation in levels rather than percentage changes because of the preponderance of zeros in our data. Median temperature projections used for this exercise are presented in Figure 11 (and by city in Figure A.6). As shown, fewer colder days and more warmer days are expected in 2055-2060. This relationship holds for all cities in our sample.

4.3.2 Projecting changes in cycling demand

Upon projecting future temperatures for each bikeshare program, we now proceed to infer changes in riding demand. Recall that we estimate the relationship

$$\ln Y_{ct} = f(W_{ct}|\Theta) + \alpha_c + \lambda_t + \delta_{cm} + \kappa_1 t_c + \kappa_2 t_c^2 + \varepsilon_{ct} \tag{7}$$

with

$$f(\cdot|\Theta) = \sum_s \gamma_s \mathbb{1}[\mathrm{T}_{ct} = s] + \sum_r \beta_r \mathbb{1}[\mathrm{P}_{ct} = r] + \eta \mathrm{Snow}_{ct}. \tag{8}$$

From this, we obtain estimates of coefficients $\hat{\gamma}$ and $\hat{\beta}$, along with fixed effects and time trends. We use these estimated coefficients and parameterize the dose-response specification at 2011-2016 levels to get a baseline measure of log duration for each city. Then, we predict what log duration would be for each city under the temperature and precipitation projections for 2055-2060. We construct projections using nine pair-wise combinations of temperature and preciptiation at their 25th percentile, median, and 75th percentile values.

The difference in log duration between 2055-2060 and 2011-2016 is our projected climate impact:

$$\Delta \ln Y_c = \ln Y_{c,t} - \ln Y_{c,t-44}, \tag{9}$$

which can be translated into a percentage change.

[19] This formula uses baseline years from 2011-2016 (current weather data). We assume that the 60-year change $\%\Delta T_{t,m,y}$ calculated in Equation 5 proceeds linearly over time, so we can remove the changes prior to the 2011-2016 by scaling by $\frac{44}{60}$.

Figure 12 presents these differences in log duration for the nine pair-wise temperature-precipitation scenarios. The median climate prediction for both temperature and precipitation will lead to a 5.8 log point increase in trip duration. Pairing the 75th percentile temperature projection with the median precipitation suggests a 13.1 log point increase. Similarly, the 25th percentile temperature projection with the median precipitation projection suggests a 2.9 log point decrease. The log difference grows monotonically with temperature but shrinks with precipitation.[20]

4.3.3 Inferring aggregate effects from bikeshare projections

Having projected the effects of climate change on bikeshare utilization, we now seek to scale up these bikeshare-specific results to produce a nationally representative measure of recreational cycling and, more speculatively, aggregate leisure demand changes. We do so at the state level to provide aggregate values for these changes and to demonstrate heterogeneity in the effects of climate change on leisure demand.

We use data from the 2016 wave of the American Time Use Survey (ATUS), which catalogs how much time Americans spend on a wide array of activities. We should note that the ATUS is nationally representative and not intended to provide representative state-level information; however, analyzing the ATUS data at the state level provides a reasonable approximation despite introducing potential measurement error (Aguiar et al., 2013).

We first calculate the annual per capita hours spent cycling for each state for our baseline year, 2016. Following Aguiar et al. (2013), we compute

$$\bar{D}_s = \sum_{i=1}^{N_s} \left(\frac{w_{is}}{\sum_{i=1}^{N_s} w_{is}} \right) D_{is}$$

where D_{is} is hours per year that individual i in state s spent on activity $D \in \{$Cycling, Outdoor recreation$\}$; N_s is the number of ATUS respondents in each state; and w_{is} is the national ATUS sampling weight.[21]

In our sample, the average person spent 0.009 hours per day or roughly 3.35 hours per year cycling. The state-level cycling demand for 2016 is shown in panel (a) of Figure 13. To understand the economic implications, we calculate the value of time spent cycling by multiplying total demand by the national average of consumer surplus derived from cycling,

[20] For context, the minimum temperature projection paired with the maximum precipitation projection (that is, roughly today's temperature with rain nearly every day, a highly unlikely scenario), we see more than a 60% reduction in duration of trips. This projection aligns with our dose-response function for precipitation, where additional days with a large quantity of rain reduce demand by roughly the same quantity as this projection. Notably, our estimates are positive for the interquartile range, centered at a 4%–6% increase, giving us confidence that climate change will tend to stimulate outdoor recreation demand.

[21] For a small number of states, we did not observe positive time spent cycling, and we replaced those values with the national average.

as obtained from the Recreational Use Values Database (Oregon State University, 2006). We plot this measure in panel (b) of Figure 13.[22]

Next, we project cycling demand and cycling value for the year 2060. We follow the procedure used to project city-level changes described above, except we adapt it to define a range of future climates in 2055-2060 at the state level. That is, we parameterize our measure of cycling demand at its 2016 level for each state, assuming the weather-leisure demand coefficients are homogeneous across states. Then, we take the average median temperature and precipitation projection for 2055-2060 and predict cycling demand under the new climate. The difference between these two levels provides an estimate of the average climate-induced change in cycling demand per day. We present these results graphically in panel (c) of Figure 13. As shown, the Northeast, Pacific Northwest, and some Mountain states will gain the most from fewer cold days. The Southeast states will see a reduction in demand.

In terms of the welfare benefits of these changes, we present the annual value of climate-induced demand changes in panel (d) of Figure 13 (we also present state-by-state projections in Table A.5 in the appendix). California, Illinois, and Washington display the largest gains in welfare due to induced demand. For California, the change in the value of cycling demand exceeds \$100 million per year (2016 USD). The Northern Rockies, Great Plains, and Southeast states see very little change in the value of induced demand. In aggregate terms, our exercise suggests that cycling alone is valued at more than \$29 billion (2016 USD) annually, and that this value stands to increase by \$894 million by 2060 as a result of additional climate-induced demand. The magnitude of this gain is larger than, or comparable to, corresponding measures for other types of recreation, such as fishing, coastal and stream recreation, and golfing (Mendelsohn and Markowski, 1999; Loomis and Crespi, 1999). This fact is especially notable because standard analyses of recreation tend to overlook everyday activities like cycling.

To assess the general magnitude of climate-induced changes in aggregate recreation, we repeat this exercise for our overall measure of outdoor recreation in Figure 14, which is comprised of activities similar to cycling—that is, leisure activities that are performed primarily outdoors and are more enjoyable when it is not too cold, too warm, or too wet.[23] The weather-response functions for these activities, shown in Figure 10, are similar to those of bikeshare usage (Figure 5). We adopt the consumer surplus value for cycling and apply it to each activity in our measure of outdoor recreation. This choice is driven by the assump-

[22] The Recreational Use Values Database (Oregon State University, 2006) reports a mean consumer surplus value of \$47.52 per day (2016 USD) for leisure cycling from 17 primary studies. Our analysis of the primary studies suggests an average of two-hour cycling trips, so we divide the given value by 2 to scale consumer surplus into an hourly measurement of \$23.76 per hour.

[23] The list of recreational activities, as defined in the American Time Use Survey, that our measure of outdoor recreation comprises is: playing baseball, playing basketball, biking, boating, climbing/spelunking/caving, participating in equestrian sports, fishing, playing football, golfing, hiking, hunting, playing racquet sports, participating in rodeo competitions, rollerblading, running, playing soccer, softball, walking, participating in water sports. Any activity that is performed primarily indoors (e.g., bowling) or is primarily a winter activity (e.g., skiing) is removed from our measure of recreation.

tion that all leisure demand has common opportunity costs.[24] Further, we assume that all outdoor recreation has a common dose-response function to fluctuations in weather. Both of these assumptions are strong, although we believe this provides a reasonable first-order approximation to valuing climate-induced changes in outdoor recreation.

The general pattern of results in Figure 14 is similar to the pattern of results for cycling. California, New York, and Pennsylvania stand to gain the most in induced-leisure value, with New York experiencing more than a $3 billion welfare gain. Overall, our exercise suggests that 2016 baseline outdoor recreation is valued at more than $607 billion (2016 USD) annually, and we estimate that climate change–induced recreation demand will yield additional welfare benefits of $20.7 billion annually by 2060.[25]

4.4 Interpretation and caveats

As with any complex modeling exercise, there are numerous assumptions, uncertainties, and simplifications built into our analysis. Our state-level welfare estimates are illustrative but should be interpreted with care. For one, we use the population centroid in assigning local variables such as temperature and precipitation to states. Although this may be reasonable for relatively small states like those in the Northeast, it will create inaccuracies in our estimates for larger, more climatologically diverse states like California and Texas. We also assume that projected weather changes between 1995-2000 and 2055-2060 can essentially be prorated to shorter time frames, even though climate change may in fact take place in a nonlinear fashion. Furthermore, we use a parsimonious measure of temperature and employ a particular method for assigning local weather variables from different weather stations, although the robustness checks shown above suggest that these choices do not unduly influence our results. Moreover, we apply a uniform value for cycling consumer surplus, although individuals' valuation of cycling is likely to vary from place to place.

In spite of these caveats, we think that these projections provide useful insights into the scale of climate change effects on leisure and how these effects are distributed across states. In particular, we show that climate will induce large, positive effects on leisure and that benefits will accrue especially to states with large populations and high baseline leisure demand. Alternative assumptions, such as nonlinear progression of temperature changes over time or different methods for assigning local variables to state-level calculations, can easily

[24]This assumption is supported by theory according to the equimarginal principle. Empirically, this assumption may actually bias our valuation downward. As shown in Table 2 of Chan and Wichman (2018), the per-day value for cycling ($47.52) tends to be lower than for other outdoor recreation activities, such as hiking ($78.27), running ($60.37), and boating ($83.34). Alternatively, if we value opportunity costs at the full wage rate, as in, e.g., Becker (1965), Ashenfelter and Greenstone (2004), or Deacon and Sonstelie (1985), our results are virtually identical.

[25]Note that this estimate comprises induced warm-weather recreation only. If the entire winter sporting industry, valued at $12.2 billion annually (Burakowski and Magnusson, 2012), were to collapse, our net estimates of climate impacts on recreation would still be positive.

be incorporated into our projection framework and will affect results in predictable ways. Moreover, while such adjustments to our protocol may yield minor changes in the quantitative estimates, they are unlikely to alter the overall story and interpretation of our results. Lastly, our hourly measure of consumer surplus aligns quite well with the average hourly wage (i.e., pretax median household income divided by 2,080), which is often used as a proxy for the opportunity cost of time.

That said, there remains one outstanding issue that *does* have an important bearing on our interpretation. In overlaying climate projections onto our dose-response function, we implicitly assume that the estimated weather-leisure relationship will remain stable over time. This essentially takes for granted that adaptation or sorting will not appreciably affect how leisure demand responds to weather, which could lead us to overestimate the leisure benefits from warming. For example, riders may "adapt" to warming by becoming less tolerant of frigid riding conditions. Although they will benefit from warmer temperatures overall, they will also have a larger demand response (and, therefore, welfare loss) on the days that cold temperatures do arise. This countervailing effect is ignored if adaptation is assumed away. Likewise, as individuals acclimate to higher temperatures, they may also begin to "take for granted" warmer days, thus muting the leisure benefits from warming.

However, we should note that this issue is not unique to our paper alone; this caveat applies to any paper that estimates a dose-response function and uses that relationship to project future climate impacts. In all such cases, the analyst allows the *value* of variables such as temperature and precipitation to change according to climate projections while assuming that the *underlying structure* of the dose-response relationship remains unchanged.

As a virtue of our high-quality data, we can shed some light on the magnitude of potential bias from adaptation. Returning to Figure 7, panels A and B, we see that different regions respond somewhat differently to temperature changes. To the extent that the observed variation is attributable to acclimatization (e.g., residents of cold cities are less sensitive to cold temperature because of frequent exposure), we can get a sense for how influential adaptation is. We see that there is little dispersion across cities at moderate temperatures, so our results will be unaffected if climate change primarily shifts the distribution of temperatures in this range. However, there is some dispersion at extreme cold and warm temperatures, with nearly a twofold difference in responsiveness for days below 30 degrees. If residents of cold regions acclimatize to future climate by behaving like their warm-weather counterparts, then they will become more sensitive to cold riding conditions, thus reducing the overall leisure benefits from warming. As a second dimension of adaptation, we also find evidence of intraday substitution patterns. Our welfare values are based on daily-level estimates, so they implicitly assume that such intraday substitution is costless. This, too, could lead us to overestimate the benefits from additional leisure opportunities, as we neglect the costs of adaptive substitution behavior. However, because these concerns are relevant for only a small subset of our data and because our overall modeling framework will tend to generate conservative estimates of true welfare changes as described in Section 2, we do not believe these adaptation pathways to be of first-order importance.

We should also note that our analysis is partial equilibrium in nature. We have not accounted for the fact that increases in leisure will necessarily entail less time spent on other activities. Although such substitution effects do not affect valuation estimates at the margin, they could be significant in a general equilibrium framework. The gains in leisure value from climate change could be negated, for example, by lower labor productivity. Such effects are important to keep in mind when interpreting our results, especially because of the scope and scale of climate change impacts.

5 Discussion and implications

Climate change will have far-reaching effects on all aspects of society, and there has been great scientific interest in characterizing its multifarious impacts on agriculture, industry, and ecosystems. In this paper, we obtain causal estimates of how weather influences outdoor recreation behavior by analyzing a unique and detailed data set on bicycling activity. Drawing from tens of millions of bicycle trips, we estimate a dose-response relationship between weather and leisure precisely, and we use these estimates in tandem with time-use surveys and an ensemble of global climate models to project future climate impacts. In doing so, we offer a fresh angle on the problem of climate change by quantifying its implications for nonmarket recreation activities.

Our research is distinctive in part because it takes advantage of an exceptionally rich data set. The quality of the data allows for a more precise and deeper understanding of how climate change will influence recreational demand and welfare. Our work also examines an everyday recreation activity that is typically not accounted for in analyses of recreation and leisure (and certainly not in the climate impact literature). We demonstrate that such activities have a significant role to play in welfare and are critical to include when studying climate change impacts. Our results suggest that climate change will have a sizable, positive impact on leisure by midcentury, with economic gains of nearly $900 million per year for cycling alone and, more speculatively, $20.7 billion per year for aggregate outdoor recreation. Although uncertainty is inevitable for projections of this sort, our analytical approach gives us confidence that the sign of our results is correct and that the overall welfare effect is, if anything, conservative. We run a battery of robustness checks—using different temperature specifications, functional forms, and weightings—all of which tell the same overall story.

This research adds to the broader literature on climate change impacts. Although climate change will indubitably bring about many costs for society, our work suggests that these losses will, at least in some small part, be offset by accompanying changes in leisure opportunities.

