Recreational Preferences in Boating

Perceived Utility and Risk on the Water

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ECON 4010/6010 - Applied Microeconomics and Public Policy
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11 Nov. 2024

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1 Introduction

When we're bored, we engage in recreational activities. In the summer, these usually include water. No matter how fun an activity may be, however, recreational activities can be thought of sitting on a spectrum of risk. After all, swimming in the ocean carries more risk than swimming in a pool, and kayaking on a cold, rainy day carries more risk than kayaking on a warm, sunny day; moreover, we choose a level of recreation that satisfies our assessment of the associated risk. Because people are naturally risk averse, we can think of the choice of recreation as maximizing an individual's utility given the presence of certain conditions — weather, day of the week, etc.

We take data from Boating In Boston at Cochituate State Park in Natick, Massachusetts. The location offers swimming, a public boat launch, and limited walking trails. The park itself can be accessed from I-90. Boating In Boston, the park's major concessioner, offers hourly boat rentals for a variety of single and multi-person watercraft, including ocean kayaks, tandem Kayaks, canoes, stand-up paddleboards (SUPs), peddleboats, and sail boats.

Figure 1: The Rental Operation at Lake Cochituate, Natick, Massachusetts[6]

One would anticipate that the number of boat reservations in a given day depends on the day of the week (especially if such a day was a Saturday, Sunday, or federal holiday) and the weather. One also might anticipate that the *projected forecast* may matter more than the actual weather. This is inline with an expectation of utility assessment as people are making decisions based on available information. Other important factors may include the presence bacteria in the water (cyanobacteria and e. coli predominantly) as sufficiently high concentrations lead to posted advisories and the closure of the park to swimming. We anticipate that barriers to the beachfront depressed daily rentals significantly.

This paper aims to assess if the posting of advisories and the forecasted weather, as opposed to *actual weather* observed, affected daily boat rentals at Lake Cochituate. To this end, we employ R to conduct a statistical analysis and produce a model that selects the features that explain the variance in the number of boats rented in a given day. We look at a regression covering all boats at the aggregate level and analyze its various features.

1.1 Data Collected

Daily rental information is exported from the Lake Cochituate FareHarbor Dashboard (FareHarbor being the point of sale system used by the company) for the months of peak operation: June, July, and August. This data includes every booked "Item", its respective "Booking ID", whether or not the reservation was "Canceled?", and the reservation's "Start Date" in a given month. We remove bookings that have a non-zero "Canceled?" field because they do not add to a given day's rental total. The bookings are then grouped by day, the date being stored in `Date` and the total number of reservations is contained in the `Total` variable. Because we anticipate a seasonal effect in rental numbers, we demean the `Total` variable by `Date` and elide `Date` from our later analysis. Information for the daily forecast for the months of June, July, and August are taken from Weather Underground and are paired with this data, giving the `High` and `Low` temperature variables (in degrees Fahrenheit), the `Rain` variable (in inches); and the `ForecastSunny`, `ForecastCloudy`, and `ForecastRainy` dummy variables to represent the reported forecast. Including these forecast dummies permits a differentiation between the expected and actual weather in a given day because of weather-dependent risk aversion. Cyanobacteria and e. coli concentrations in (stored in `Cyano` and `Ecoli`, respectively) are taken from publicly available state and municipal laboratory results; and if bacterial incidence exceeds an advisory threshold, or if a visual bloom is present, we assign a value of `1` to the `Advise` binary variable. We include the `Weekend` and `Holiday` dummies to account for significant increases in boat reservations on days with greater traffic into the park.