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Table 1: Summary statistics for bikeshare data

City	First month	Last month	Full sample: Daily obs.	No. trips	Ave. trips (trips/day)	Duration (1000 hours)	Ave. duration (hours/day)
Austin	201312	201702	1104	550,420	499	263	238
Boston	201107	201612	1749	5,116,385	2,925	1,313	751
Chattanooga	201207	201512	1256	163,914	131	579	461
Chicago	201306	201612	1282	9,993,244	7,795	2,858	2,229
Denver	201004	201612	2161	1,934,816	895	954	442
Hoboken	201510	201612	444	169,482	382	94	212
Los Angeles	201607	201612	178	98,641	554	40	227
Mexico City	201002	201607	2315	34,813,696	15,038	8,194	3,540
Minneapolis*	201006	201611	1450	2,240,726	1,545	440	303
Montreal*	201404	201705	692	11,366,431	16,425	2,586	3,738
New York	201307	201612	1276	36,902,024	28,920	9,514	7,456
Philadelphia	201504	201612	617	1,084,768	1,758	441	715
Pittsburgh	201505	201612	581	138,884	239	127	218
San Francisco	201308	201508	733	669,959	914	206	281
Seattle	201410	201612	811	263,136	324	87	107
Washington, DC	201009	201612	2295	15,462,158	6,737	4,664	2,032
Total			18,944	120,968,684	6,386	32,360	1,708
			Weekends only				
Austin			315	220,399	700	125.0	397
Boston			499	1,216,145	2,437	407.9	817
Chattanooga			358	72,314	202	487.6	1,362
Chicago			367	2,853,608	7,775	1,038.1	2,829
Denver			615	546,737	889	355.3	578
Hoboken			126	40,008	318	28.6	227
Los Angeles			51	26,436	518	15.1	296
Mexico City			662	5,204,986	7,863	1,434.2	2,166
Minneapolis*			414	727,113	1,756	145.1	350
Montreal*			199	2,789,221	14,016	696.0	3,497
New York			363	8,813,202	24,279	2,675.3	7,370
Philadelphia			175	279,172	1,595	150.9	862
Pittsburgh			166	48,565	293	55.8	336
San Francisco			210	83,176	396	62.4	297
Seattle			231	65,326	283	32.5	141
Washington, DC			654	4,292,460	6,563	1,675.2	2,561
Total			5,405	27,278,868	5,047	9,384.7	1,736

Notes: * Minneapolis' and Montreal's programs operate only between April 1 (15) and November 30 (15), respectively.

Table 2: Model results for temperature and precipitation bins on log quantity of trips

Dep. var.: ln(Trips)	(1)	(2)	(3)	(4)	(5)	(6)
Temp. bin: $\leq 30°F$	-1.12	-1.76	-1.72	-1.74	-1.43	-1.35
	(0.74)	(0.18)	(0.18)	(0.18)	(0.14)	(0.15)
Temp. bin: $30 - 40°F$	-0.82	-1.07	-1.02	-1.03	-0.84	-0.80
	(0.69)	(0.13)	(0.13)	(0.14)	(0.10)	(0.10)
Temp. bin: $40 - 50°F$	-0.63	-0.58	-0.53	-0.53	-0.43	-0.41
	(0.52)	(0.07)	(0.07)	(0.07)	(0.05)	(0.06)
Temp. bin: $50 - 60°F$	-0.60	-0.25	-0.20	-0.18	-0.17	-0.15
	(0.25)	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)
Temp. bin: $70 - 80°F$	-0.25	0.05	0.05	0.05	0.04	0.05
	(0.35)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)
Temp. bin: $> 80°F$	-0.55	-0.20	-0.25	-0.24	-0.08	-0.04
	(0.65)	(0.07)	(0.07)	(0.07)	(0.04)	(0.04)
Precip. bin: $0.01 - 0.25$ in.	-0.20	-0.15	-0.16	-0.16	-0.16	-0.16
	(0.18)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Precip. bin: $0.25 - 0.50$ in.	-0.46	-0.50	-0.53	-0.53	-0.50	-0.50
	(0.31)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
Precip. bin: $0.50 - 0.75$ in.	-0.69	-0.62	-0.61	-0.63	-0.60	-0.59
	(0.30)	(0.10)	(0.09)	(0.09)	(0.09)	(0.08)
Precip. bin: $0.75 - 1$ in.	-0.82	-0.68	-0.68	-0.70	-0.66	-0.64
	(0.35)	(0.10)	(0.10)	(0.09)	(0.10)	(0.09)
Precip. bin: > 1 in.	-1.18	-0.78	-0.79	-0.80	-0.77	-0.78
	(0.38)	(0.15)	(0.15)	(0.15)	(0.15)	(0.14)
$\mathbb{1}\{\text{Snowfall}\}$	-0.59	-0.33	-0.32	-0.32	-0.30	-0.31
	(0.40)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)
Observations	5,405	5,405	5,405	5,405	5,405	5,405
R-squared	0.15	0.86	0.90	0.91	0.93	0.94
City FE:	–	Y	Y	Y	Y	Y
Month FE:	Y	Y	Y	Y	Y	Y
Day-of-week FE:	Y	Y	Y	Y	Y	Y
Month-of-sample FE:	–	–	–	–	–	Y
City-by-month-of-sample FE:	–	–	–	–	Y	Y
City-specific time trend:	–	–	Linear	Quadratic	Quadratic	Quadratic

Notes: Dependent variable is the natural log of the number of trips each day. Robust standard errors clustered at the city level are presented in parentheses.

Table 3: Model results for temperature and precipitation bins on log duration of trips

Dep. var.: ln(Duration)	(1)	(2)	(3)	(4)	(5)	(6)
Temp. bin: $\leq 30°$F	-1.80	-2.06	-2.09	-2.12	-1.69	-1.59
	(0.61)	(0.26)	(0.23)	(0.21)	(0.15)	(0.16)
Temp. bin: $30 - 40°$F	-1.20	-1.14	-1.18	-1.24	-0.95	-0.90
	(0.53)	(0.24)	(0.18)	(0.15)	(0.11)	(0.12)
Temp. bin: $40 - 50°$F	-0.84	-0.55	-0.56	-0.60	-0.46	-0.43
	(0.42)	(0.17)	(0.12)	(0.09)	(0.09)	(0.10)
Temp. bin: $50 - 60°$F	-0.57	-0.19	-0.22	-0.22	-0.21	-0.18
	(0.17)	(0.10)	(0.06)	(0.06)	(0.06)	(0.07)
Temp. bin: $70 - 80°$F	0.03	0.18	0.09	0.08	0.07	0.08
	(0.31)	(0.12)	(0.07)	(0.06)	(0.04)	(0.04)
Temp. bin: $> 80°$F	-0.13	-0.21	-0.33	-0.31	-0.12	-0.05
	(0.61)	(0.11)	(0.10)	(0.10)	(0.06)	(0.07)
Precip. bin: $0.01 - 0.25$ in.	-0.22	-0.15	-0.20	-0.21	-0.18	-0.19
	(0.13)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
Precip. bin: $0.25 - 0.50$ in.	-0.56	-0.60	-0.69	-0.68	-0.61	-0.62
	(0.26)	(0.09)	(0.08)	(0.07)	(0.09)	(0.08)
Precip. bin: $0.50 - 0.75$ in.	-0.75	-0.61	-0.77	-0.78	-0.72	-0.70
	(0.30)	(0.20)	(0.12)	(0.12)	(0.13)	(0.13)
Precip. bin: $0.75 - 1$ in.	-1.01	-0.79	-0.85	-0.90	-0.80	-0.79
	(0.33)	(0.17)	(0.15)	(0.13)	(0.15)	(0.14)
Precip. bin: > 1 in.	-1.18	-0.70	-0.85	-0.88	-0.82	-0.84
	(0.31)	(0.33)	(0.24)	(0.22)	(0.24)	(0.21)
$\mathbb{1}\{\text{Snowfall}\}$	-0.45	-0.45	-0.41	-0.41	-0.41	-0.40
	(0.32)	(0.07)	(0.08)	(0.08)	(0.09)	(0.09)
Observations	5,405	5,405	5,405	5,405	5,405	5,405
R-squared	0.15	0.70	0.80	0.84	0.86	0.87
City FE:	–	Y	Y	Y	Y	Y
Month FE:	Y	Y	Y	Y	Y	Y
Day-of-week FE:	Y	Y	Y	Y	Y	Y
Month-of-sample FE:	–	–	–	–	–	Y
City-by-month-of-sample FE:	–	–	–	–	Y	Y
City-specific time trend:	–	–	Linear	Quadratic	Quadratic	Quadratic

Notes: Dependent variable is the natural log of the duration of trips each day. Robust standard errors clustered at the city level are presented in parentheses.

Table 4: Model results for alternative nonlinear specifications for weather effects on log quantity of trips

Dep. var.: ln(Trips)	(1)	(2)	(3)	(4)
$\mathbb{1}\{\text{Ave. Temp.} \leq 60°F\}$	-0.21	-0.16		
	(0.05)	(0.05)		
$\mathbb{1}\{\text{Ave. Temp.} > 80°F\}$	-0.09	-0.09		
	(0.03)	(0.02)		
$\mathbb{1}\{\text{Ave. Temp.} \leq 60°F\} \times$ Precip.		-0.57		
		(0.11)		
$\mathbb{1}\{\text{Ave. Temp.} > 80°F\} \times$ Precip.		0.25		
		(0.08)		
Ave. Temp.			0.08	0.04
			(0.01)	(0.02)
$(\text{Ave. Temp.})^2$			-0.00	0.00
			(0.00)	(0.00)
$(\text{Ave. Temp.})^3$				-0.00
				(0.00)
Precip.	-0.57	-0.36	-0.93	-0.94
	(0.10)	(0.10)	(0.20)	(0.20)
$(\text{Precip.})^2$			0.21	0.21
			(0.13)	(0.13)
$\mathbb{1}\{\text{Snowfall}\}$	-0.64	-0.62	-0.32	-0.31
	(0.07)	(0.07)	(0.06)	(0.06)
Observations	5,405	5,405	5,405	5,405
R-squared	0.93	0.93	0.94	0.94

Notes: Dependent variable is the natural log of the number of trips each day. All models include city fixed effects, city-by-month fixed effects, month-of-sample fixed effects, city-specific quadratic time trends, day-of-week fixed effects, and year-by-month effects. Robust standard errors clustered at the city level are presented in parentheses.

Table 5: Model results for alternative nonlinear specifications for weather effects on log duration of trips

Dep. var.: ln(Duration)	(1)	(2)	(3)	(4)
$\mathbb{1}\{\text{Ave. Temp.} \leq 60°F\}$	-0.24	-0.16		
	(0.08)	(0.08)		
$\mathbb{1}\{\text{Ave. Temp.} > 80°F\}$	-0.12	-0.11		
	(0.04)	(0.04)		
$\mathbb{1}\{\text{Ave. Temp.} \leq 60°F\} \times$ Precip.		-0.85		
		(0.14)		
$\mathbb{1}\{\text{Ave. Temp.} > 80°F\} \times$ Precip.		0.13		
		(0.20)		
Ave. Temp.			0.09	0.05
			(0.01)	(0.02)
$(\text{Ave. Temp.})^2$			-0.00	0.00
			(0.00)	(0.00)
$(\text{Ave. Temp.})^3$				-0.00
				(0.00)
Precip.	-0.65	-0.33	-1.17	-1.19
	(0.15)	(0.13)	(0.26)	(0.26)
$(\text{Precip.})^2$			0.31	0.31
			(0.13)	(0.13)
$\mathbb{1}\{\text{Snowfall}\}$	-0.80	-0.77	-0.43	-0.42
	(0.09)	(0.09)	(0.10)	(0.10)
Observations	5,405	5,405	5,405	5,405
R-squared	0.86	0.86	0.88	0.88

Notes: Dependent variable is the natural log of the duration of trips each day. All models include city fixed effects, city-by-month fixed effects, month-of-sample fixed effects, city-specific quadratic time trends, day-of-week fixed effects, and year-by-month effects. Robust standard errors clustered at the city level are presented in parentheses.