Our collected data is summarized in Table 1:

Variable	μ	σ	**Min**	**Max**
Date	2024-07-16	NA	2024-06-01	2024-08-31
High ($°F$)	80.41	7.591	66.00	98.00
Low ($°F$)	65.55	5.189	54.00	76.00
Rain (in.)	0.099	0.271	0	2.050
Cyano (cells/mL)	13331	12367.2	480	42000
Advise	0.076	0.267	0	1
Ecoli (CFU/100mL)	42.72	100.17	1.00	387.00
Weekend	0.293	0.458	0	1
Holiday	0.033	0.179	0	1
ForecastSunny	0.337	0.475	0	1
ForecastCloudy	0.609	0.491	0	1
ForecastRainy	0.054	0.228	0	1
Total (# reservations)	30.57	26.54	0	151

Table 1: FareHarbor Reservation Data with Additional Features

2 Literature Review

2.1 Risk Perception in Leisure Sports

Kim and Kang discuss the effects of *proxemics* — which are, "the perceived crowding and risk perception of individuals within particular spaces."[4] — on outdoor leisure activities in the presence of social distancing behavior during the COVID-19 pandemic. In particular, Kim and Kang focus on the individual risk perception of crowding by asking 400 survey participants the following four questions:

> "Did you expect crowdedness to keep you from having fun before visiting the space for leisure sports activity?" "Did you expect crowdedness to restrict activities before visiting the space for leisure sports activities?" "Did crowdedness in the space for leisure sports activities keep you from having fun?" and "How did crowdedness in the space for leisure sports activities affect availabilities?"

They find statistically significant evidence that risk perception depends on the leisure activity's respective space, and of interest that, "...social distancing measures do not sufficiently reduce perceived crowding and risk perception..." Kim and Kang conclude that, "...it is necessary to reduce the fear of risk factors and crowdedness felt by people..." participating in outdoor leisure sports.

Although COVID-19 is not the focus of this paper, it is clear that risk perception would lead to the same kind of behavior for any contaminent. It is also worth highlighting that, "...risk is perceived through media in many cases, thus indicating that media use is closely related to risk perception..." and therefore the perceived danger of cyanobacteria blooms and e. coli as communicated entirely through barriers and large warning signs likely amplified risk perception.

2.2 Risk in outdoor activities

Dickson, Chapman, and Hurrell[2] consider risk as an *attractive* force and queried a group of young adults involved in risky outdoor activities, such as caving, mountain biking, etc., about what their riskiest decision was. Dickson et al. conclude that risk satisfies one or several of Glasser's list of psychological needs, namely "the need to belong... the need for power... the need for freedom... [and] the need for fun..." To determine if risk in outdoor activities was perceived or real, Dickson et al. look at the Australian National Accident Incidence Report Form Database (NAIFRD) and the NSW Youth Sports Injury Report (NYSIR), voluntary accident reporting databases that convey information about sports injuries during 1995–1999. They make the surprising observation that young adults were, "twice as likely to be injured... playing Rugby Union than Rock Climbing..., and more than twice as likely to be injured playing Netball as Snow Skiing..." Moreover, Dickson et al. find that, "[the] activities that may be traditionally considered high risk often had the lowest number of injuries." Dickson et al.'s finding that the risk of such activities is overblown, paired with that of Kim and Kang, implies that credible signals of risk — like the weather forecast and bacterial warnings — cause a higher level of precaution than the true danger necessitates. We therefore expect that these features be significant in our coming analysis.

2.3 Weather as risk

Verbos and Brownlee[8] developed a Weather Dependency Framework (WDF) to assess the weather dependence of certain outdoor activities as they claim research into weather dependence is, "important to outdoor recreation to facilitate effective and efficient weather-related decision-making." Clearly, then it is an underlying factor of the recreational risk assessment of the consumer. Verbos and Brownlee define weather dependence as, "the degree to which a specific outdoor recreation activity is reliant on particular weather and resulting conditions." The two cite skiing and golfing as being highly weather dependent, as both rely on precipitation and temperature, but at opposite ends of the spectrum — skiing requires high precipitation in cold weather, and golfing little precipitation in warm weather. Verbos and Brownlee's WDF models the relationship between an individual's assessment of the weather and their participation in their preferred outdoor recreational activity. Tucker and Gilliland[7] further demonstrate that poor and extreme weather limit outdoor recreation, implying a strong seasonal effect as later validated by Verbos and Brownlee.

For boating there is a strong summer seasonal effect as warm temperatures and low precipitation are the ideal conditions. Thus, we anticipate higher reservation numbers when these conditions are met. Other conditions, such as the state park's institutional seasonality and perceived congestion[4] are anticipated to increase boat rentals as well because the same conditions that positively affect rental numbers also positively affect the number of beach goers. We anticipate that as the beach fills, perceived congestion leads people to the next best water activity: boating.

Tucker and Gilliland define seasonal effects as meteorological conditions, where, "'bad weather' [is] a perceived barrier to participation in physical activity..." As per Kim[4], media is a major component of risk aversion and awareness. Therefore, reported forecasting is an essential component of an individual's assessment of recreational risk *in addition* to the actual perceived weather. Interestingly, Tucker and Gilliland indicate that, "One day of rain may prevent individuals from engaging in activity on that day..." but, "ongoing precipitation may decrease levels of physical activity for extended periods of time." In our analysis rain may therefore not be a significant deterrent to overall recreation. The two recommend increasing the activity levels of children by, "encouraging them to spend time outdoors..." as, "...children are less active in winter than other seasons," because of the time they spend in school. As school districts in Massachusetts went in and out of their summer recess at different times, we anticipate greater variation in the total boat reservation numbers in the months of May and September because of this seasonal effect. We restrict our analysis to June–August to best eliminate this effect. Nevertheless, it is likely that demand is depressed into the beginning of June and through the end of August because of summer recesses.

2.4 Cyanobacteria & E. Coli

Pitosis, Jackson, and Wood[5] indicate that cyanobacteria, also known as blue-green algae, blooms are, "frequent during the summer in temperate lakes." Waterways with cyanobacteria blooms are known to, "[cause] death among animals which had drunk the contaminated water" because of the presence of neurotoxins, hepatoxins, and lipopolysaccharide endotoxins. The concentration of these toxins trend with, "solar radiation, surface water temperature, pH, and percentage oxygen saturation..." As Lake Cochituate is bordered by a major highway and by an interstate, it is likely that pH is quite low. The public boat launch also opens up the lake to greater contamination from boats that have cyanobacteria scum on their hulls or that are carriers of freshwater mussels which are, "capable of accumulating the peptide toxin... [and] could also accumulate this or similar peptide toxins from other strains of cyanobacteria," lowering the fish population and further raising the oxygen concentration. Summer heat, winds, and precipitation also enhance the likelihood of cyanobacteria blooms. Although Pitosis et al. indicate that at the time of publication, cyanobacteria toxins had not accounted for human death, exposure to these toxins cause, "allergic reactions and skin irritations... [and] ingestion-related illnesses..." which are likely given frequent submersion when swimming or boating. These symptoms are especially acute among children.

Massachusetts state law[3] thus requires waterways close to swimming (which would include boating activities with a high likelihood of immersion, like paddleboarding) for as long as either a bloom can be visually identified or if cyanobacteria concentrations exceed 70,000 cells/mL. If this threshold is exceeded or if a visual bloom was identified, access to Lake Cochituate's beach would be restricted by bright orange lattice with large barriers and signage indicating the presence of cyanobacteria and its potential harms. As media, digital or physical, is a large component of risk assessment[4] and people are likely to react to the perceived assessment of risk posed by media per Dickson et al.[2] we anticipate a significant drop in rental activity even if the likelihood of immersion is relatively low.

Another common contaminant in Massachusetts waterways is e. coli, a bacteria commonly carried by fecal matter from geese and dogs that washes up after major rain storms[1]. Given that the same factors that affect the incidence of cyanobacteria also affect the incidence of e. coli, we anticipate that high concentrations of e. coli will also negatively affect rental performance.

3 Critical Analysis

3.1 OLS Regression with Backward Stepwise Selection

To conduct our analysis we use ordinary least squares (OLS) linear regression. Although an OLS regression permits limited flexibility, its estimated parameters retain an interpretability that is otherwise lost in a more flexible model. We first construct an OLS regression containing all variables, but we deselect the `ForecastSunny` to prevent perfect multicolinearity. We also omit `Ecoli` and `Cyano` because, when included, they induce multicolinearity with `Advise` — reaching a VIF of over 70 — because the relevant indicator (and cause of risk averse behavior) of the presence of e. coli and cyanobacteria is the placing of a public advisory. Because we time-demeaned `Total`, we also remove `Date` from our regression. We then run backward stepwise selection on the resulting formula to only select the parameters with statistical meaning. From backward stepwise selection on our OLS model, we arrive at the following model:

$$\begin{aligned}\widehat{Total} = -55.77 + 1.189 \cdot High + 13.73 \cdot Advise + 32.28 \cdot Weekend \\ + 62.36 \cdot Holiday - 7.674 \cdot ForecastCloudy - 23.90 \cdot ForecastRainy\end{aligned}$$