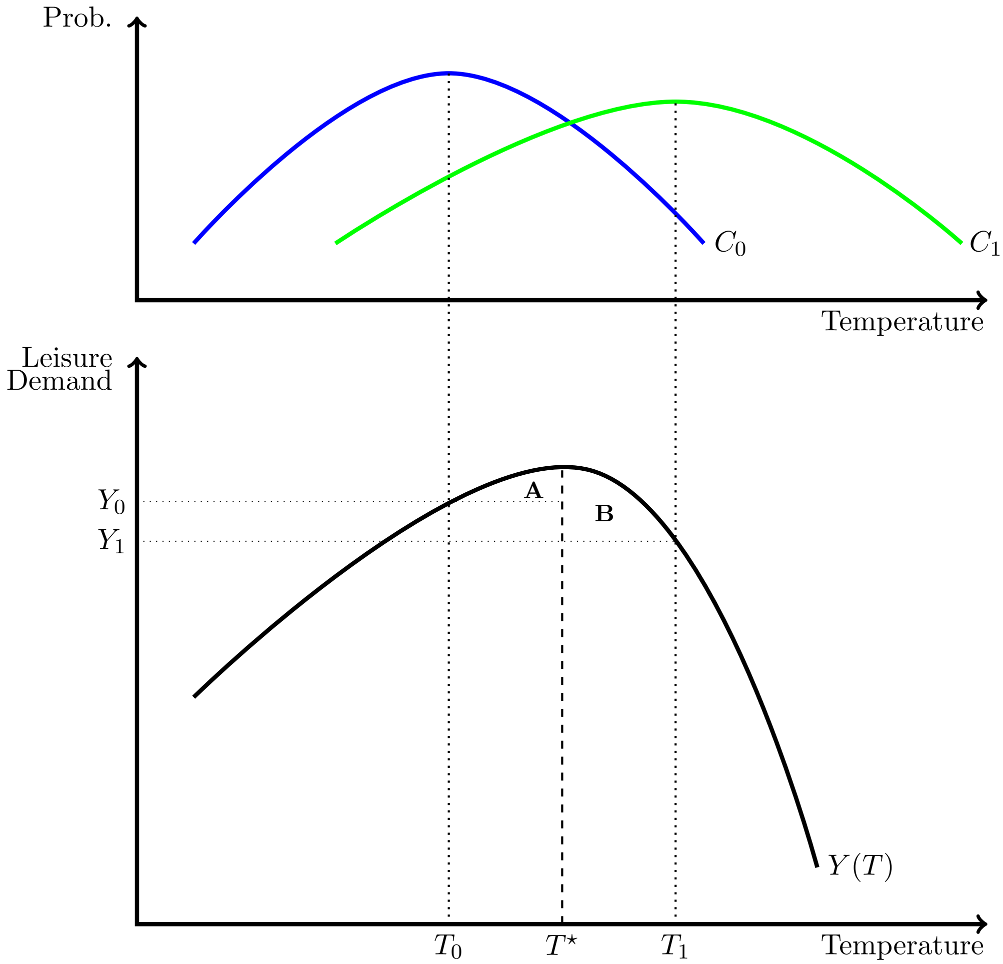


Figure 1: Stylized depiction of leisure demand as a function of temperature

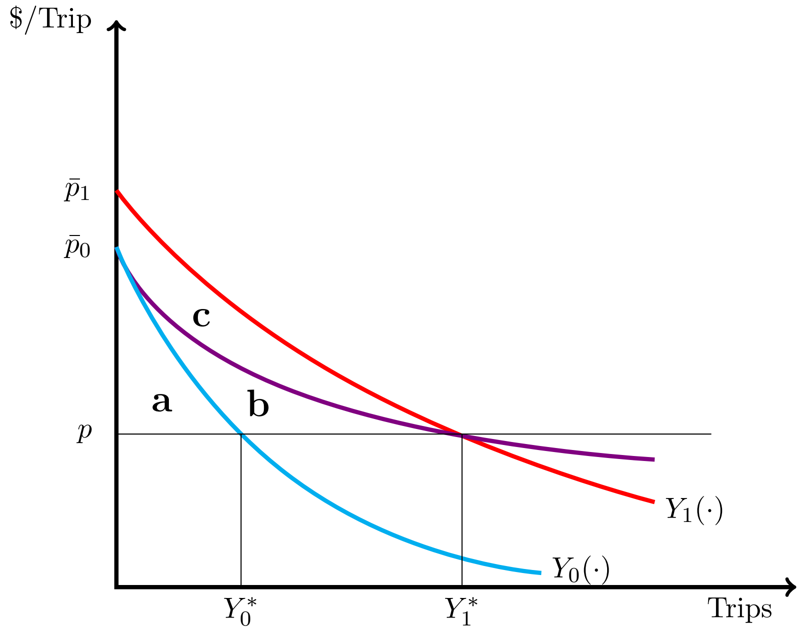
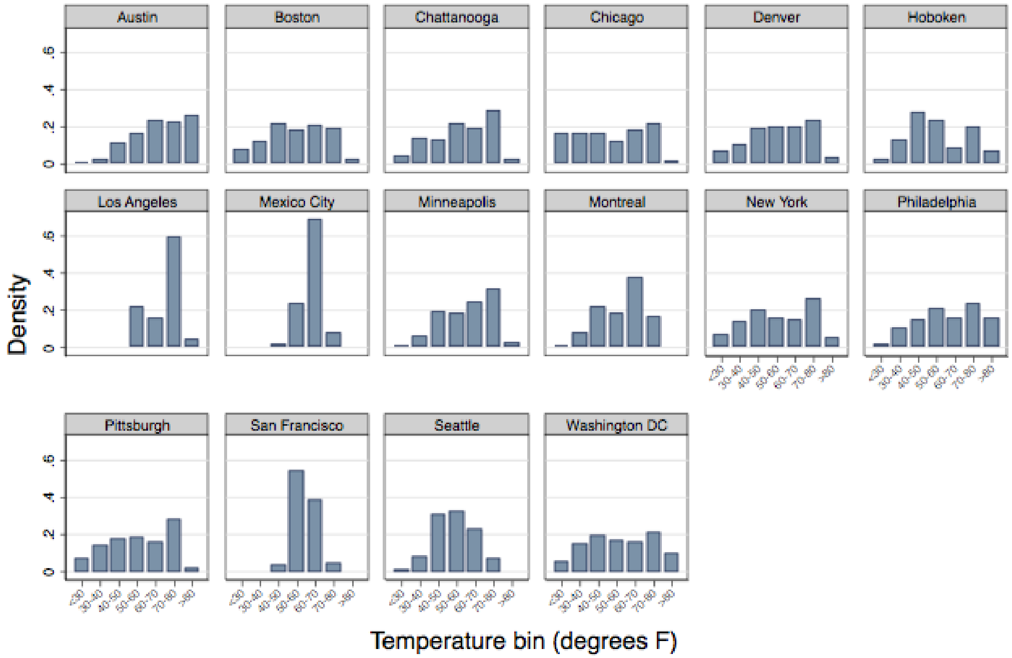
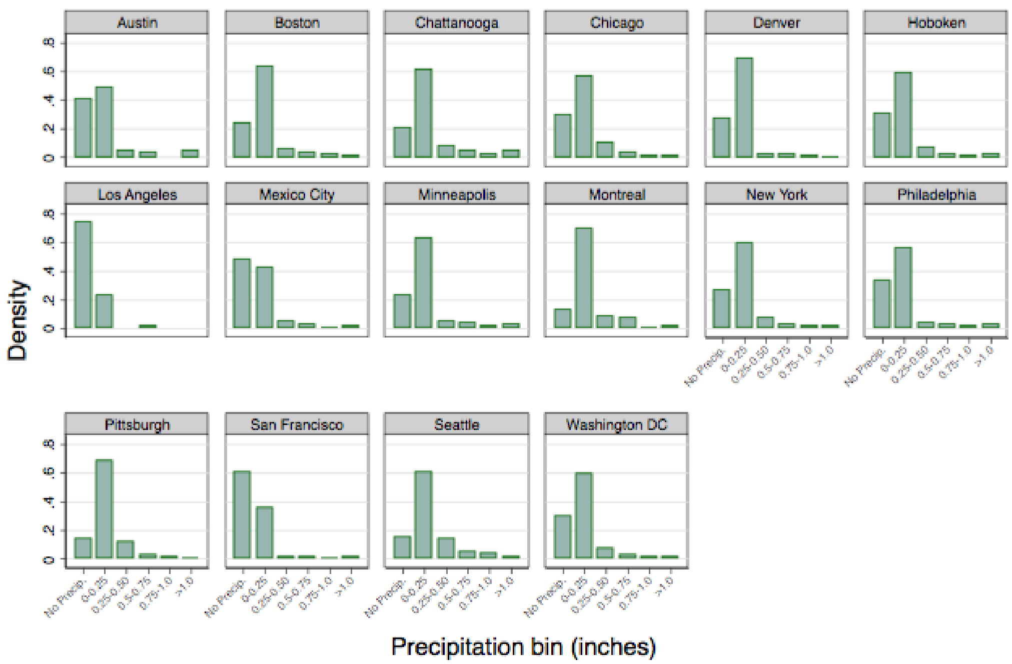


Figure 2: Welfare change from weather changes. Changing weather shifts demand from $Y_0(\cdot)$ to $Y_1(\cdot)$. The original consumer surplus is the area a while the new consumer surplus is the area $a+b+c$, yielding $\Delta CS = b+c$. In the absence of the full demand curve, we approximate $\Delta CS \approx \frac{Y_1^*}{Y_0^*}CS_0 - CS_0$, which is captured by the area b. This approximation will, in most standard cases, provide a conservative or exact estimate of the true change in welfare. While it is possible to conceive of a function that violates this, we are unaware of any commonly-used empirical demand functions that do so. Chan and Wichman (2018) provide more detailed analysis.

Figure 3: Location of cities included in sample

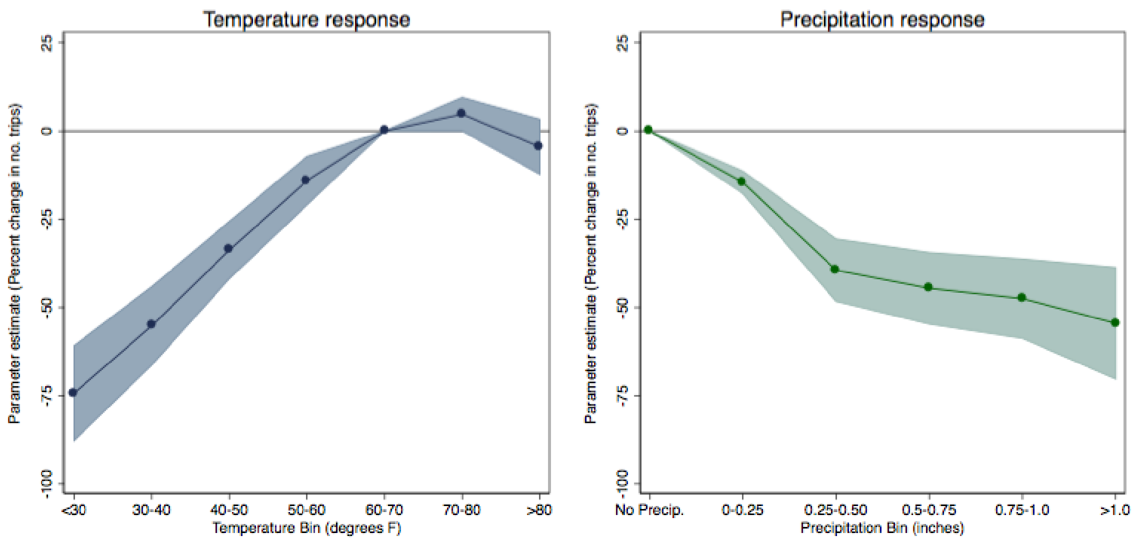


(a) Distribution of daily temperature observations in 10-degree bins

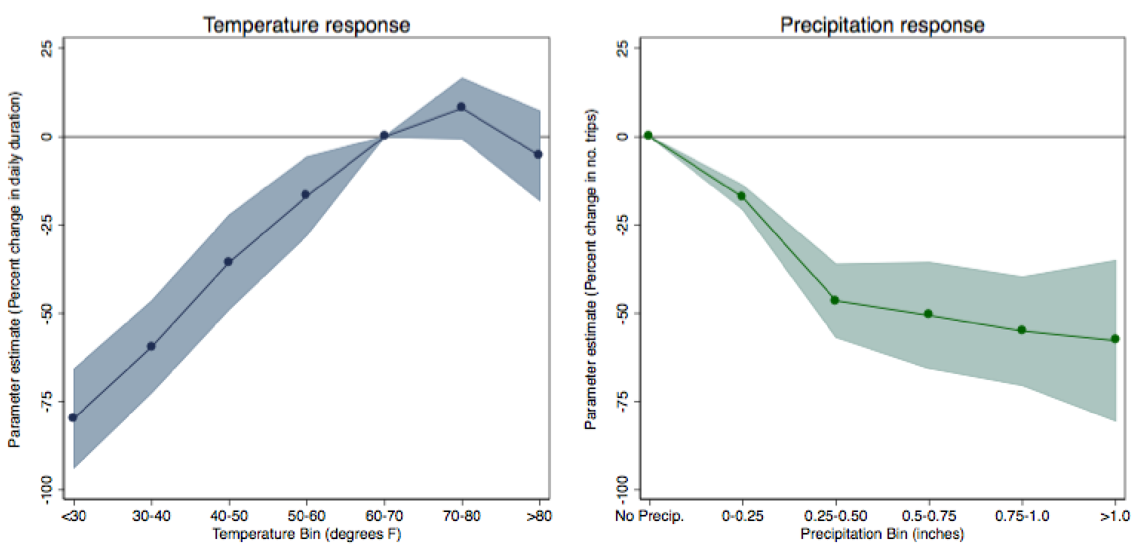


(b) Distribution of daily precipitation observations in $\frac{1}{4}$-inch bins

Figure 4: Distribution of daily average temperatures and precipitation by city. Note that these distributions display values only for weekends for which bikeshare data are available in each city. Because the Minneapolis and Montreal programs do not operate in the winter, winter weather in these cities is not reflected in their respective graphs.



(a) Percent change (and 95% CI) in quantity of trips due to changes in daily average temperatures and daily precipitation



(b) Percent change (and 95% CI) in total duration of trips due to changes in daily average temperatures and daily precipitation

Figure 5: Nonlinear relationship between cycling demand and daily weather

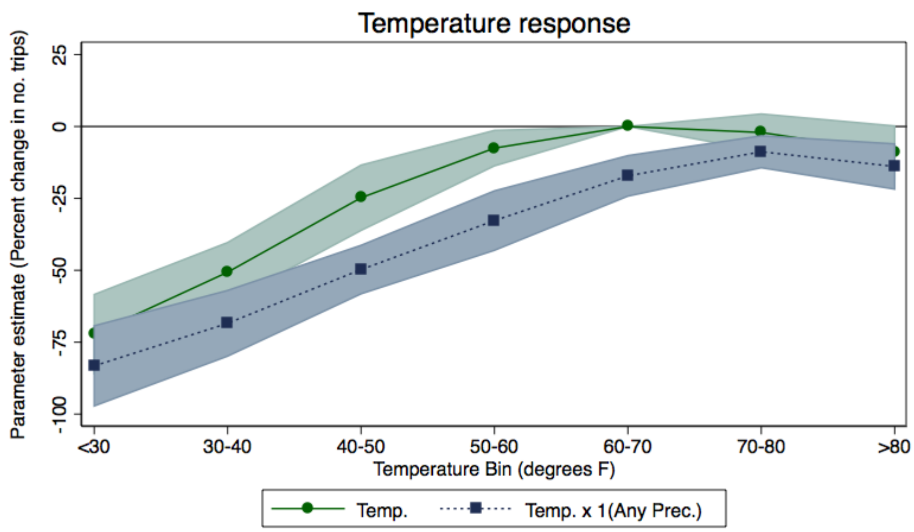
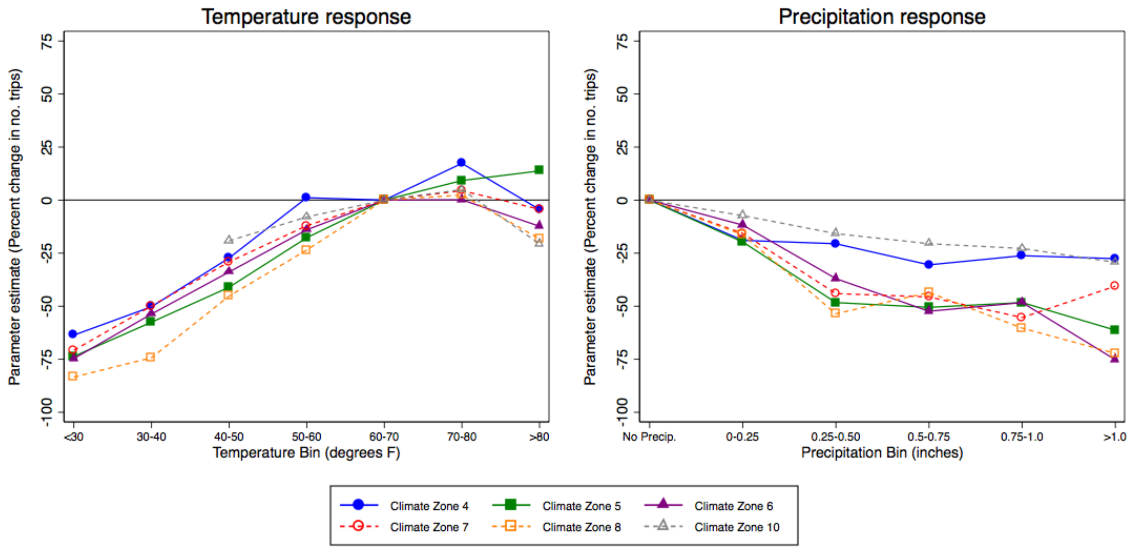
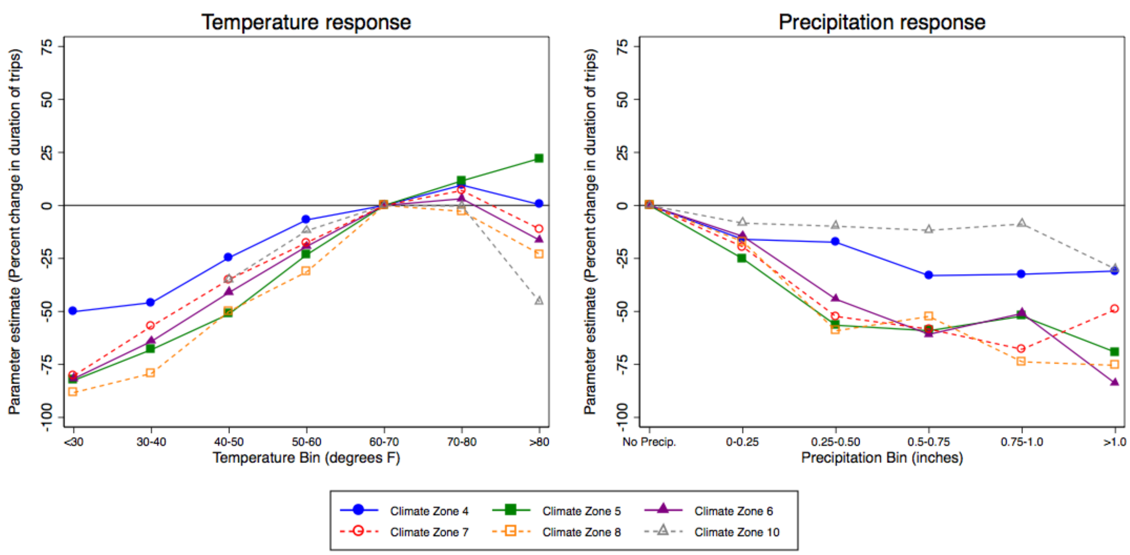


Figure 6: Percent change (and 95% CI) in quantity of trips due to changes in daily average temperatures on days with/without precipitation

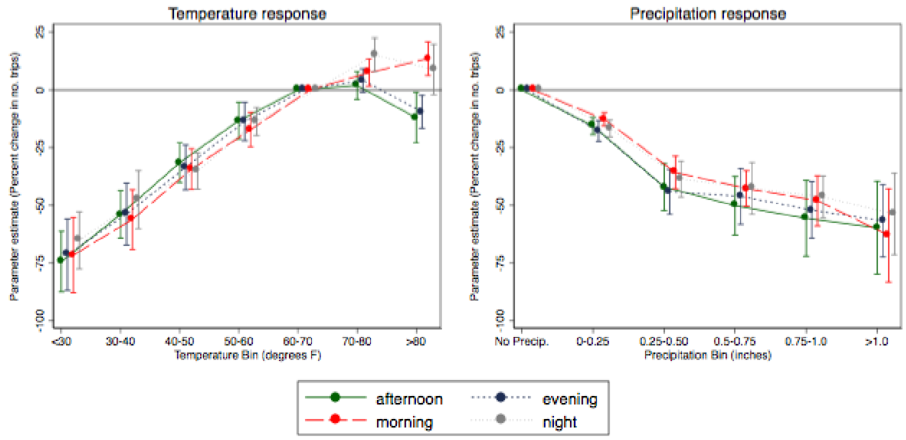


(a) Percent change in quantity of trips due to changes in daily average temperatures and daily precipitation by climate zone

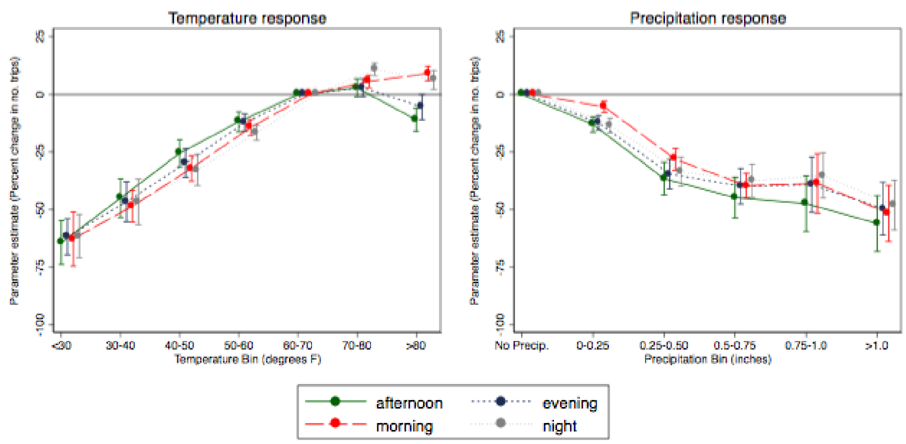


(b) Percent change in total duration of trips due to changes in daily average temperatures and daily precipitation by climate zone

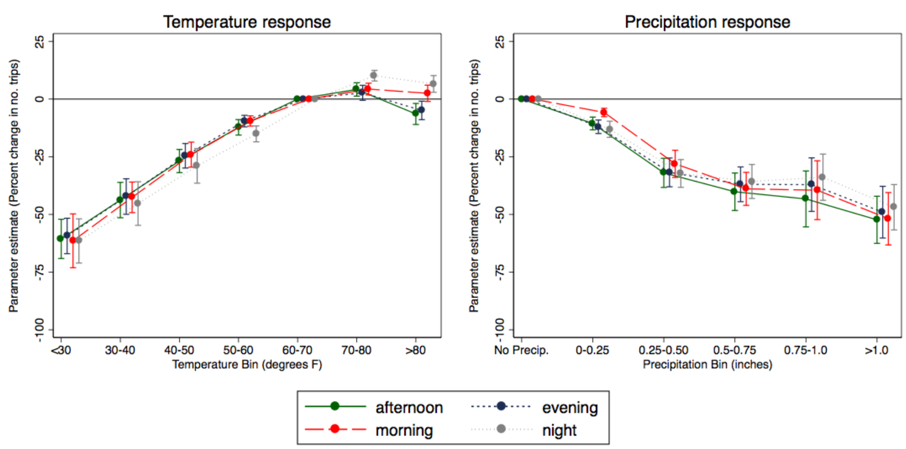
Figure 7: Nonlinear relationship between cycling demand and daily weather by climate zone



(a) Intraday substitution on weekends

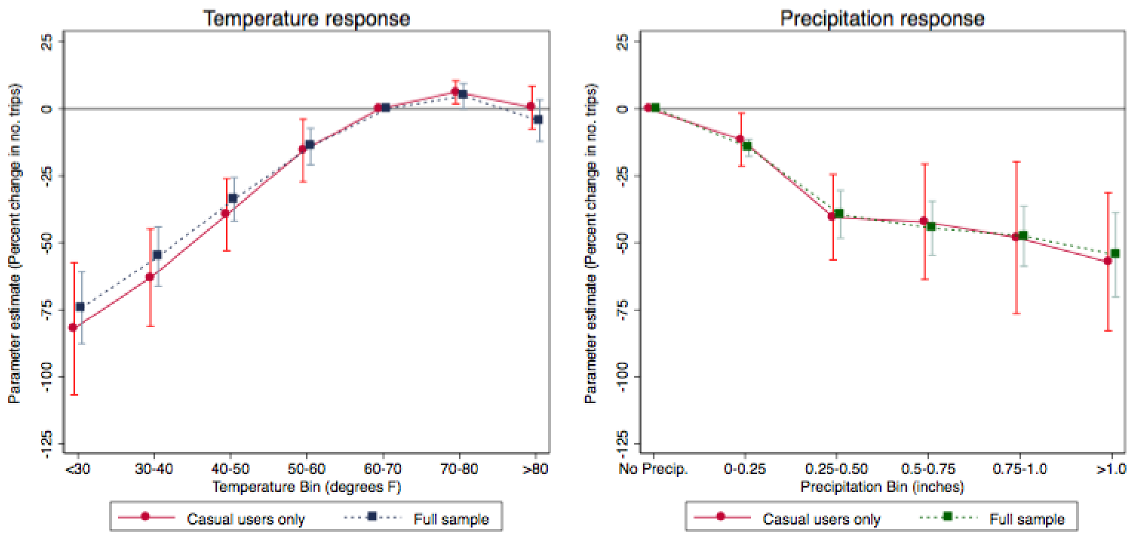


(b) Intraday substitution on federal holidays

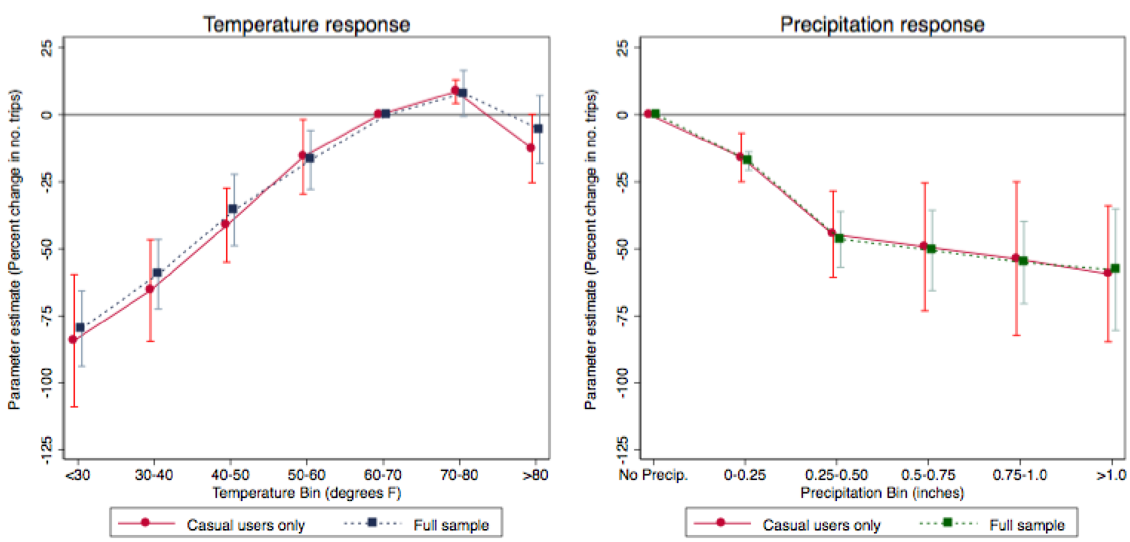


(c) Intraday substitution on weekdays

Figure 8: Nonlinear relationship between log quantity of trips and weather conditional on time of day. Morning is defined as 5AM–10AM; afternoon is 10AM–3PM; evening is 3PM–8PM; and night is 8PM–12AM. All times are local.

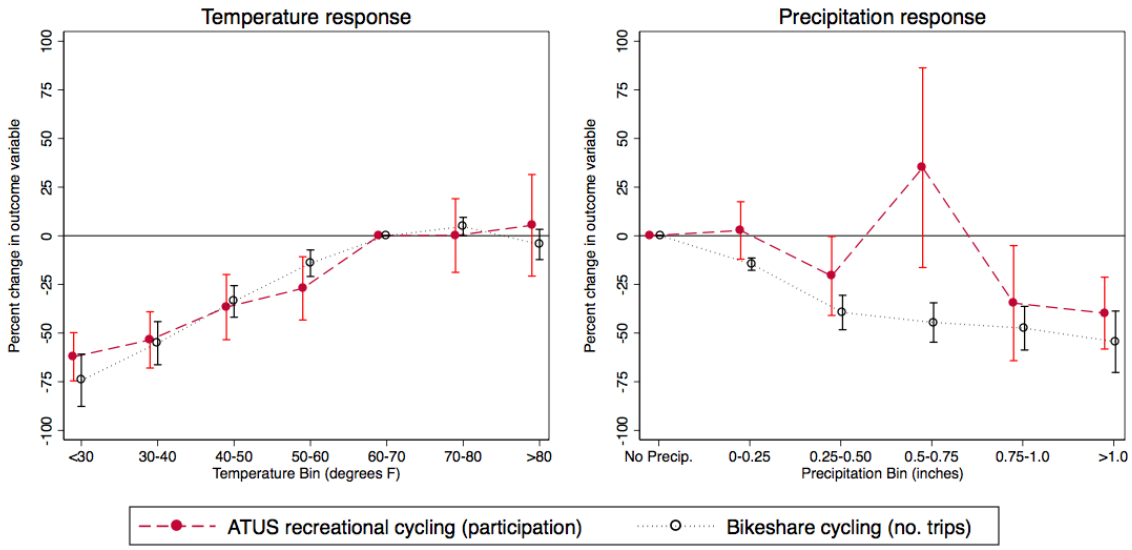


(a) Percent change (and 95% CI) in quantity of trips due to changes in daily average temperatures and daily precipitation for casual users relative to primary results

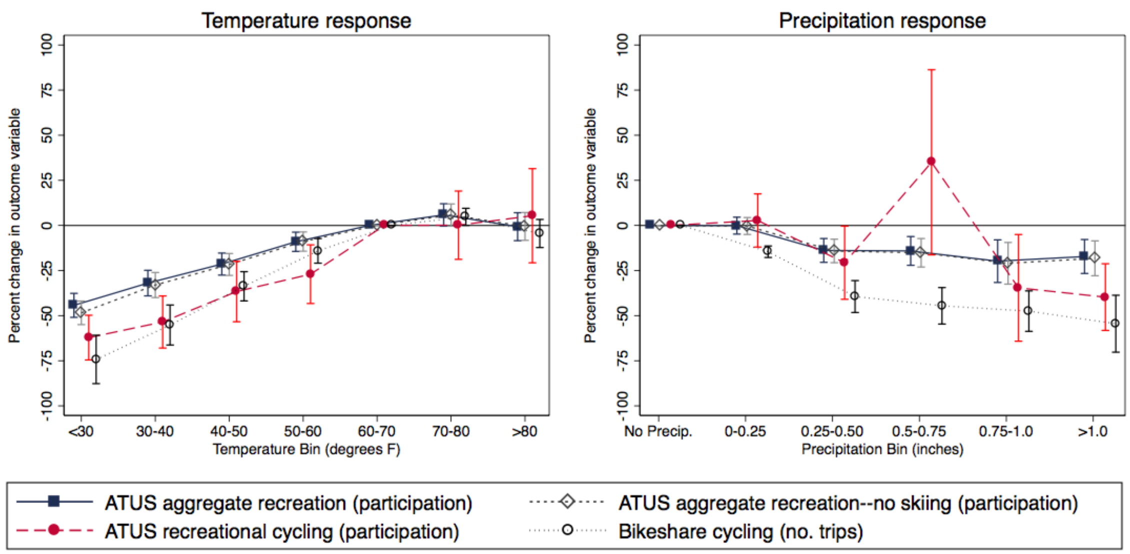


(b) Percent change (and 95% CI) in total duration of trips due to changes in daily average temperatures and daily precipitation for casual users relative to primary results

Figure 9: Nonlinear relationship between cycling demand and daily weather for casual users relative to primary results



(a) Percentage effects for estimates using ATUS data (cycling)



(b) Percentage effects for estimates using ATUS data (cycling & aggregate recreation)

Figure 10: Comparing bikeshare estimates with 2003-2016 ATUS recreation participation changes. Bikeshare estimates are the same as presented in Figure 5a. All ATUS estimates are percentage effects (relative to weighted sample mean participation rates) estimated in a logit model. Dependent variable is whether a household participated in a given activity (recreation, recreation (omitting winter sports), or recreation cycling). All ATUS models include climate region fixed effects, season fixed effects, and yearly fixed effects. Standard errors are clustered at the climate-region-by-year level. ATUS models are adjusted for sampling weights to account for the nationally representative survey design.