Figure 2 depicts the relationship between `Total` and `Date`, where the blue bullets are the actual data points and the red function is our regression product, $\widehat{Total}$:

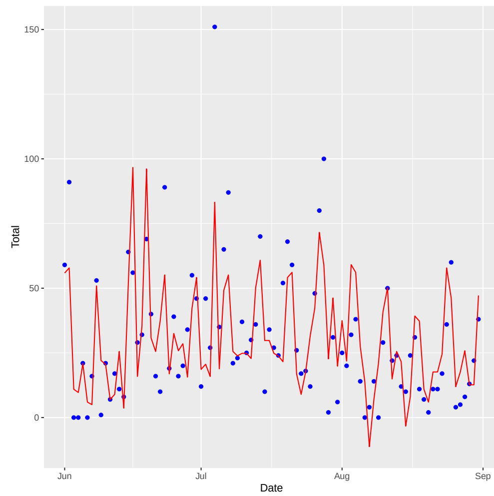

Figure 2: Total Reservations vs. Date for FareHarbor Rental Information

As the `Total` variable is heteroskedastic, we look for robust standard errors. Table 2 shows each estimate with its respective robust standard error, t-value, and p-value:

Variable	Estimate	σ	t-value	$P(>\|t\|)$
(Intercept)	-55.77	18.87	-2.955	0.004
High	0.992	0.237	4.183	≈ 0
Advise	13.73	7.803	1.759	0.082
Weekend	32.28	4.370	7.388	≈ 0
Holiday	62.36	27.97	2.229	0.028
ForecastCloudy	-7.674	3.135	-2.448	0.016
ForecastRainy	-23.90	6.842	-3.494	≈ 0

Table 2: OLS Regression Results With Backward Stepwise Selection

with a heteroskedasticity robust $P(> F) = 0.396$ and $R^2 = 0.606$. We note that backward stepwise selection removed `Rain` and `Low`, but kept `ForecastRainy` and `ForecastCloudy`. We expect this result because the publicly available forecast is what determines the perceived risk of recreation, not the actual amount of rainfall or, within the summer months, the low temperature; moreover, if a day is projected to be cold and rain, or just cloudy, consumers self-select away from water recreation. Conversely, we expect a statistically significant and positive `High` because we anticipate increased water recreation activity as the daily temperature increases.

Of interest is that the `Advise` variable is not statistically significant at the $\alpha = 0.05$ level. We do not expect this result because the presence of cyanobacteria and e. coli limited access to the park's beach and required the state post notices. Per Kim[4], this action should increase risk aversion and lead consumers to select away from water activities. It is nevertheless possible that the factors positively affecting cyanobacteria and e. coli growth also positively affect `Total`: namely, the daily high temperature and increased traffic in the park on weekends and holidays. Another possibility is that people who traveled to the park for the beach under the bacterial advisory selected into water recreation at a greater rate than when the advisory was lifted. Consequently, the advisory effect is offset.

When we break down our data into its component parts — single kayaks, tandem kayaks, and so on — and reconduct our analysis, we find very weak correlation: regressing on `Kayak`, `Tandem`, `Sup`, `Sail`, `Canoe` gives R^2 values of 0.258, 0.365, 0.224, 0.076, and 0.354, respectively. Although this is disappointing, we anticipate this because our observation of risk aggregates to boat reservations as a whole. On the individual level, we do not have enough information to satisfactorily describe the variance. Figure 3 illustrates the relationship between the reservation of each boat type and time:

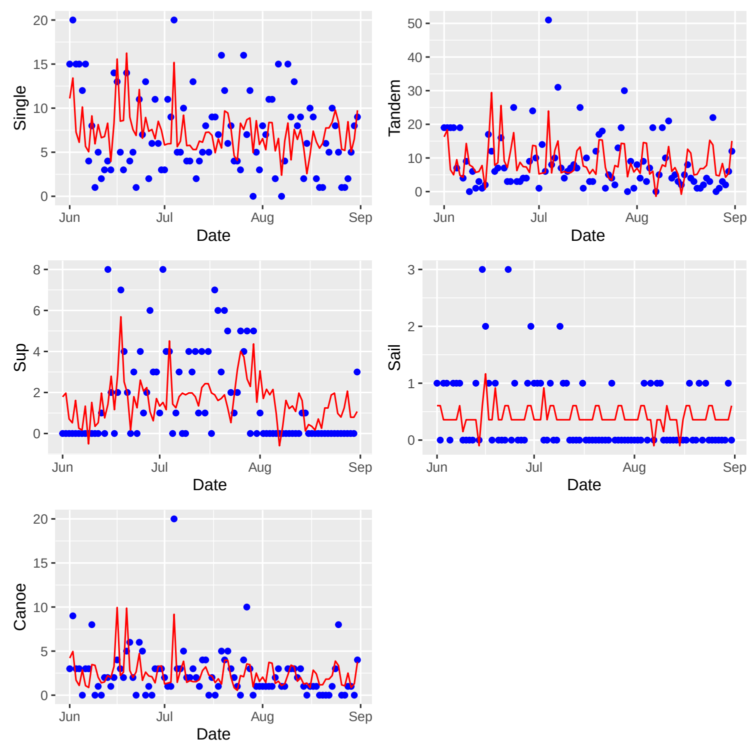

Figure 3: Component Reservations vs. Date for FareHarbor Rental Information

Despite the poor correlation overall, the regression for stand-up paddleboards stands out because it is the only model to significantly feature `Advise`. We arrive at the following model:

Variable	Estimate	σ	t-value	$P(>\|t\|)$
(Intercept)	-5.46	1.86	-2.94	≈ 0
High	0.09	0.02	4.27	≈ 0
Advise	1.76	0.59	2.98	≈ 0
Holiday	2.89	0.59	4.88	≈ 0
ForecastCloudy	-0.62	0.49	-1.29	0.20
ForecastRainy	-1.39	0.59	-2.34	0.02

Table 3: OLS Regression Results for `SUP` With Backward Stepwise Selection

When the state instituted a bacterial advisory (i.e., `Advise=1`), Boating In Boston was asked to limit, "high immersion likelihood" activities which directly restricted its ability to rent paddleboards. We therefore anticipate a statistically significant impact of bacterial advisories on paddleboard rentals as confirmed. The statistically significant coefficient of `ForecastRainy` also confirms our previous results.

3.2 Conclusion

This paper aimed to parse out the effect of perceptions of risk on recreational preferences in boating. Through an analysis of FareHarbor rental information from Boating In Boston at Lake Cochituate, Massachusetts we find, at aggregate, that bacterial advisories did not statistically affect daily boat rentals. These advisories did, however, strongly depress SUP rentals.

We also found at aggregate that daily low temperatures and precipitation were not statistically significant indicators of daily boat rentals. The recorded daily high temperature and a reported rainy or cloudy forecast, on the other hand, were statistically significant indicators, with the latter two features having a negative effect and the former feature a positive one. We interpret this as being consistent with an aversion to perceived risk; moreover, people with credible information of a poor forecast on a given day will preemptively select out of outdoor, water recreation even if the forcecast turns out to be clear. Holidays and weekends were also strong, positive indicators of boat rental traffic.

In the context of hospitality services and outdoor recreation, we find strong evidence that weather is an indicator of rental activity. We therefore recommend that cencessioners have robust plans of action for days with poor forecasts, including limiting scheduled staff or reducing hours. Days with positive indicators — i.e., those that fall on weekends or holidays and have a good forecast — are likely subject Kim and Kang's study of "crowdedness", where high traffic induces movement from one form of recreation to another. Incentivizing this behavior with signage and targeted advertising could increase recreation overall and augment revenue.

References

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