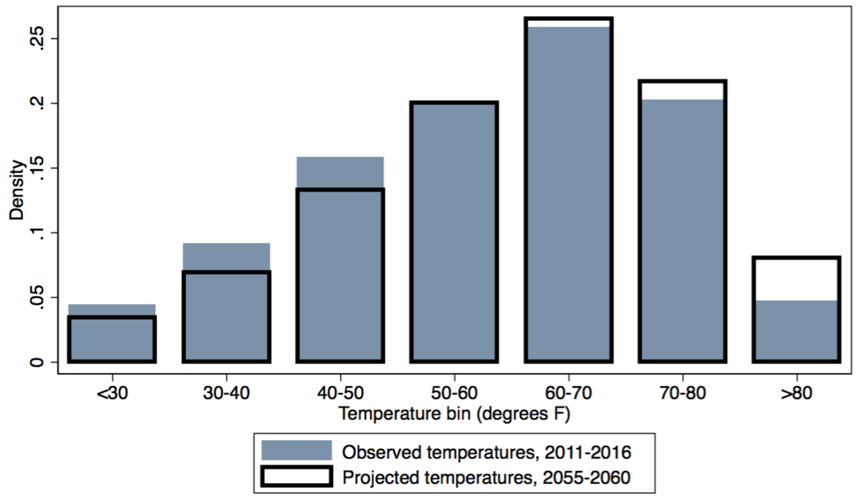


Figure 11: Distribution of temperatures on weekends in sample (blue) and projected temperatures for corresponding days in 2055-2060 (black). Projected temperatures are percentage changes from observed baseline for the median projection from 15 climate models in the CMIP3 ensemble reporting the A1B ("business-as-usual") climate scenario.

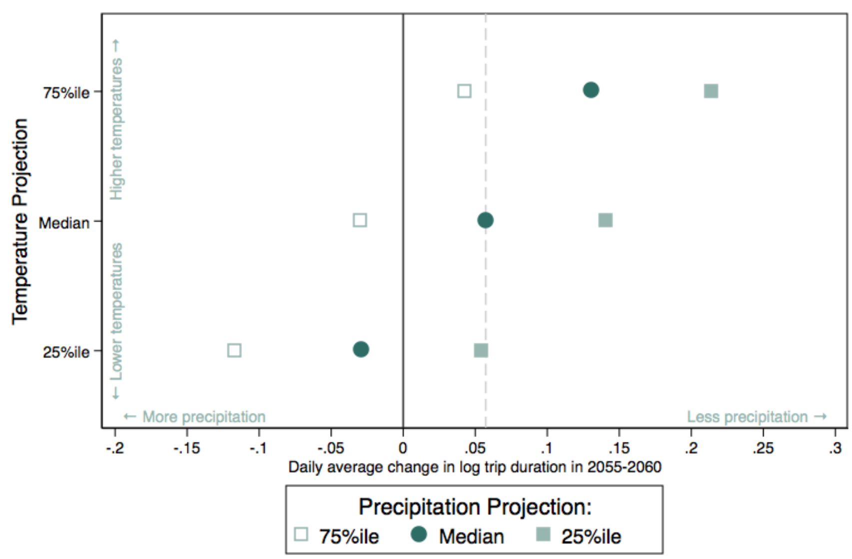
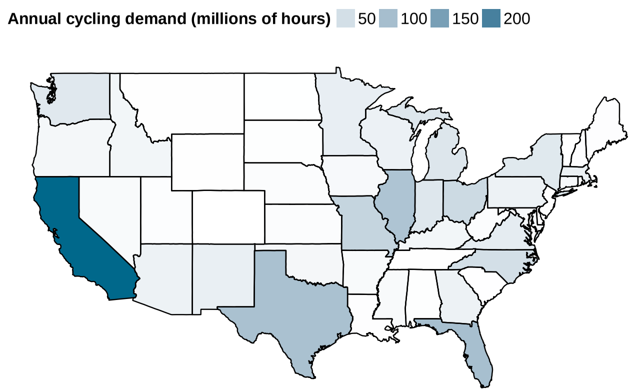
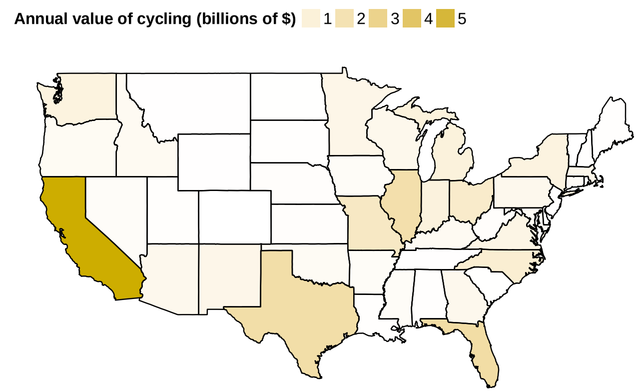


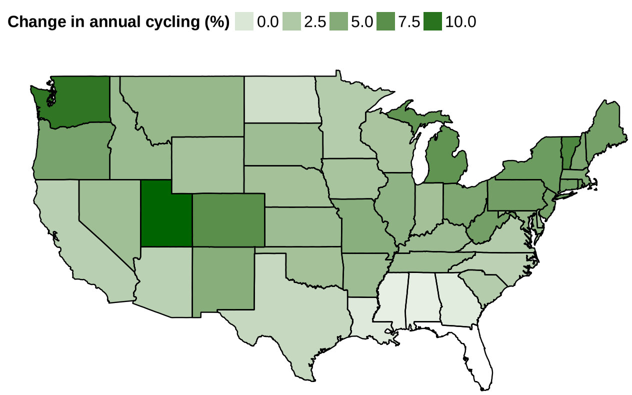
Figure 12: Projected effects of temperature and precipitation on changes in the log duration of bicycle trips in 2055-2060. Projected temperatures are percentage changes from observed baseline for the 25th percentile, median, and 75th percentile projection from 15 climate models in the CMIP3 ensemble reporting the A1B ("business-as-usual") climate scenario.



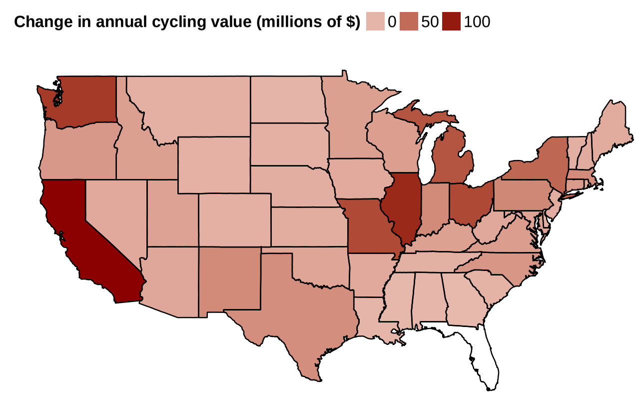
(a) Annual cycling demand in 2016 (in millions of hours)



(b) Value of annual cycling demand in 2016 (in billions of 2016 USD)

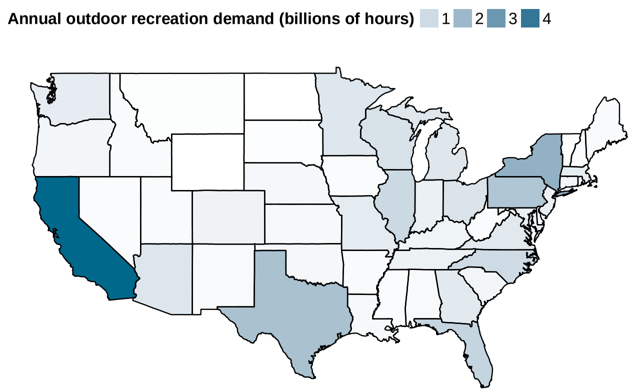


(c) Projected percentage change by 2060

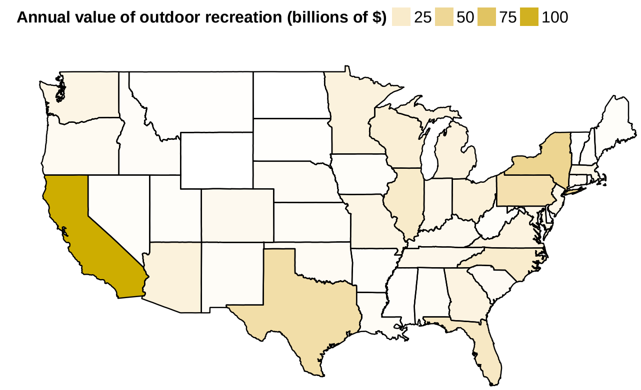


(d) Projected annual change by 2060 (in millions of 2016 USD)

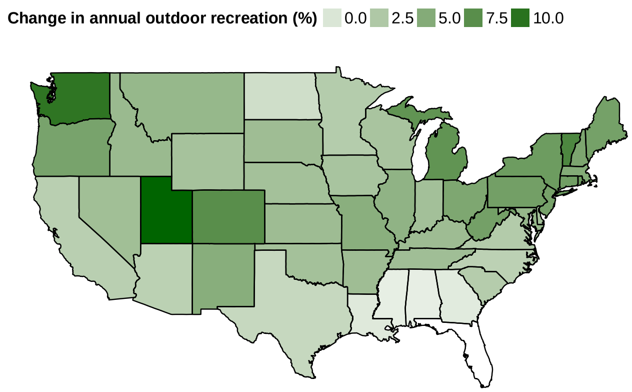
Figure 13: Current levels and projected changes in cycling demand and its value by state. Values calculated from the American Time Use Survey and the median CMIP3 model projections for average daily temperature and precipitation during 2055-2060. Values are calculated as the number of hours spent cycling multiplied by national average consumer surplus estimates from the Recreation Use Values Database. The percentage changes are calculated by assuming common coefficients at their 2011-2016 levels and predicting changes in demand due to changes in the temperature and precipitation distribution.



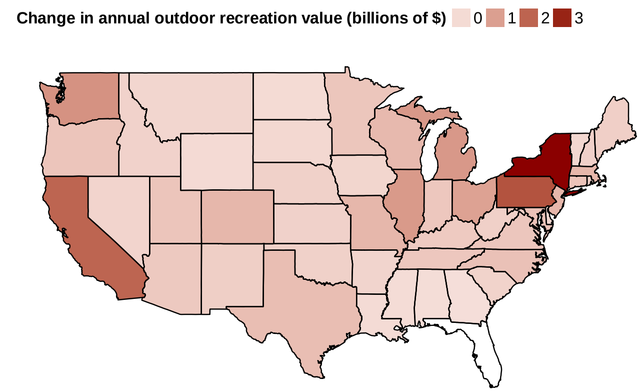
(a) Annual outdoor leisure demand in 2016 (in millions of hours)



(b) Value of annual outdoor leisure demand in 2016 (in billions of 2016 USD)



(c) Projected percentage change by 2060



(d) Projected annual change by 2060 (in billions of 2016 USD)

Figure 14: Current levels and projected changes in recreation demand and its value by state. Values calculated from the American Time Use Survey and the median CMIP3 model projections for average daily temperature and precipitation during 2055-2060. Values are calculated as the number of hours spent recreating multiplied by national average consumer surplus estimates from the Recreation Use Values Database. The percentage changes are calculated by assuming common coefficients at their 2011-2016 levels and predicting changes in demand due to changes in the temperature and precipitation distribution.

FOR ONLINE PUBLICATION

Online appendix for
The effects of climate on leisure demand: Evidence from North America
Nathan W. Chan & Casey J. Wichman
March 1, 2018

Table A.1: City-specific model results for nonlinear effect of temperature and precipitation bins on log quantity of trips

Dep. var.: ln(Trips)	(1) AUS	(2) BOS	(3) CHA	(4) CHI	(5) DEN	(6) HOB	(7) LA	(8) MXC	(9) MIN	(10) MON	(11) NYC	(12) PHI	(13) PIT	(14) SF	(15) SEA	(16) DC
Temp. bin: $\leq 30°$F	-2.68	-1.24	-2.21	-1.43	-1.59	-2.11			-0.95	-0.93	-1.02	-1.33	-1.22		-0.84	-0.58
	(0.17)	(0.18)	(0.30)	(0.16)	(0.18)	(0.46)			(0.35)	(0.20)	(0.12)	(0.29)	(0.42)		(0.32)	(0.13)
Temp. bin: $30-40°$F	-1.69	-0.76	-1.21	-1.02	-0.75	-0.97			-0.69	-0.47	-0.57	-0.34	-1.17		-0.73	-0.30
	(0.44)	(0.12)	(0.20)	(0.14)	(0.13)	(0.19)			(0.16)	(0.17)	(0.10)	(0.20)	(0.37)		(0.17)	(0.09)
Temp. bin: $40-50°$F	-0.64	-0.44	-0.66	-0.60	-0.30	-0.70		-0.04	-0.31	-0.44	-0.37	-0.29	-0.74	-0.53	-0.18	-0.10
	(0.17)	(0.08)	(0.16)	(0.11)	(0.10)	(0.16)		(0.09)	(0.09)	(0.11)	(0.07)	(0.16)	(0.31)	(0.08)	(0.13)	(0.08)
Temp. bin: $50-60°$F	-0.39	-0.27	-0.34	-0.17	0.02	-0.36	-0.19	-0.05	0.01	-0.22	-0.17	-0.06	-0.66	-0.16	0.07	-0.02
	(0.12)	(0.05)	(0.13)	(0.10)	(0.06)	(0.13)	(0.20)	(0.03)	(0.08)	(0.07)	(0.05)	(0.12)	(0.27)	(0.03)	(0.07)	(0.06)
Temp. bin: $70-80°$F	0.15	-0.00	0.03	0.15	-0.02	-0.07	-0.04	0.07	0.16	0.01	-0.01	-0.22	-0.03	0.06	-0.10	0.10
	(0.13)	(0.03)	(0.11)	(0.06)	(0.04)	(0.11)	(0.18)	(0.03)	(0.05)	(0.04)	(0.04)	(0.10)	(0.11)	(0.04)	(0.07)	(0.07)
Temp. bin: $> 80°$F	-0.01	-0.24	-0.61	0.17	-0.20	-0.11	-0.31		-0.04		-0.04	-0.18	-0.72			0.04
	(0.15)	(0.08)	(0.39)	(0.10)	(0.07)	(0.12)	(0.19)		(0.14)		(0.05)	(0.10)	(0.23)			(0.10)
Precip. bin: $0.01-0.25$ in.	-0.24	-0.13	-0.22	-0.23	-0.06	-0.27	0.22	-0.08	-0.21	-0.12	-0.09	-0.18	-0.43	-0.07	-0.18	-0.13
	(0.06)	(0.04)	(0.09)	(0.05)	(0.04)	(0.07)	(0.19)	(0.04)	(0.05)	(0.05)	(0.03)	(0.05)	(0.12)	(0.03)	(0.06)	(0.03)
Precip. bin: $0.25-0.50$ in.	-0.75	-0.49	-0.82	-0.68	-0.73	-0.70		-0.13	-0.23	-0.50	-0.30	-0.61	-0.81	-0.33	-0.75	-0.36
	(0.25)	(0.08)	(0.19)	(0.10)	(0.24)	(0.22)		(0.05)	(0.09)	(0.09)	(0.07)	(0.25)	(0.19)	(0.18)	(0.11)	(0.07)
Precip. bin: $0.50-0.75$ in.	-0.35	-0.85	-0.99	-0.64	-0.78	-0.33	-0.34	-0.09	-0.36	-0.70	-0.53	-0.16	-0.95	-1.08	-0.74	-0.42
	(0.16)	(0.11)	(0.19)	(0.15)	(0.32)	(0.36)	(0.18)	(0.04)	(0.13)	(0.12)	(0.09)	(0.11)	(0.34)	(0.13)	(0.11)	(0.17)
Precip. bin: $0.75-1$ in.		-0.61	-1.04	-0.63	-0.84	-0.62		-0.10	-0.30	-0.40	-0.69	-0.31	-0.47	-1.00	-0.89	-0.53
		(0.15)	(0.37)	(0.39)	(0.20)	(0.19)		(0.07)	(0.11)	(0.18)	(0.15)	(0.12)	(0.42)	(0.08)	(0.18)	(0.20)
Precip. bin: > 1 in.	-1.05	-1.60	-0.67	-0.72	-1.54	-0.64		-0.11	-0.32	-1.14	-0.96	-0.34	-1.48	-1.49	-1.83	-0.43
	(0.32)	(0.37)	(0.19)	(0.10)	(0.10)	(0.44)		(0.04)	(0.10)	(0.08)	(0.18)	(0.16)	(0.38)	(0.08)	(0.20)	(0.26)
$\mathbb{1}${Snowfall}		-0.16	-0.52	-0.30	-0.43	-0.04			-0.55	-0.13	-0.21	-0.33	-1.18		-0.10	-0.30
		(0.09)	(0.27)	(0.11)	(0.08)	(0.16)			(0.21)	(0.13)	(0.09)	(0.16)	(0.20)		(0.11)	(0.08)
Observations	315	499	358	367	615	126	51	662	414	199	363	175	166	210	231	654
R-squared	0.61	0.92	0.73	0.91	0.76	0.85	0.83	0.92	0.78	0.81	0.88	0.82	0.79	0.80	0.85	0.83

Notes: Dependent variable is the natural log of the number of trips each day. Each column presents results for a single city in alphabetical order. Column (1) is Austin, TX, and column (16) is Washington, DC. Coefficients are marginal effects and should not be interpreted directly as percentage effects. All models include city fixed effects, city-by-month fixed effects, month-of-sample fixed effects, city-specific quadratic time trends, day-of-week fixed effects, and year-by-month effects. Robust standard errors clustered at the city level are presented in parentheses.

Table A.2: City-specific model results for nonlinear effect of temperature and precipitation bins on log duration of trips

Dep. var.: ln(Duration)	(1) AUS	(2) BOS	(3) CHA	(4) CHI	(5) DEN	(6) HOB	(7) LA	(8) MXC	(9) MIN	(10) MON	(11) NYC	(12) PHI	(13) PIT	(14) SF	(15) SEA	(16) DC
Temp. bin: $\leq 30°$F	-3.11	-1.75	-2.86	-1.88	-1.70	-1.82			-0.57	-1.06	-1.29	-1.67	-2.15		-1.12	-0.98
	(0.20)	(0.22)	(0.52)	(0.20)	(0.21)	(0.78)			(0.51)	(0.24)	(0.12)	(0.39)	(0.59)		(0.59)	(0.17)
Temp. bin: $30 - 40°$F	-2.03	-1.10	-1.37	-1.34	-0.95	-1.71			-0.60	-0.64	-0.82	-0.58	-1.57		-0.92	-0.51
	(0.51)	(0.15)	(0.32)	(0.17)	(0.16)	(0.32)			(0.17)	(0.21)	(0.11)	(0.24)	(0.50)		(0.26)	(0.13)
Temp. bin: $40 - 50°$F	-0.68	-0.63	-0.90	-0.81	-0.29	-1.01		-0.08	-0.27	-0.59	-0.54	-0.51	-0.99	-1.12	-0.30	-0.19
	(0.18)	(0.10)	(0.25)	(0.14)	(0.11)	(0.23)		(0.10)	(0.12)	(0.13)	(0.09)	(0.17)	(0.38)	(0.24)	(0.18)	(0.11)
Temp. bin: $50 - 60°$F	-0.54	-0.37	-0.51	-0.23	0.01	-0.56	-0.17	-0.03	-0.06	-0.31	-0.24	-0.16	-0.99	-0.42	-0.03	-0.05
	(0.14)	(0.07)	(0.23)	(0.12)	(0.08)	(0.20)	(0.36)	(0.03)	(0.11)	(0.09)	(0.06)	(0.16)	(0.31)	(0.13)	(0.09)	(0.09)
Temp. bin: $70 - 80°$F	0.07	0.01	-0.06	0.19	0.02	0.19	-0.17	0.04	0.09	-0.00	-0.00	-0.16	-0.08	0.04	-0.15	0.17
	(0.12)	(0.05)	(0.22)	(0.07)	(0.06)	(0.15)	(0.29)	(0.04)	(0.08)	(0.05)	(0.05)	(0.13)	(0.14)	(0.12)	(0.10)	(0.10)
Temp. bin: $> 80°$F	-0.08	-0.27	-1.07	0.25	-0.27	0.04	-0.76		0.02		-0.06	-0.22	-0.85			0.05
	(0.15)	(0.11)	(0.48)	(0.11)	(0.08)	(0.20)	(0.39)		(0.16)		(0.07)	(0.14)	(0.19)			(0.14)
Precip. bin: $0.01 - 0.25$ in.	-0.27	-0.17	-0.23	-0.31	-0.05	-0.31	0.43	-0.10	-0.17	-0.16	-0.12	-0.22	-0.52	-0.11	-0.21	-0.17
	(0.07)	(0.04)	(0.16)	(0.06)	(0.05)	(0.13)	(0.31)	(0.04)	(0.07)	(0.06)	(0.03)	(0.06)	(0.15)	(0.06)	(0.08)	(0.04)
Precip. bin: $0.25 - 0.50$ in.	-0.79	-0.56	-1.00	-0.86	-0.90	-0.79		-0.03	-0.18	-0.66	-0.41	-0.68	-1.06	-0.38	-0.98	-0.48
	(0.21)	(0.09)	(0.27)	(0.12)	(0.36)	(0.30)		(0.07)	(0.13)	(0.11)	(0.08)	(0.31)	(0.27)	(0.28)	(0.17)	(0.09)
Precip. bin: $0.50 - 0.75$ in.	-0.38	-1.12	-1.46	-0.84	-0.94	-0.95	0.09	-0.11	-0.39	-0.86	-0.63	-0.02	-1.10	-0.19	-1.09	-0.59
	(0.16)	(0.14)	(0.32)	(0.16)	(0.42)	(0.47)	(0.32)	(0.05)	(0.13)	(0.15)	(0.11)	(0.19)	(0.39)	(0.52)	(0.18)	(0.25)
Precip. bin: $0.75 - 1$ in.		-0.58	-1.39	-0.71	-0.78	-0.14		0.11	-0.37	-0.50	-0.86	-0.41	-0.77	-0.77	-1.35	-0.80
		(0.18)	(0.53)	(0.38)	(0.24)	(0.28)		(0.13)	(0.20)	(0.24)	(0.17)	(0.13)	(0.59)	(0.20)	(0.25)	(0.25)
Precip. bin: > 1 in.	-1.02	-2.06	-0.85	-0.91	-2.02	-2.10		-0.06	-0.36	-1.41	-1.06	-0.36	-2.17	-1.85	-2.46	-0.59
	(0.34)	(0.47)	(0.27)	(0.13)	(0.13)	(1.20)		(0.05)	(0.15)	(0.11)	(0.18)	(0.15)	(0.49)	(0.26)	(0.34)	(0.37)
$\mathbb{1}${Snowfall}		-0.22	-0.22	-0.34	-0.61	0.38			-0.33	-0.21	-0.20	-0.32	-1.49		-0.15	-0.44
		(0.11)	(0.44)	(0.12)	(0.10)	(0.34)			(0.24)	(0.16)	(0.09)	(0.18)	(0.31)		(0.17)	(0.10)
Observations	315	499	358	367	615	126	51	662	414	199	363	175	166	210	231	654
R-squared	0.59	0.92	0.58	0.91	0.75	0.70	0.64	0.85	0.96	0.80	0.91	0.78	0.80	0.52	0.83	0.79

Notes: Dependent variable is the natural log of the number of trips each day. Each column presents results for a single city in alphabetical order. Column (1) is Austin, TX, and column (16) is Washington, DC. Coefficients are marginal effects and should not be interpreted directly as percentage effects. All models include city fixed effects, city-by-month fixed effects, month-of-sample fixed effects, city-specific quadratic time trends, day-of-week fixed effects, and year-by-month effects. Robust standard errors clustered at the city level are presented in parentheses.

Table A.3: Model results for alternative data sources and variable definitions for temperature on log quantity of trips

	(1) Wet-bulb temp.	(2) Wet-bulb temp. (max.)	(3) Dry-bulb temp.	(4) Dry-bulb temp. (max.)	(5) Max. temp.	(6) Max. temp.	(7) Min. temp.	(8) Min. temp.	(9) Ave. temp.	(10) Ave. temp.
Temp. bin: $\leq 30°$F	-1.32	-1.52	-1.71	-1.76	-1.49	-1.44	-0.50	-0.68	-1.24	-1.35
	(0.21)	(0.25)	(0.24)	(0.26)	(0.17)	(0.11)	(0.08)	(0.11)	(0.15)	(0.15)
Temp. bin: $30-40°$F	-0.73	-0.93	-1.06	-1.16	-0.98	-1.03	-0.21	-0.29	-0.71	-0.80
	(0.10)	(0.13)	(0.14)	(0.16)	(0.13)	(0.11)	(0.07)	(0.08)	(0.11)	(0.10)
Temp. bin: $40-50°$F	-0.34	-0.59	-0.63	-0.75	-0.60	-0.62	-0.09	-0.14	-0.33	-0.41
	(0.06)	(0.08)	(0.08)	(0.09)	(0.07)	(0.07)	(0.04)	(0.04)	(0.06)	(0.06)
Temp. bin: $50-60°$F	-0.07	-0.22	-0.23	-0.36	-0.25	-0.28	-0.05	-0.03	-0.15	-0.15
	(0.04)	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)
Temp. bin: $70-80°$F	-0.04	0.05	0.02	0.22	0.16	0.15	-0.16	-0.08	0.01	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.02)	(0.02)
Temp. bin: $> 80°$F	-0.09	-0.06	-0.06	0.24	0.20	0.19		-0.20	-0.11	-0.04
	(0.09)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)		(0.03)	(0.04)	(0.04)
Precip. bin: $0.01-0.25$in.	-0.14	-0.12	-0.13	-0.09	-0.13	-0.13	-0.16	-0.16	-0.16	-0.16
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Precip. bin: $0.25-0.50$in.	-0.49	-0.46	-0.46	-0.40	-0.45	-0.45	-0.52	-0.52	-0.50	-0.50
	(0.07)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
Precip. bin: $0.50-0.75$in.	-0.61	-0.57	-0.57	-0.50	-0.56	-0.53	-0.60	-0.61	-0.60	-0.59
	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
Precip. bin: $0.75-1$in.	-0.66	-0.65	-0.63	-0.57	-0.61	-0.62	-0.65	-0.66	-0.65	-0.64
	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.09)
Precip. bin: > 1in.	-0.77	-0.75	-0.73	-0.68	-0.71	-0.72	-0.78	-0.77	-0.78	-0.78
	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Distance weighting?	–	–	–	–	–	Y	–	Y	–	Y
Observations	5,405	5,405	5,405	5,405	5,405	5,405	5,405	5,405	5,405	5,405
R-squared	0.94	0.94	0.94	0.95	0.94	0.94	0.93	0.93	0.94	0.94

Notes: Dependent variable is the natural log of the number of trips each day. Coefficients are marginal effects and should not be interpreted directly as percentage effects. All models include city fixed effects, city-by-month fixed effects, month-of-sample fixed effects, city-specific quadratic time trends, day-of-week fixed effects, and year-by-month effects. Robust standard errors clustered at the city level are presented in parentheses.

Table A.4: Model results for alternative data sources and variable definitions for temperature on log duration of trips

	(1) Wet-bulb temp.	(2) Wet-bulb temp. (max.)	(3) Dry-bulb temp.	(4) Dry-bulb temp. (max.)	(5) Max. temp.	(6) Max. temp.	(7) Min. temp.	(8) Min. temp.	(9) Ave. temp.	(10) Ave. temp.
Temp. bin: $\leq 30°F$	-1.58	-1.87	-2.03	-2.13	-1.79	-1.72	-0.61	-0.72	-1.48	-1.58
	(0.25)	(0.26)	(0.27)	(0.27)	(0.16)	(0.13)	(0.09)	(0.13)	(0.15)	(0.16)
Temp. bin: $30-40°F$	-0.82	-1.13	-1.23	-1.41	-1.15	-1.20	-0.25	-0.27	-0.78	-0.90
	(0.14)	(0.14)	(0.18)	(0.17)	(0.12)	(0.11)	(0.08)	(0.10)	(0.11)	(0.12)
Temp. bin: $40-50°F$	-0.37	-0.67	-0.70	-0.88	-0.67	-0.71	-0.19	-0.18	-0.35	-0.43
	(0.08)	(0.10)	(0.13)	(0.09)	(0.09)	(0.09)	(0.09)	(0.05)	(0.07)	(0.10)
Temp. bin: $50-60°F$	-0.05	-0.27	-0.24	-0.44	-0.28	-0.33	-0.11	-0.06	-0.17	-0.18
	(0.04)	(0.03)	(0.06)	(0.04)	(0.05)	(0.05)	(0.07)	(0.03)	(0.06)	(0.07)
Temp. bin: $70-80°F$	-0.04	0.02	0.00	0.20	0.19	0.17	-0.24	-0.15	0.04	0.08
	(0.04)	(0.03)	(0.03)	(0.05)	(0.06)	(0.07)	(0.05)	(0.04)	(0.05)	(0.04)
Temp. bin: $> 80°F$	0.03	-0.04	-0.07	0.19	0.25	0.21		-0.34	-0.14	-0.05
	(0.10)	(0.03)	(0.04)	(0.06)	(0.07)	(0.05)		(0.05)	(0.07)	(0.07)
Precip. bin: $0.01-0.25$in.	-0.17	-0.15	-0.16	-0.12	-0.16	-0.15	-0.20	-0.19	-0.19	-0.19
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
Precip. bin: $0.25-0.50$in.	-0.61	-0.58	-0.58	-0.51	-0.57	-0.57	-0.64	-0.63	-0.63	-0.62
	(0.09)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)
Precip. bin: $0.50-0.75$in.	-0.73	-0.67	-0.68	-0.60	-0.66	-0.64	-0.72	-0.71	-0.71	-0.70
	(0.13)	(0.12)	(0.12)	(0.11)	(0.12)	(0.11)	(0.12)	(0.13)	(0.13)	(0.13)
Precip. bin: $0.75-0.1$in.	-0.82	-0.81	-0.79	-0.73	-0.76	-0.76	-0.80	-0.80	-0.81	-0.79
	(0.15)	(0.15)	(0.15)	(0.14)	(0.14)	(0.13)	(0.15)	(0.15)	(0.14)	(0.14)
Precip. bin: > 1in.	-0.83	-0.81	-0.80	-0.74	-0.76	-0.77	-0.85	-0.83	-0.84	-0.84
	(0.22)	(0.22)	(0.21)	(0.20)	(0.21)	(0.20)	(0.21)	(0.22)	(0.21)	(0.21)
Distance weighting?	–	–	–	–	–	Y	–	Y	–	Y
Observations	5,405	5,405	5,405	5,405	5,405	5,405	5,405	5,405	5,405	5,405
R-squared	0.88	0.88	0.88	0.88	0.88	0.88	0.86	0.87	0.87	0.87

Notes: Dependent variable is the natural log of the duration of trips each day. Coefficients are marginal effects and should not be interpreted directly as percentage effects. All models include city fixed effects, city-by-month fixed effects, month-of-sample fixed effects, city-specific quadratic time trends, day-of-week fixed effects, and year-by-month effects. Robust standard errors clustered at the city level are presented in parentheses.

Table A.5: Median temperature and precipitation projections for cycling and outdoor recreation by state

	Annual Cycling Demand (hours)	Annual Pct. Change by 2060	Annual Cycling Value in 2016 ($MM)	Change in Annual Cycling Value by 2060 ($MM)	Annual Outdoor Recreation Demand (hours)	Annual Pct. Change by 2060	Annual Outdoor Recreation Value in 2016 ($MM)	Change in Annual Outdoor Recreation Value by 2060 ($MM)
Alabama	10,173	-0.71	88	-0.63	498,237	-0.71	4,321	-30.62
Arizona	57,705	1.77	500	8.86	1,907,313	1.77	16,541	292.98
Arkansas	27,444	3.42	238	8.15	380,229	3.42	3,298	112.92
California	662,263	1.88	5,743	107.96	12,197,942	1.88	105,785	1988.47
Colorado	5,222	7.49	45	3.39	906,504	7.49	7,862	588.64
Connecticut	32,846	6.09	285	17.35	731,874	6.09	6,347	386.55
Delaware	8,744	3.17	76	2.40	257,179	3.17	2,230	70.61
Florida	270,641	-2.09	2,347	-49.03	3,252,792	-2.09	28,210	-589.29
Georgia	57,816	-0.41	501	-2.08	1,660,082	-0.41	14,397	-59.70
Idaho	43,577	3.71	378	14.01	429,653	3.71	3,726	138.14
Illinois	249,626	4.27	2,165	92.54	2,926,362	4.27	25,379	1084.79
Indiana	103,351	3.19	896	28.62	1,176,189	3.19	10,200	325.70
Iowa	28,789	2.87	250	7.16	342,376	2.87	2,969	85.17
Kansas	17,811	3.50	154	5.41	509,541	3.50	4,419	154.69
Kentucky	43,813	3.50	380	13.29	891,519	3.50	7,732	270.33
Louisiana	11,662	-0.27	101	-0.27	518,213	-0.27	4,494	-12.12
Maine	12,228	5.85	106	6.20	378,720	5.85	3,284	192.03
Maryland	34,350	3.97	298	11.84	1,172,667	3.97	10,170	404.22
Massachusetts	62,560	5.04	543	27.33	1,349,295	5.04	11,702	589.40
Michigan	106,922	7.03	927	65.14	1,819,103	7.03	15,776	1108.32
Minnesota	73,353	2.17	636	13.79	1,862,853	2.17	16,155	350.10
Mississippi	27,449	-0.72	238	-1.72	305,510	-0.72	2,650	-19.13
Missouri	178,585	4.67	1,549	72.25	1,458,838	4.67	12,652	590.20
Montana	9,575	3.91	83	3.25	214,659	3.91	1,862	72.86
Nebraska	17,515	3.11	152	4.73	577,203	3.11	5,006	155.85
Nevada	27,002	3.32	234	7.77	357,632	3.32	3,102	102.88
New Hampshire	12,259	5.49	106	5.84	355,361	5.49	3,082	169.17
New Jersey	9,546	5.83	83	4.82	1,218,029	5.83	10,563	615.60
New Mexico	69,704	4.75	604	28.74	488,116	4.75	4,233	201.27
New York	96,561	6.32	837	52.91	6,059,142	6.32	52,547	3319.95
North Carolina	138,167	1.75	1,198	20.96	2,758,391	1.75	23,922	418.53
North Dakota	6,961	0.65	60	0.40	32,994	0.65	286	1.87
Ohio	157,457	5.34	1,366	72.96	2,045,571	5.34	17,740	947.90
Oklahoma	36,034	3.13	313	9.77	602,190	3.13	5,222	163.30
Oregon	38,839	5.67	337	19.09	735,686	5.67	6,380	361.61
Pennsylvania	58,651	5.99	509	30.46	4,390,334	5.99	38,075	2280.18
Rhode Island	9,702	6.25	84	5.26	262,479	6.25	2,276	142.35
South Carolina	7,278	2.16	63	1.36	687,465	2.16	5,962	128.54
South Dakota	11,157	3.43	97	3.32	173,471	3.43	1,504	51.66
Tennessee	9,446	3.35	82	2.75	1,097,878	3.35	9,521	319.38
Texas	261,953	1.16	2,272	26.32	4,784,931	1.16	41,497	480.82
Utah	12,972	11.22	113	12.62	374,576	11.22	3,248	364.45
Vermont	5,736	8.14	50	4.05	97,169	8.14	843	68.56
Virginia	82,440	2.26	715	16.18	1,721,185	2.26	14,927	337.87
Washington	98,321	9.71	853	82.76	1,440,479	9.71	12,492	1212.57
West Virginia	16,817	5.92	146	8.63	355,941	5.92	3,087	182.70
Wisconsin	60,745	2.85	527	15.02	2,250,687	2.85	19,519	556.48
Wyoming	9,119	3.03	79	2.40	34,666	3.03	301	9.12
Totals	3,390,887		29,407	894	70,049,224		607,495	20,687

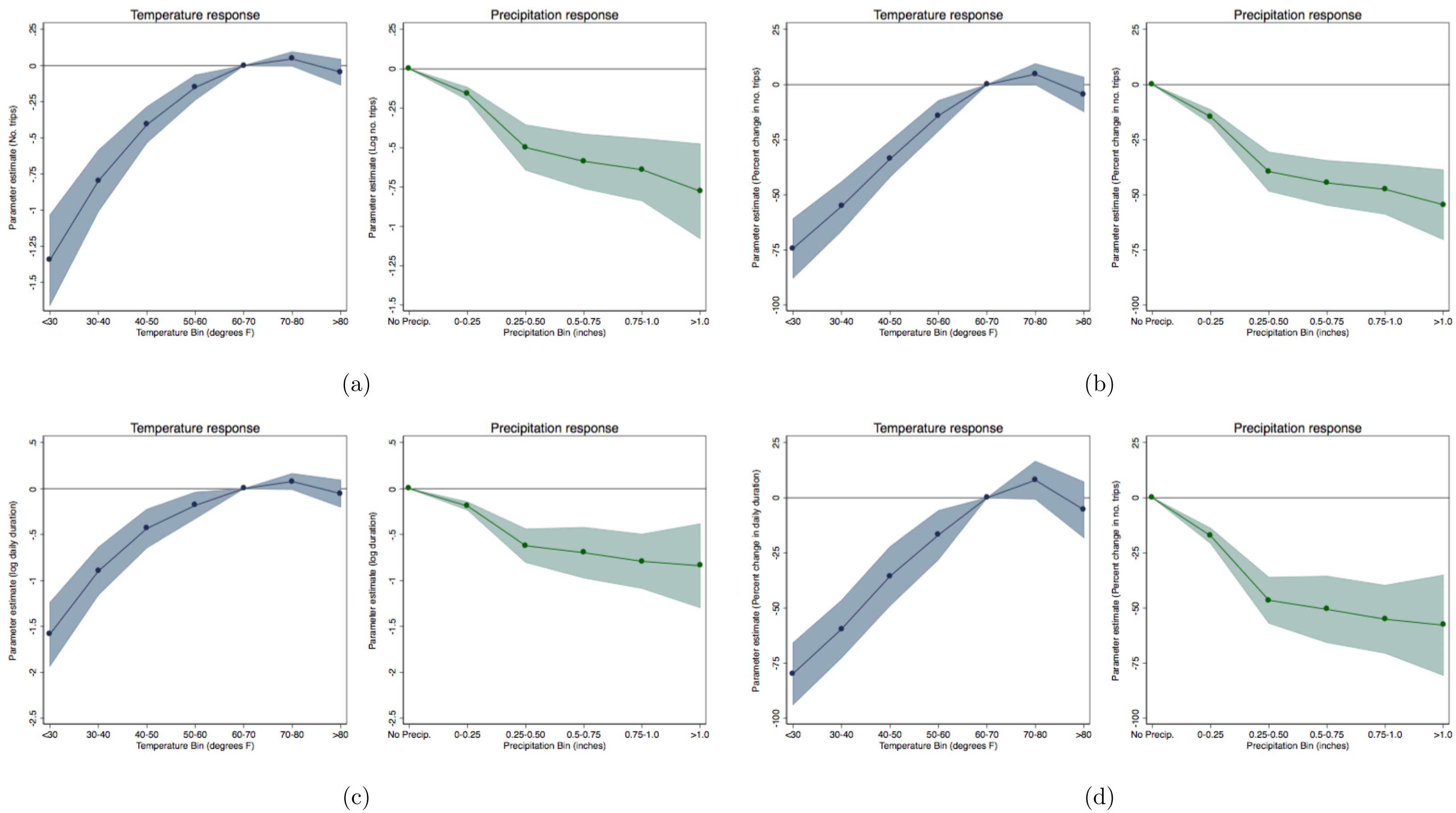
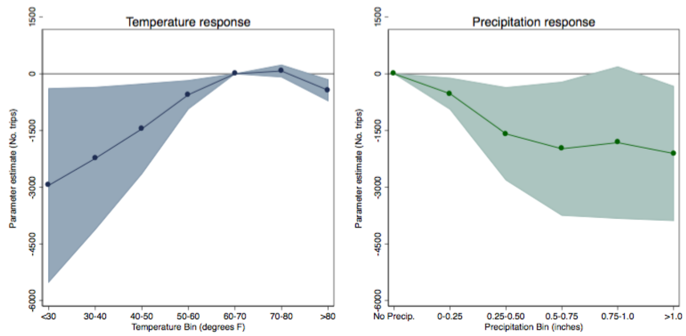
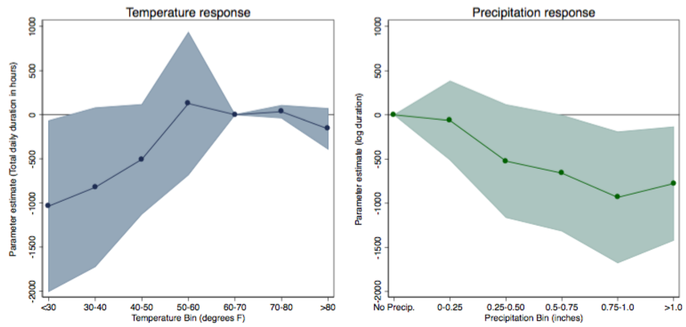


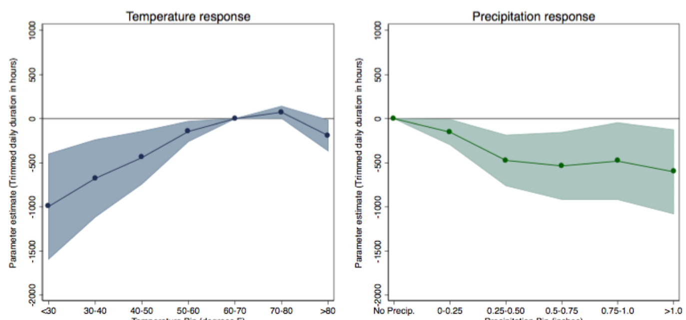
Figure A.1: Log effects vs. percentage effects. All percentage effects reported in the paper are transformed to account for the non-differentiability of discontinuous temperature bins.



(a)

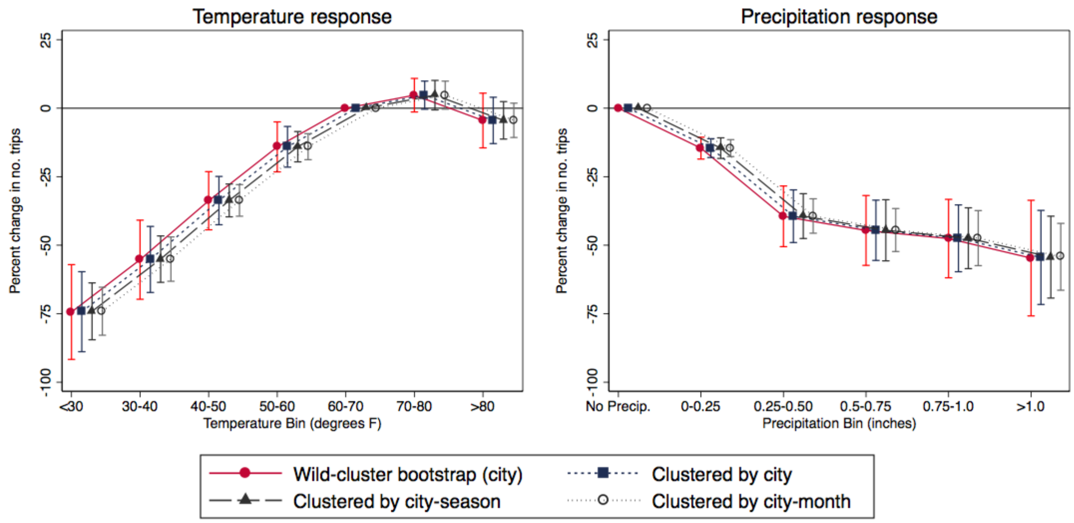


(b)

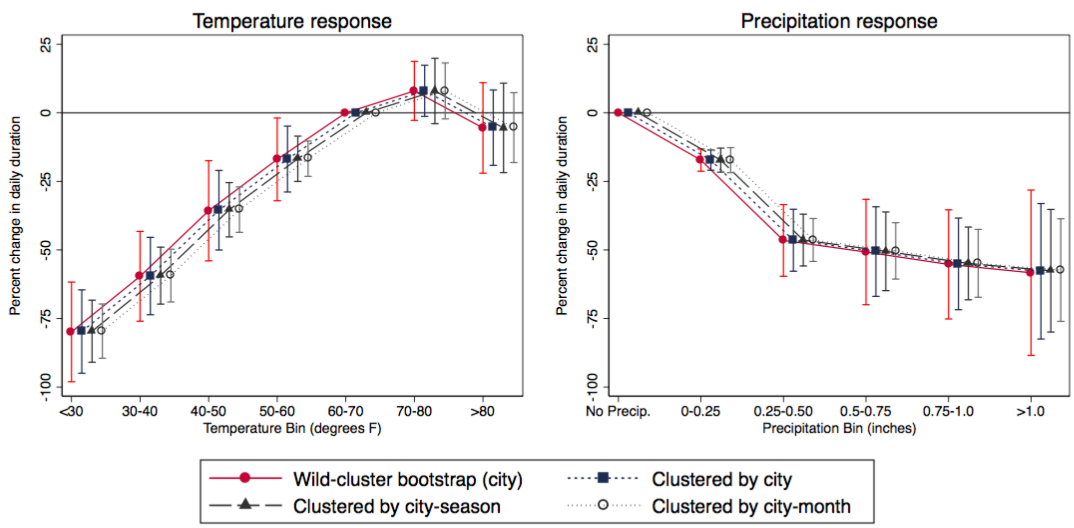


(c)

Figure A.2: Regression results in (trimmed) levels. Dependent variable in panel (a) is number of daily trips. Dependent variable in panel (b) is duration of trips. Panel (c) replicates panel (b) but trims the top/bottom 5% of the duration distribution to mitigate the effect of outliers.

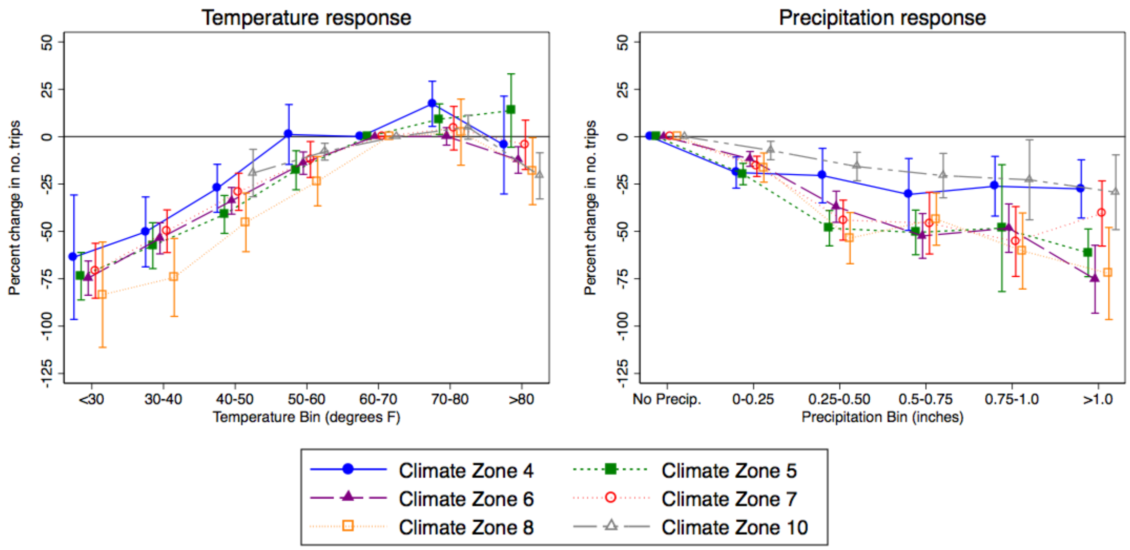


(a) Percent change (and 95% CI) in quantity of trips due to changes in daily average temperatures and daily precipitation

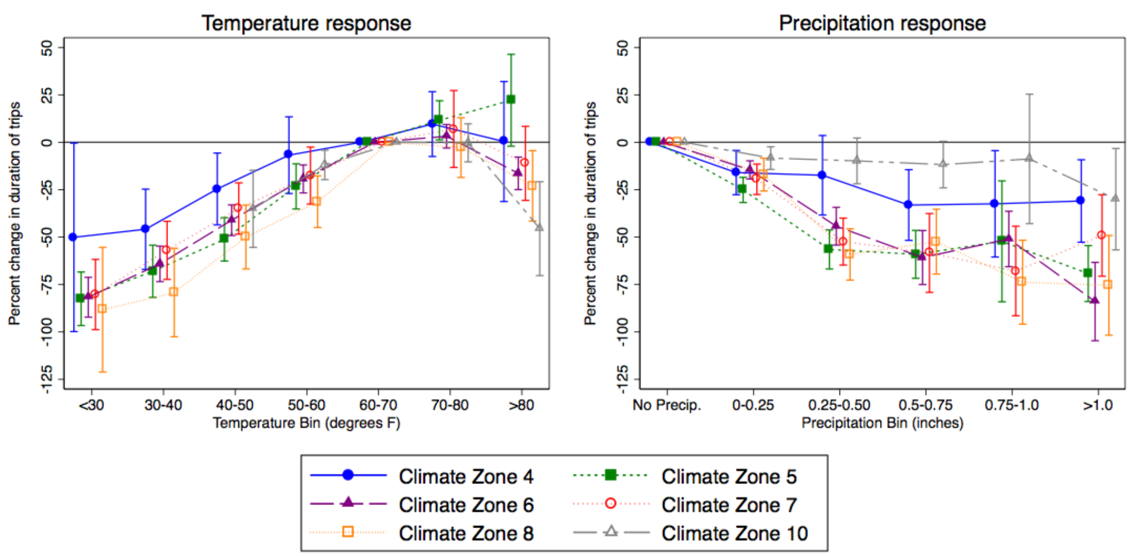


(b) Percent change (and 95% CI) in total duration of trips due to changes in daily average temperatures and daily precipitation

Figure A.3: Nonlinear relationship between cycling demand and daily weather with different standard error specifications. Our wild-cluster bootstrap procedure (clustered at the city level) provides a 95 percent confidence interval around our marginal effects by bootstrapping the Wald test statistic (imposing the null hypothesis of $\beta = 0$) with 10,000 replications. Statistics presented in this figure use the implied standard error that would produce the 95 percent confidence interval from our bootstrap procedure, suggested by Cameron and Miller (2015), using standard critical values from the t-distribution. Although the wild-cluster bootstrap is intended primarily to provide critical values for the rejection rate of a test statistic, we require an estimate of the standard error of our estimated marginal effects to calculate estimates of percentage effects and their confidence intervals.



(a) Percent change in quantity of trips due to changes in daily average temperatures and daily precipitation by climate zone



(b) Percent change in total duration of trips due to changes in daily average temperatures and daily precipitation by climate zone

Figure A.4: Nonlinear relationship between leisure demand and daily weather by climate zone with 95 percent confidence intervals

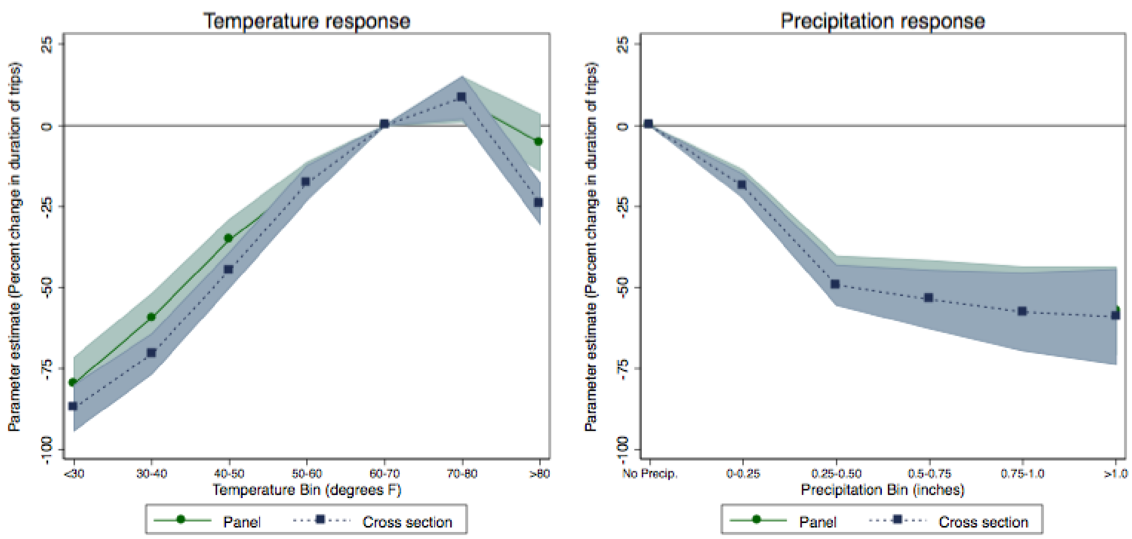


Figure A.5: Percentage change (and 95% CI) in quantity of trips due to changes in daily average temperatures using panel vs. cross-sectional variation

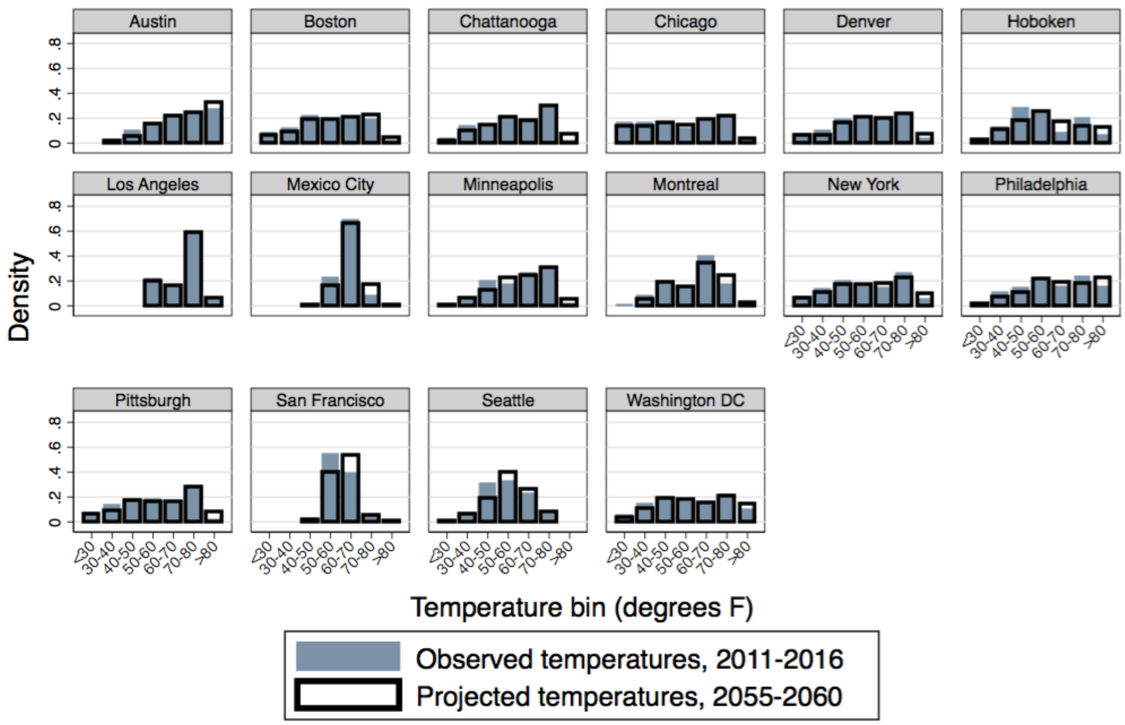
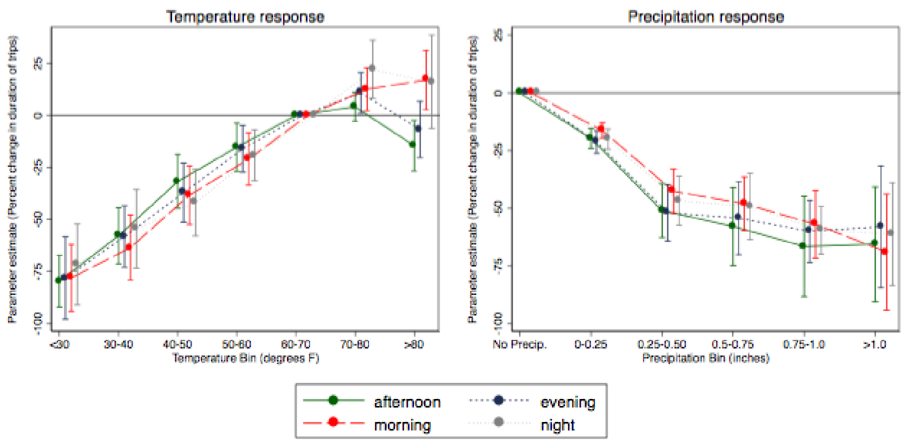
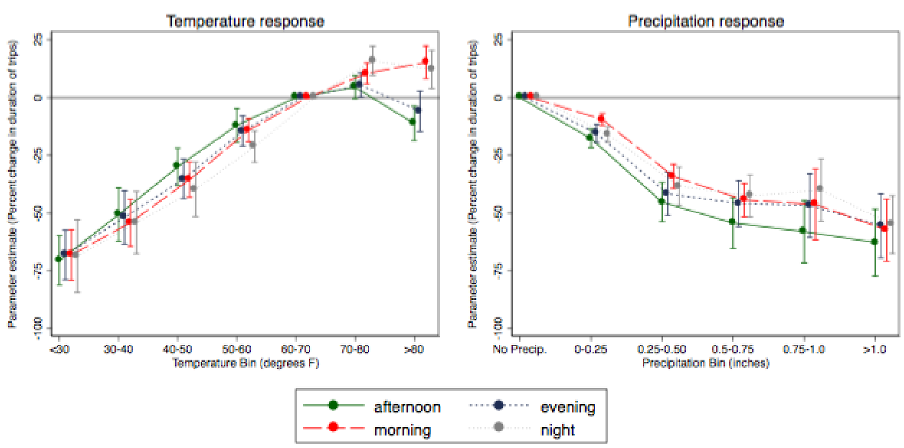


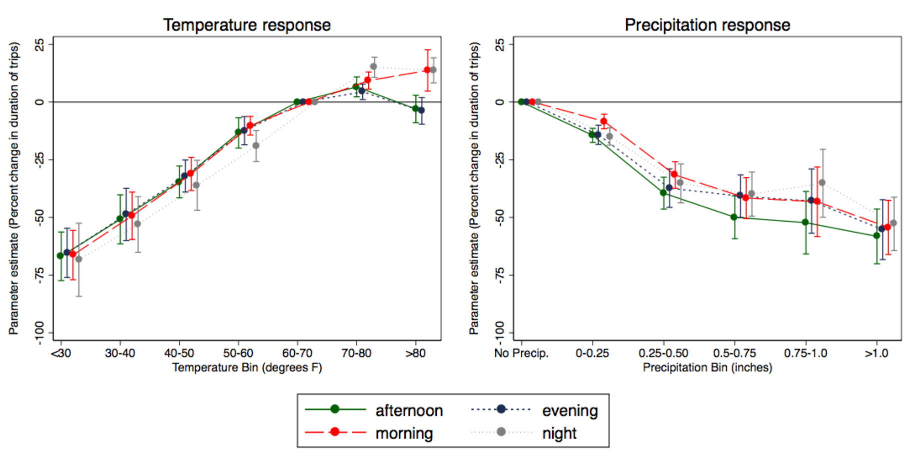
Figure A.6: City-specific distributions of temperatures on weekends in sample (blue) and projected temperatures for corresponding days in 2055-2060 (black). Projected temperatures are percentage changes from observed baseline for the median projection from 15 climate models in the CMIP3 ensemble reporting the A1B ("business-as-usual") climate scenario.



(a) Intraday substitution on weekends



(b) Intraday substitution on federal holidays



(c) Intraday substitution on weekdays

Figure A.7: Nonlinear relationship between log duration of trips and weather conditional on time of day. Morning is defined as 5AM–10AM; afternoon is 10AM–3PM; evening is 3PM–8PM; and night is 8PM–12AM. All times are local.